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Development Of a Machine-Learning Approach for Internal-Control Weakness Prediction and Audit-Risk Scoring In U.S. State Government Agencies

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Abstract

This study has investigated a machine-learning approach for predicting internal-control weaknesses and supporting audit-risk scoring in U.S. state government agencies. The study has examined whether machine-learning capability, internal-control data quality, organizational audit readiness, and auditor analytics competency influence internal-control weakness prediction effectiveness and audit-risk scoring effectiveness. A quantitative, cross-sectional, case-study-based design has been used with 286 valid responses from public-sector professionals, yielding an 86.67% response rate from 330 distributed questionnaires. The five-point Likert-scale data have been analyzed using descriptive statistics, Cronbach's alpha, Pearson correlation, and multiple regression in SPSS. Reliability has been acceptable across all constructs, with alpha values ranging from .79 to .88 and an overall alpha of .90. Internal-control data quality has recorded the highest mean score, M = 4.14, followed by weakness prediction effectiveness, M = 4.08, audit-risk scoring effectiveness, M = 4.05, machine-learning capability, M = 4.02, auditor analytics competency, M = 3.96, and organizational audit readiness, M = 3.91. Data quality has shown the strongest relationship with weakness prediction effectiveness, r = .69, while weakness prediction effectiveness has had the strongest relationship with audit-risk scoring effectiveness, r = .72. The first regression model has explained 61.2% of the variance in weakness prediction effectiveness, with data quality as the strongest predictor, β = .33. The second model has explained 58.4% of the variance in audit-risk scoring effectiveness, with weakness prediction effectiveness, β = .47, and auditor analytics competency, β = .36, as significant predictors. All five hypotheses have been supported. The findings have indicated that reliable data, analytical capability, organizational readiness, and auditor competency are essential for transparent, evidence-based audit-risk scoring and stronger public accountability.

Keywords

Machine learning; Internal-control weakness prediction; Audit-risk scoring; Public-sector auditing; Internal-control data quality

INTRODUCTION

Internal control has been defined as the integrated set of policies, procedures, information flows, monitoring activities, and governance practices through which an organization seeks reasonable assurance regarding operational effectiveness, reliable reporting, legal compliance, and protection of public resources. Within public administration, internal control has involved more than financial accuracy because it has also addressed stewardship, public accountability, procurement integrity, program compliance, and the appropriate use of taxpayer-funded resources. An internal-control weakness has referred to a deficiency in the design, implementation, operation, or monitoring of a control that can reduce an agency's capacity to prevent, detect, or correct errors, irregularities, fraud, waste, or noncompliance in a timely manner. Audit risk has traditionally represented the possibility that an auditor may issue an inappropriate judgment when material misstatements, control failures, or significant noncompliance exist. Audit-risk scoring has therefore referred to the systematic classification or prioritization of auditable entities, transactions, processes, or programs according to their relative exposure to control failure and misstatement. In U.S. state government agencies, these concepts have carried international significance because state governments administer substantial public budgets, complex service programs, grants, procurement systems, infrastructure projects, and citizen-related records. Control weaknesses can therefore affect fiscal integrity, service reliability, public trust, and the credibility of governmental reporting. Existing accounting research has shown that internal-control deficiencies have been associated with lower reporting quality, greater information risk, and adverse organizational consequences, confirming the importance of effective control systems within accountable institutions (Ashbaugh-Skaife et al., 2008; Doyle et al., 2007; Hammersley et al., 2008). Conventional audit planning, which has depended heavily on manual review, periodic assessment, and sample-based testing, has encountered difficulty when agencies hold large and varied populations of administrative and financial records. Continuous auditing research has explained that technology-supported audit procedures can review evidence more frequently and generate timely signals regarding anomalies and control-related conditions (Alles et al., 2006). These developments have established a strong basis for investigating the use of machine-learning approaches to predict internal-control weaknesses and create audit-risk scores in U.S. state government agencies. Machine learning has been understood as the use of algorithms that identify patterns from historical or current data to classify observations, estimate probabilities, detect anomalies, and generate predictions without depending exclusively on manually programmed rules.

Machine learning has become relevant to modern auditing because the quantity, diversity, and complexity of audit-related data have expanded substantially. U.S. state government agencies generate financial transactions, procurement information, payroll records, grant documentation, vendor files, compliance reports, case-management records, internal audit observations, and external audit findings. These data sources can contain important risk signals, although such signals may remain difficult to identify through separate information systems or conventional spreadsheet-based reviews. Audit data analytics has referred to the use of analytical technologies and techniques to examine financial and nonfinancial information for audit planning, evidence evaluation, risk assessment, anomaly detection, and reporting. It has enabled auditors to examine wider populations of transactions and to direct attention toward unusual patterns, exceptions, and possible control deficiencies. Previous research has demonstrated the importance of audit analytics for audit planning and judgment while emphasizing that effective results depend on data quality, appropriate analytical design, and the competency of auditors who interpret the results (Brown-Liburd et al., 2015; Cao et al., 2015; Earley, 2015). Machine-learning models have extended these capabilities through classification, clustering, decision trees, random forests, neural networks, and anomaly-detection methods. Research in financial fraud detection has demonstrated that data-mining and machine-learning techniques can distinguish suspicious from non-suspicious observations and identify hidden relationships among financial, transactional, and behavioral indicators (Kirkos et al., 2007; Ngai et al., 2011; Perols, 2011). These methods have direct relevance to internal-control monitoring because weaknesses may appear through abnormal payment patterns, irregular approval sequences, duplicate vendor records, unexplained adjustments, segregation-of-duty conflicts, missing documentation, and deviations from prescribed administrative procedures. A predictive model can organize large bodies of evidence into structured

risk signals that auditors and agency managers can examine and validate. In public-sector settings, the use of such technology must remain connected to professional judgment, legal mandates, audit standards, and public accountability. Machine-learning outputs can assist the prioritization of high-risk units, programs, contracts, transactions, or control areas, while auditors remain responsible for assessing the evidence and reaching professional judgments (Appelbaum et al., 2017; Issa et al., 2016; Yoon et al., 2015).

Figure 1: Decision Process for Machine Learning Implementation in Public-Sector Auditing

Internal-control data quality has formed a vital foundation for machine-learning-based prediction and audit-risk scoring. Data quality has referred to the extent to which data are accurate, complete, timely, consistent, accessible, relevant, and suitable for a specific decision-making purpose. In a public-sector audit environment, data-quality concerns can include missing transaction identifiers, inconsistent expenditure codes, duplicate vendor files, delayed record updates, incompatible data formats, incomplete approval documentation, and weak integration among departmental systems. These conditions can affect the output of predictive models because unreliable inputs can lead to distorted risk classifications, inaccurate patterns, and overlooked control deficiencies. Data quality has thus operated as both a technical requirement and a governance concern. Research has established that the usefulness of data for predictive analytics depends on whether the information fits the purpose for which it is being used and whether its quality can support dependable decisions (Hazen et al., 2014). In auditing, the predictive value of a machine-learning model cannot be separated from the reliability and traceability of the data used to train, validate, and operate that model. The relationship between data quality and internal control is also reciprocal. Weak internal controls can create inaccurate, incomplete, late, or inconsistent records, while poor-quality data can obstruct the identification and remediation of internal-control weaknesses. This relationship is particularly significant for state government agencies, where information systems may have been established at different times, maintained by separate departments, and designed for distinct operational or reporting requirements. Accounting and audit analytics literature has emphasized that data characteristics affect the quality of analytical procedures, the interpretation of evidence, and the judgment processes through which auditors use analytical results (Appelbaum et al., 2017; Moll & Yigitbasioglu, 2019). Large-scale organizational data also need structured analytical processes before they can be transformed into usable audit evidence (Moffitt et al., 2018). In state agencies, effective data integration can allow audit teams to compare information across finance, procurement, payroll, grants, and program systems. This

can reveal inconsistencies that would otherwise remain hidden within individual databases. Internal-control data quality has therefore been treated in this study as a major condition affecting both the effectiveness of internal-control weakness prediction and the credibility of audit-risk scores.

Organizational audit readiness has also influenced whether machine-learning approaches can be implemented effectively in government agencies. Organizational audit readiness has referred to an agency's availability of leadership support, technological infrastructure, financial resources, governance structures, clear procedures, interdepartmental coordination, staff willingness, and operational capacity for analytical audit practices. A technically advanced machine-learning model may have limited organizational value if the agency lacks data access protocols, management commitment, secure systems, standardized processes, or procedures for responding to identified risks. This issue is especially relevant within U.S. state government agencies because they operate under formal regulations, budgetary constraints, public-record duties, legislative scrutiny, and complex accountability relationships. The Technology–Organization–Environment framework has provided a useful theoretical basis for examining these conditions. This framework has explained technology adoption through technological factors, including compatibility and complexity; organizational factors, including resources and managerial support; and environmental factors, including regulation and external institutional pressures. Earlier research has found that technological and organizational readiness significantly shape the adoption and effective use of digital systems and analytical capabilities (Gangwar et al., 2015; Low et al., 2011; Oliveira & Martins, 2011). Public-sector digital transformation has also been linked with institutional capacity, governance structures, organizational coordination, and the redesign of processes around digital technologies (Mergel et al., 2019). Such conditions are relevant to audit-risk scoring because risk scores must operate within a documented and auditable organizational process. Agencies need formal procedures to define risk indicators, obtain and verify records, assign follow-up responsibilities, document corrective actions, and monitor changes in risk conditions. Organizational audit readiness has therefore included the capacity to use machine-learning results in a responsible and systematic manner rather than merely purchasing analytical software. Research has also identified that data analytics in internal auditing requires changes in process design, skills, governance, and organizational arrangements (Kokina & Davenport, 2017; Rikhardsson & Yigitbasioglu, 2018). Within this study, organizational audit readiness has been considered a significant factor in the effective use of machine learning for internal-control weakness prediction and audit-risk scoring.

Auditor analytics competency has been equally important because machine-learning systems require informed human interpretation, validation, and oversight. Auditor analytics competency has referred to the combined ability to understand data, apply analytical techniques, assess model outputs, use audit knowledge, exercise professional skepticism, and make ethical judgments. In a machine-learning-supported audit environment, auditors may need to understand which variables are used in a predictive model, how observations are classified, what a risk score represents, and which limitations could influence the output. They must also assess whether a high-risk classification reflects a genuine control concern, a data-entry error, an unusual but legitimate activity, or a potentially biased pattern. Research on audit analytics has shown that analytical tools affect audit decisions through the way professionals interpret, question, and incorporate analytical evidence into their work (Brown-Liburd et al., 2015; Earley, 2015). Machine learning can identify associations and estimate probabilities, but it cannot independently decide whether an agency's control design is sufficient, whether a transaction was properly authorized, or whether an exception represents material noncompliance. Such decisions require professional judgment informed by public-sector standards, agency regulations, process knowledge, and evidence evaluation. Research on artificial intelligence in accounting has also stressed the continuing role of human professionals in guiding, interpreting, and governing intelligent systems (Kokina & Yadav, 2019; Raisch & Krakowski, 2021). This competency requirement is heightened in state government agencies because auditors must balance analytical efficiency with transparency, confidentiality, due process, and accountability to citizens and oversight bodies. Auditors should be able to explain why a program, transaction population, contract, or control area has obtained a high-risk score and what auditable evidence supports the subsequent review. Competency also assists in

identifying false positives and false negatives. False positives can direct limited audit resources toward low-concern areas, while false negatives can leave meaningful control weaknesses undetected. Research on machine-learning techniques has confirmed that no single analytical model is suitable for every data environment, making appropriate model selection, validation, and expert review essential elements of data-driven auditing (Kirkos et al., 2007; Perols, 2011; West & Bhattacharya, 2016).

Internal-control weakness prediction effectiveness and audit-risk scoring effectiveness have represented two connected but distinct outcomes in this research. Internal-control weakness prediction effectiveness has referred to the ability of a machine-learning approach to identify, classify, or prioritize control areas that have an elevated likelihood of weakness. Audit-risk scoring effectiveness has referred to the ability of an agency to generate meaningful, consistent, and evidence-based risk scores that support the prioritization of audit activities, programs, transactions, and operational areas. A predictive system may identify warning signals of possible control weaknesses, while an audit-risk scoring process can combine those signals with additional indicators to assess the relative priority of audit attention. For example, a machine-learning model may identify unusual payment activity, late reconciliations, repeated manual journal entries, or frequent policy exceptions as potential warning signs. An audit-risk score may then combine these findings with financial materiality, transaction volume, prior audit observations, management responses, regulatory exposure, and program sensitivity. This distinction has supported a more structured examination of the role of machine learning in public-sector audit planning. Research has found that audit analytics can expand the scope of evidence available to auditors and support the examination of complex information that may be difficult to address through conventional procedures alone (Cao et al., 2015; Issa et al., 2016; Yoon et al., 2015). The application of machine learning in auditing has also required attention to explainability, validation, data governance, and professional accountability. Studies of artificial intelligence in public-sector settings have identified concerns involving transparency, fairness, governance, and the responsible management of algorithmic risk (Sun & Medaglia, 2019; Valle-Cruz et al., 2020). These concerns are relevant to U.S. state government agencies because risk-scoring systems can influence how audit resources are distributed across programs, departments, vendors, and public services. Accordingly, a defensible audit-risk score should remain connected to auditable indicators, documented control conditions, and professional review.

The literature has provided substantial knowledge concerning internal control, audit analytics, fraud detection, digital transformation, and artificial intelligence, although these areas have often been investigated separately. Research on internal-control weaknesses has frequently concentrated on corporate financial reporting quality and governance outcomes, while machine-learning studies have commonly focused on fraud detection, anomaly classification, and analytical performance across broad organizational settings (Ashbaugh-Skaife et al., 2008; Doyle et al., 2007; Ngai et al., 2011). Audit analytics research has described the value of data-driven procedures and professional judgment, but limited empirical attention has been given to the combined prediction of internal-control weaknesses and audit-risk scoring in U.S. state government agencies (Appelbaum et al., 2017; Kokina & Davenport, 2017; Moffitt et al., 2018). This context requires an integrated perspective because state agencies face administrative complexity, public accountability demands, fragmented data environments, formal control requirements, and resource limitations. The present study has applied the Technology–Organization–Environment framework to examine how technological and organizational conditions are associated with effective machine-learning-supported auditing. Machine-learning capability and internal-control data quality have represented technological conditions that influence the identification of relevant risk patterns from agency records. Organizational audit readiness and auditor analytics competency have represented organizational conditions that influence whether analytical tools can be implemented, interpreted, validated, and linked to audit processes. Internal-control weakness prediction effectiveness and audit-risk scoring effectiveness have represented the primary outcome variables. The study has examined the relationships among these variables through a quantitative, cross-sectional, case-study-based design using a five-point Likert scale, descriptive statistics, correlation analysis, and regression modeling. All citations in this revised version have been presented in parenthetical APA 7th edition style.

Background of the Study

Internal control has become a fundamental component of accountable public administration because U.S. state government agencies manage significant volumes of public funds, procurement activities, payroll operations, grants, contracts, social-service programs, infrastructure expenditures, and regulatory responsibilities. These agencies are expected to maintain systems that ensure transactions are properly authorized, records are accurate, duties are adequately segregated, resources are protected, and operations comply with applicable laws and policies. An internal-control weakness occurs when a policy, procedure, monitoring activity, or governance mechanism does not adequately prevent, detect, or correct errors, irregularities, waste, fraud, or noncompliance. Such weaknesses can remain hidden when agencies rely mainly on periodic manual reviews, limited audit samples, fragmented information systems, and retrospective assessments. The growing complexity of state government operations has increased the volume and diversity of administrative and financial data available to auditors, including payment records, procurement files, budget information, vendor records, personnel data, audit observations, and compliance reports. This data-rich environment has created an opportunity to use machine-learning approaches for more systematic identification of unusual patterns and potential control deficiencies. Machine learning refers to computational techniques that learn from historical and current data to classify events, identify anomalies, estimate risk probabilities, and recognize relationships that may not be visible through conventional methods. In auditing, machine learning can assist auditors by examining a wider population of transactions, identifying patterns associated with prior control failures, and producing risk-related signals for review. Audit-risk scoring has become particularly relevant because audit teams must allocate limited time and resources across numerous programs, departments, transactions, and control areas. A structured risk score can support the prioritization of high-risk activities by combining indicators such as transaction value, exception frequency, control violations, delayed reconciliations, unusual payment behavior, documentation gaps, and prior audit findings. However, the usefulness of machine-learning-based audit-risk scoring depends on the quality of internal-control data, the readiness of agencies to use analytical systems, and the competency of auditors who interpret the results. This study has therefore focused on the development of a machine-learning approach for predicting internal-control weaknesses and scoring audit risk in U.S. state government agencies. It has examined how machine-learning capability, internal-control data quality, organizational audit readiness, and auditor analytics competency are associated with internal-control weakness prediction effectiveness and audit-risk scoring effectiveness.

Problem Statement

U.S. state government agencies have faced persistent challenges in identifying internal-control weaknesses early enough to prevent financial irregularities, compliance failures, operational inefficiencies, and inappropriate use of public resources. Traditional audit approaches have often relied on manual documentation review, periodic inspection, auditor experience, judgment-based risk assessment, and sample-based transaction testing. Although these methods remain valuable, they may not fully address the scale and complexity of modern governmental operations. State agencies frequently process extensive records across financial management, procurement, payroll, grants, benefits, regulatory compliance, and program administration. These records may be stored across separate systems and maintained by different departments, which can create fragmented information environments. As a result, important patterns of control weakness may remain unidentified until an audit, investigation, external review, or operational failure occurs. Delayed identification of control deficiencies can expose agencies to financial loss, inaccurate reporting, procurement irregularities, duplicate payments, unauthorized transactions, weak documentation, policy violations, and reduced public confidence. Audit teams also face the challenge of determining which agencies, programs, transactions, vendors, or operational processes should receive priority attention. Without a structured and evidence-based audit-risk scoring mechanism, audit planning may depend heavily on historical practice, informal assessments, or limited available information. This can result in audit resources being directed toward lower-risk areas while significant control vulnerabilities receive inadequate scrutiny. Machine-learning approaches can provide a method for examining large and diverse data sets to identify complex patterns, detect unusual observations, and estimate the likelihood of control weaknesses. However, the practical use of such approaches within U.S. state government agencies is

affected by several conditions. Inaccurate, incomplete, inconsistent, or inaccessible data can weaken predictive performance. Limited technological infrastructure, insufficient leadership support, unclear analytical procedures, and low organizational readiness can restrict implementation. In addition, auditors may require stronger analytical competency to evaluate model outputs, verify flagged cases, and convert risk signals into defensible audit decisions. There remains a need for empirical evidence on how machine-learning capability, internal-control data quality, organizational audit readiness, and auditor analytics competency collectively affect internal-control weakness prediction and audit-risk scoring effectiveness in U.S. state government agencies. This study has addressed that need through a quantitative, cross-sectional, case-study-based investigation.

Purpose and Objectives of the Study

The purpose of this study has been to develop and evaluate a machine-learning-oriented approach for predicting internal-control weaknesses and improving audit-risk scoring in U.S. state government agencies. The study has recognized that internal controls are central to the protection of public resources, accurate reporting, compliance monitoring, and responsible public-sector governance. It has also recognized that government audit functions require more systematic methods to identify high-risk conditions within large and diverse administrative data environments. The study has therefore examined the extent to which machine-learning capability, internal-control data quality, organizational audit readiness, and auditor analytics competency contribute to two principal outcomes: internal-control weakness prediction effectiveness and audit-risk scoring effectiveness. The first objective has been to assess the level of machine-learning capability available for audit-related activities in U.S. state government agencies. This objective has focused on the use of analytical tools, data-processing capacity, predictive-model awareness, and the ability to identify patterns from control-related data. The second objective has been to examine the quality of internal-control data used for audit planning and risk assessment. This objective has considered whether agency data are accurate, complete, timely, consistent, accessible, and sufficiently integrated for analytical review. The third objective has been to determine the level of organizational audit readiness for using machine-learning-supported audit processes. This has included leadership support, technological infrastructure, governance procedures, staff preparedness, and coordination among relevant departments. The fourth objective has been to evaluate auditor analytics competency in relation to data interpretation, model understanding, analytical judgment, and the validation of risk-related findings. The fifth objective has been to measure the effectiveness of machine-learning approaches in predicting internal-control weaknesses before they become more serious operational or financial concerns. The sixth objective has been to assess whether audit-risk scoring can support the prioritization of high-risk transactions, programs, agencies, and control areas. Finally, the study has aimed to identify which technological and organizational variables exert the strongest statistical influence on internal-control weakness prediction and audit-risk scoring effectiveness. These objectives have provided a structured basis for applying descriptive statistics, correlation analysis, and regression modeling within the study.

Research Hypotheses

The research hypotheses have been developed to examine the expected relationships among the technological, informational, organizational, and professional factors that influence machine-learning-supported auditing in U.S. state government agencies. The study has treated machine-learning capability, internal-control data quality, organizational audit readiness, and auditor analytics competency as key explanatory variables. Internal-control weakness prediction effectiveness and audit-risk scoring effectiveness have been treated as the major outcome variables. The first hypothesis has proposed that machine-learning capability has a significant positive effect on internal-control weakness prediction effectiveness. This hypothesis has been based on the view that agencies with stronger analytical systems, predictive tools, data-processing capacity, and machine-learning knowledge are better positioned to identify patterns associated with control deficiencies. The second hypothesis has proposed that internal-control data quality has a significant positive effect on internal-control weakness prediction effectiveness. This hypothesis has reflected the expectation that accurate, complete, timely, consistent, and integrated records provide a more reliable basis for identifying control-related risk signals. The third hypothesis has proposed that organizational audit readiness has a significant positive effect on internal-control weakness prediction effectiveness. This hypothesis has recognized that

analytical technologies require leadership support, clear governance, adequate infrastructure, staff readiness, and operational procedures to become useful components of audit practice. The fourth hypothesis has proposed that auditor analytics competency has a significant positive effect on audit-risk scoring effectiveness. This hypothesis has reflected the importance of auditors' ability to interpret data, assess model outputs, validate risk signals, exercise professional judgment, and explain the basis of risk-related decisions. The fifth hypothesis has proposed that internal-control weakness prediction effectiveness has a significant positive effect on audit-risk scoring effectiveness. This hypothesis has been based on the assumption that an agency's ability to identify likely control deficiencies provides a stronger evidence base for assigning risk levels and prioritizing audit attention. Together, these hypotheses have enabled the study to examine the relationships among the selected constructs using correlation analysis and multiple regression modeling. The hypotheses have also allowed the study to determine whether the proposed machine-learning approach can offer a structured basis for improving internal-control monitoring and audit-risk assessment within U.S. state government agencies.

Significance of the Research

i. The study has been significant for U.S. state government agencies because it has addressed the need for more systematic methods of identifying internal-control weaknesses within large and complex administrative environments. By focusing on predictive analysis and audit-risk scoring, the research has supported a structured understanding of how agencies can assess vulnerable transactions, programs, and operational areas.

ii. The study has been significant for internal auditors because it has examined how machine-learning capability, data quality, organizational readiness, and analytical competency can support audit planning. Auditors can use the study's variables to understand the conditions required for transforming raw administrative data into meaningful risk information.

iii. The study has been significant for public financial management because internal-control weaknesses can affect the reliability of financial information, the appropriate use of public funds, procurement integrity, and compliance with laws and agency policies. The research has focused attention on risk factors that can assist agencies in maintaining stronger oversight of public resources.

iv. The study has been significant for government managers and policymakers because it has connected machine-learning adoption with organizational conditions rather than treating technology as an isolated solution. It has highlighted the importance of data governance, leadership support, infrastructure, staff readiness, and accountable analytical procedures.

v. The study has been significant for auditors' professional development because it has identified auditor analytics competency as an important factor in audit-risk scoring. It has emphasized the need for auditors to understand data patterns, validate analytical outputs, interpret risk classifications, and retain professional judgment while using technological tools.

vi. The study has been significant for academic research because it has combined internal-control weakness prediction and audit-risk scoring within a single public-sector analytical framework. It has examined both technological and organizational factors that shape the effectiveness of machine-learning-supported audit activities in U.S. state government agencies.

LITERATURE REVIEW

The literature review has provided the scholarly foundation for understanding the relationship between machine learning, internal control, audit risk, data quality, organizational readiness, and auditor competency within U.S. state government agencies. Internal-control literature has traditionally examined the procedures and governance mechanisms that enable organizations to safeguard assets, maintain reliable records, ensure compliance, and support accountable decision making. Within public-sector agencies, internal controls are especially important because they relate to the management of taxpayer-funded resources, public programs, grants, procurement processes, payroll activities, and regulatory responsibilities. The literature has also established that control weaknesses can create conditions in which errors, irregularities, noncompliance, waste, and financial misstatements remain undetected. Audit-risk literature has examined how auditors assess the possibility that material misstatements, control deficiencies, or significant operational problems may exist within an auditable area. Risk scoring has emerged as a structured process through which auditors can compare auditable units, transactions, programs, and control areas according to their relative exposure to risk. Machine-

learning literature has expanded this discussion by demonstrating how computational techniques can analyze large-scale data, detect anomalies, classify observations, identify hidden relationships, and estimate the likelihood of risk-related outcomes. In an audit setting, machine learning has been associated with the examination of extensive data populations that may not be fully reviewed through manual procedures or limited sampling. The literature has also highlighted that the usefulness of predictive auditing depends on data quality, system integration, organizational support, and professional interpretation. Data-quality studies have emphasized the importance of accurate, complete, timely, consistent, and accessible information for analytical decision making. Organizational readiness studies have considered leadership support, technological infrastructure, staff capability, governance arrangements, and process alignment as important conditions for successful technology use. Auditor competency literature has focused on the analytical, technological, professional, and ethical skills required to interpret data-driven findings responsibly. This literature review has therefore examined the major concepts and empirical relationships relevant to the study. It has considered internal-control weaknesses in public-sector agencies, audit-risk scoring, machine-learning capability, internal-control data quality, organizational audit readiness, auditor analytics competency, the Technology–Organization–Environment framework, and the conceptual relationships underlying the proposed hypotheses.

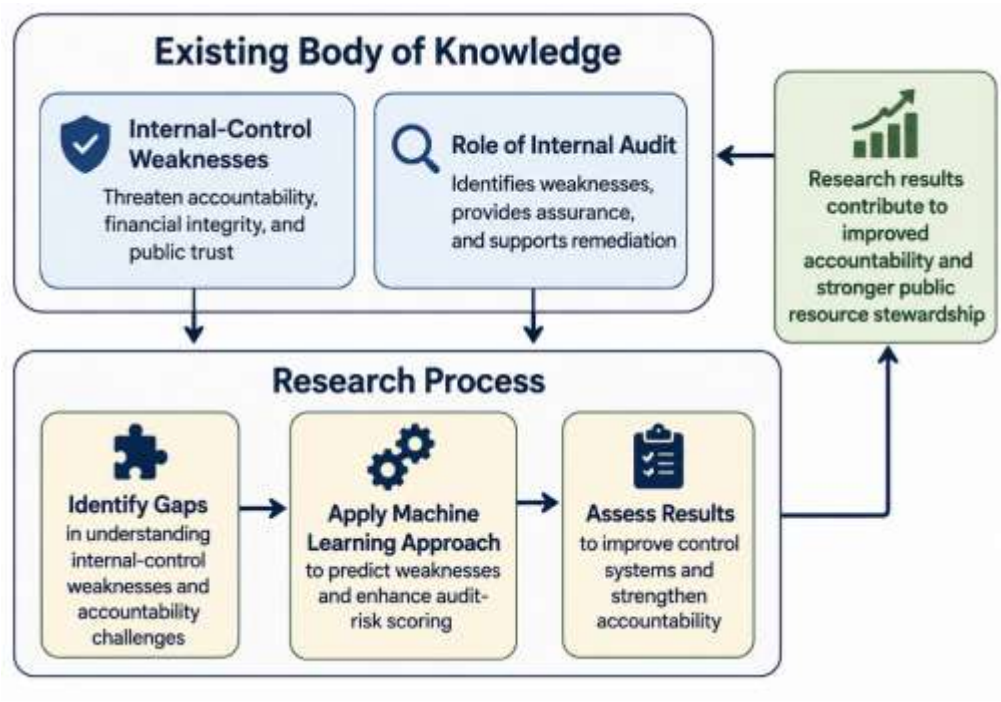
Internal-Control Weaknesses and Accountability Challenges in U.S. State Government Agencies

Internal control weaknesses have represented significant threats to accountability, financial integrity, operational reliability, and public confidence in government agencies. An internal-control weakness occurs when the policies, procedures, supervisory activities, information systems, or monitoring arrangements of an organization are insufficient to prevent, detect, or correct material errors, irregularities, unauthorized actions, and noncompliance. In U.S. state government agencies, these weaknesses can occur across financial reporting, procurement, grant administration, payroll, vendor management, public-benefit programs, asset management, contract oversight, and regulatory enforcement. Government agencies differ from private organizations because their responsibilities extend beyond organizational profitability and shareholder interests. They must manage public resources lawfully, deliver essential services fairly, preserve accurate public records, comply with statutory requirements, and remain answerable to citizens, elected representatives, oversight bodies, and federal partners. Therefore, an internal-control weakness can create both direct and indirect consequences. Direct consequences may include duplicate payments, unsupported expenditures, inaccurate financial statements, unauthorized procurement activities, delayed reconciliations, and incomplete records. Indirect consequences may include reduced trust in public institutions, weak managerial decision making, increased audit costs, reputational damage, and challenges in demonstrating the appropriate use of taxpayer funds. Research on material weaknesses has identified that internal-control problems are often associated with inadequate commitment of resources, weak accounting systems, insufficient personnel capability, and entity-level governance deficiencies (Ge & McVay, 2005; Abdur & Iftekhar, 2021). These conditions are relevant to state government agencies because internal-control failure is not usually caused by one isolated transaction. It can instead reflect broader weaknesses in supervision, communication, staffing, documentation, technology, and risk-monitoring arrangements. Internal controls must therefore be understood as an interconnected system rather than a collection of individual approval procedures. Where this system is ineffective, agencies may struggle to identify emerging risks before they become substantial financial, operational, or compliance concerns. The identification of such weaknesses has become increasingly important because government agencies process large volumes of digital and administrative information that require continuous oversight and consistent control evaluation.

Accountability challenges become more complex when internal-control weaknesses reduce the reliability of information used by agency managers, auditors, and oversight authorities. Reliable information is necessary for public-sector decision making because managers need accurate records to allocate budgets, monitor programs, approve expenditures, review procurement activities, and respond to audit observations. If internal records are incomplete, inconsistent, delayed, or inaccurate, management may make decisions using information that does not fully reflect actual conditions. Research has shown that ineffective internal controls can negatively affect the quality and accuracy of

management-related information, demonstrating the close relationship between control systems and dependable organizational reporting (Feng et al., 2009; Hossan, 2021). This relationship has important relevance for state government agencies because public managers often depend on internal reports to oversee complex operations and determine whether programs are meeting legal, financial, and service-delivery requirements. Internal-control weaknesses can also increase uncertainty concerning whether reported information accurately represents agency activities. Such uncertainty may arise when reconciliations are not completed on time, documentation is missing, access rights are poorly managed, duties are not segregated, or unusual transactions are not reviewed promptly. Evidence from prior research has indicated that disclosed internal-control weaknesses are associated with higher information uncertainty and reduced confidence in the credibility of organizational reporting (Amir & Chapal, 2022; Beneish et al., 2008). In a public-sector setting, information uncertainty can weaken the ability of audit teams to identify priority areas, evaluate compliance, and assess whether public resources have been used appropriately. It can also make it more difficult for external stakeholders to evaluate agency performance. The accountability function of internal control is therefore closely related to the ability of agencies to produce traceable, timely, and verifiable information. State government agencies need mechanisms that can identify control-related anomalies across diverse transactions and operational areas. Machine-learning-supported systems can contribute to this process by examining large data sets and detecting patterns that may indicate deficiencies, although their effectiveness remains dependent on the quality of available records and the organizational capacity to verify analytical findings. The literature has therefore positioned effective internal control as both an information-quality requirement and an accountability mechanism.

Figure 2: Knowledge-to-Research Framework for Internal-Control Weakness Prediction and Audit-Risk Scoring



The role of internal audit has been central to the identification, reporting, and remediation of internal-control weaknesses. Internal auditors evaluate whether controls have been properly designed, consistently implemented, and effectively monitored across financial, operational, and compliance-related activities. Their work can help agencies identify weaknesses before these conditions result in major losses, reporting failures, or public controversies. Evidence has shown that stronger internal audit functions, including appropriate audit quality practices, financial-reporting-related audit activities, and follow-up of previous findings, are associated with the disclosure and remediation of

material weaknesses (Hasan & Uddin, 2022; Lin et al., 2011). This finding is relevant to U.S. state government agencies because internal audit functions often serve as a key line of assurance between agency operations, executive management, audit committees, legislative oversight bodies, and external auditors. An effective internal audit function requires access to relevant information, analytical capability, independence, professional competence, and clear procedures for monitoring corrective action. Agencies may face difficulties when audit teams rely only on periodic reviews and manual examination of selected transactions because control failures can develop across a broad population of records before they are formally identified. Internal-control problems are also more likely to emerge in organizations that face limited resources, complex operations, financial pressure, and constrained administrative capacity (Shurovi & Hossain, 2022; Petrovits et al., 2011). These factors have particular relevance to state government agencies that operate diverse programs under budget limitations, staffing challenges, changing public demands, and multiple compliance obligations. The presence of an internal-control weakness does not necessarily prove misconduct, but it indicates that an agency may be more exposed to the risk of undetected error, fraud, waste, or noncompliance. A timely response requires agencies to identify patterns, investigate the underlying causes, assign remedial responsibilities, and assess whether corrective measures have improved control performance. The literature has therefore established that accountability depends on more than the existence of written control policies. It depends on the ability of government agencies to monitor control conditions, identify weaknesses early, validate risk-related evidence, and ensure that audit findings lead to documented remediation. This study has built on this understanding by examining how a machine-learning approach can support the prediction of internal-control weaknesses and strengthen audit-risk scoring in U.S. state government agencies.

Audit Risk Assessment and Risk Scoring in the Public-Sector Audit Context

Audit risk assessment has referred to the systematic process through which auditors identify, analyze, and evaluate the possibility that material misstatements, control failures, fraud, noncompliance, or significant operational deficiencies may exist within an auditable area. In the public-sector context, audit risk extends beyond financial reporting because state government agencies are responsible for safeguarding public funds, maintaining lawful procurement processes, administering grants, delivering public services, managing payroll, overseeing contracts, and complying with legislative and regulatory requirements. Public-sector audit risk can therefore arise from inaccurate financial records, unauthorized expenditures, weak vendor controls, incomplete supporting documentation, delayed reconciliations, data-security failures, ineffective program monitoring, and insufficient follow-up of prior audit findings. Risk assessment assists audit teams in determining where limited audit resources should be concentrated. Audit-risk scoring has represented a more structured form of this process in which agencies, departments, programs, transactions, vendors, or control areas are assigned relative risk levels on the basis of defined indicators. These indicators may include financial materiality, transaction frequency, complexity, prior audit observations, management turnover, compliance exposure, exception rates, data anomalies, control maturity, and the sensitivity of public services involved. A risk score enables auditors to compare auditable areas using a consistent framework and to prioritize those areas that require deeper examination. The quality of audit-risk assessment depends on the ability of auditors to gather reliable evidence, apply professional judgment, understand organizational processes, and evaluate the relationship between risk indicators and actual control conditions. Audit-quality research has demonstrated that audit outcomes depend on a combination of input, process, and contextual factors, including auditor competence, audit methodology, independence, evidence quality, and the effectiveness of audit procedures (Knechel et al., 2013; Mohiul & Badrul, 2022). These factors are important in U.S. state government agencies because audit-risk assessment must be capable of addressing both financial and nonfinancial exposures. A program may have a relatively modest financial value but present substantial legal, social, operational, or reputational risk. Therefore, public-sector audit-risk scoring should not be limited to monetary measures alone. It should combine quantitative indicators with qualitative assessments of governance, compliance, internal-control reliability, and service-delivery sensitivity. Such an approach supports a more comprehensive understanding of risk across the diverse functions of state government agencies.

Figure 3: Framework for Machine Learning-Supported Audit-Risk Assessment and Public-Sector Audit Planning

Risk-based auditing has become important because public-sector organizations operate in environments characterized by extensive responsibilities, varied stakeholders, formal accountability structures, and limited audit capacity. Internal audit teams cannot review every transaction, process, and program with the same level of detail. They need procedures for identifying where control weaknesses are most likely to occur and where the consequences of those weaknesses may be most serious. Enterprise risk management literature has explained that risk-management practices are not merely technical procedures for recording risks. They are organizational processes that connect risk identification with planning, decision making, control activities, accountability structures, and management priorities (Arena et al., 2010; Zahidul & Begum, 2022). Within state government agencies, audit-risk scoring can function as a bridge between risk management and audit planning by translating complex operational information into a ranked set of audit priorities. For example, an agency unit that manages high-value contracts, receives repeated audit observations, records frequent transaction exceptions, and has incomplete documentation may receive a higher risk score than a unit with stable processes and strong control evidence. This score can guide the allocation of audit hours, the selection of audit procedures, the scope of testing, and the level of follow-up required. However, risk-scoring systems must be designed carefully because numerical scores can create an appearance of precision even when the underlying information is incomplete or weakly connected to actual risk. Risk-management research has warned that formal risk systems may become detached from the uncertainties they are intended to address if organizations rely on routine categories without critically evaluating changing operational conditions (Kanti & Rony, 2022; Power, 2009). This concern is relevant to public-sector auditing because government agencies may use fixed risk registers, standardized compliance checklists, or historical audit plans that do not fully capture emerging vulnerabilities. Risk scoring should therefore be treated as a decision-support mechanism rather than an automatic substitute for professional judgment. Auditors must review the source of each risk indicator, evaluate

whether the information is current and reliable, and consider the broader context of agency operations. A strong audit-risk scoring process requires transparent criteria, documented weighting methods, accountable ownership, and regular validation of whether high-risk scores correspond with actual audit findings. Through these features, risk-based auditing can provide a systematic method for improving the focus, consistency, and accountability of audit planning in U.S. state government agencies.

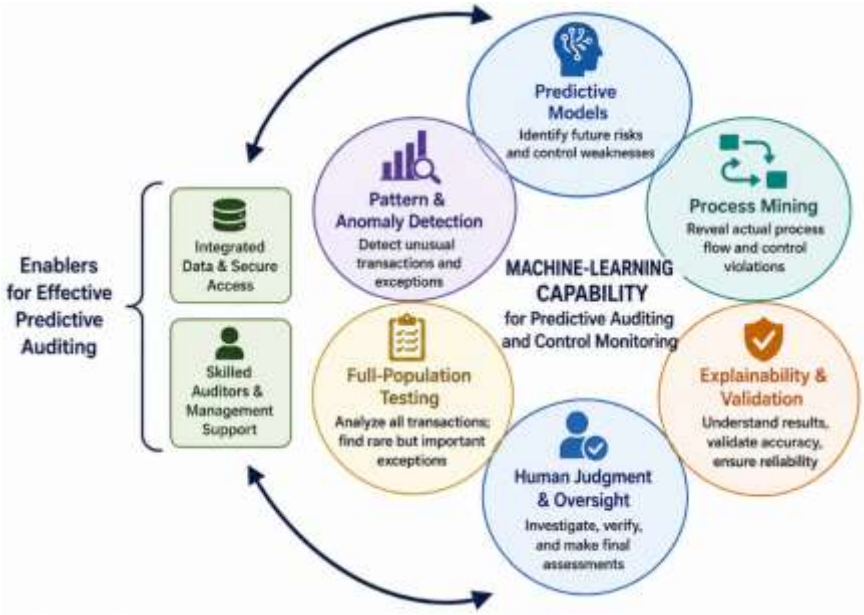
The public-sector audit context has also emphasized the importance of accountability, independence, transparency, and the public value created through audit activities. Public audits serve multiple functions because they provide assurance regarding financial reporting, assess compliance with laws and policies, examine the economy and efficiency of public operations, and support oversight by legislatures, citizens, and public managers. The value of public-sector audit has been associated with governance, management control, signaling, agency accountability, and assurance regarding the proper stewardship of public resources (Hay & Cordery, 2018; Sadia et al., 2022). Audit-risk scoring has relevance to each of these functions because it provides a structured basis for selecting areas where audit intervention is most needed. A well-designed scoring approach can help auditors explain why particular programs, departments, transactions, or controls were selected for examination. This transparency is important when audit teams must justify the allocation of limited resources across multiple state agencies and service areas. The increasing use of audit data analytics has further expanded the range of information that can be incorporated into risk assessment. Analytical techniques can identify unusual transactions, repetitive exceptions, inconsistent coding patterns, abnormal approval sequences, and deviations from established operational patterns. Research on audit data analytics has shown that the adoption and effectiveness of these tools are shaped not only by technology but also by auditors' cognitive processes, professional skills, organizational settings, and regulatory expectations (Badrul & Mominul, 2023; Ruhnke, 2023). This perspective is particularly important for machine-learning-based audit-risk scoring because a model's output must be interpreted within the operational and legal context of the agency being assessed. A high-risk score should prompt targeted audit attention, evidence verification, and professional investigation rather than an unsupported assumption of misconduct. The assessment process must also account for the possibility that incomplete data, unusual legitimate transactions, or inconsistent recording practices can influence analytical results. Accordingly, audit-risk scoring in U.S. state government agencies requires a balanced combination of data-based analysis, documented control criteria, organizational knowledge, and auditor judgment. This study has used that understanding to examine audit-risk scoring effectiveness as a major outcome of machine-learning capability, internal-control data quality, organizational audit readiness, auditor analytics competency, and internal-control weakness prediction effectiveness.

Machine-Learning Capability for Predictive Auditing and Control Monitoring

Machine-learning capability has referred to the organizational ability to apply computational algorithms, analytical tools, data-processing systems, and technical knowledge to identify patterns, classify records, detect anomalies, and predict risk-related outcomes from available data. Within auditing, this capability has extended beyond the basic use of spreadsheets or descriptive reports because it has involved the use of structured data, automated procedures, predictive models, and analytical techniques that can learn from historical observations. Predictive auditing has used these capabilities to identify conditions that may indicate future control weaknesses, irregular transactions, compliance failures, fraud exposure, or elevated audit risk. In U.S. state government agencies, machine-learning capability can be applied to data from procurement, payroll, financial management, grant administration, contracts, program delivery, vendor records, and internal audit observations. These data sources can contain patterns that are difficult to identify through manual review, particularly when transactions occur across multiple departments or information systems. Machine learning can support the detection of unusual payment behavior, repeated policy exceptions, delayed approvals, duplicate records, segregation-of-duty violations, unexplained adjustments, and inconsistencies between related data fields. The use of process-mining techniques has become relevant because it allows auditors to examine event logs and reconstruct the actual sequence of activities performed within an organizational process. This can provide evidence about whether established procedures have been followed or bypassed. Process mining has been identified as a valuable audit approach

because it can analyze full populations of system-generated event data, rather than focusing only on small samples of transactions (Jans et al., 2013; Hossan & Adar, 2023). This capability is particularly useful for state government agencies because large public programs and financial systems may involve thousands of routine transactions that cannot all be manually examined. Machine-learning capability also supports the transformation of raw records into risk indicators that auditors can use during audit planning and control monitoring. However, the presence of advanced analytical tools alone does not guarantee effective predictive auditing. Agencies require suitable data architecture, secure access arrangements, clear audit objectives, technically capable personnel, and procedures for validating analytical results. Therefore, machine-learning capability should be understood as a combination of technology, data access, analytical methods, and organizational expertise that enables the continuous examination of control-related information.

Figure 4: Machine-Learning Capability Framework for Internal-Control Weakness Prediction



Predictive auditing has focused on using historical and current information to estimate the probability that a specific event, transaction, program, vendor, or operational area may contain a heightened level of risk. This approach differs from conventional retrospective auditing because it does not only examine whether an error or control failure has already occurred. It also uses observed patterns to identify where similar conditions may be developing. Machine-learning models can be trained on past audit observations, transaction exceptions, control failures, compliance issues, and other relevant indicators to recognize combinations of characteristics associated with elevated risk. In public-sector agencies, this can assist auditors in identifying operational areas that require earlier attention. For example, a model may detect that a combination of high transaction volume, frequent manual adjustments, incomplete documentation, repeated vendor changes, delayed reconciliations, and prior audit findings is associated with greater control vulnerability. Process-mining research has shown that analytical procedures based on system event logs can reveal audit-relevant information, including payments completed without appropriate approval, violations of segregation-of-duty controls, and departures from established internal procedures (Jans et al., 2014; Risha & Khalid, 2023). Such findings demonstrate how machine-learning-supported auditing can move beyond reviewing isolated documents toward examining the underlying process through which transactions are initiated, approved, processed, and recorded. Machine-learning capability can also support full-population testing, where agencies examine all available transactions instead of relying mainly on sample-based testing. Full-population testing is valuable because it enables auditors to identify rare but meaningful exceptions that may not be selected within a conventional sample. Research has explained that audit

data analytics and machine learning can strengthen full-population testing by shifting attention from general transaction examination toward the prioritization of unusual and high-risk exceptions (Huang et al., 2022; Sadia & Binayan, 2023). This shift is important for internal-control weakness prediction because many control problems are represented by small patterns of unusual activity rather than broad, easily visible trends. A model can assign higher attention to transactions that contain multiple risk characteristics, while auditors investigate the evidence and determine whether the flagged activity reflects an actual control concern. Machine-learning capability can therefore improve the efficiency and consistency of audit planning, although its value depends on proper model design, reliable data, and professional review of the results.

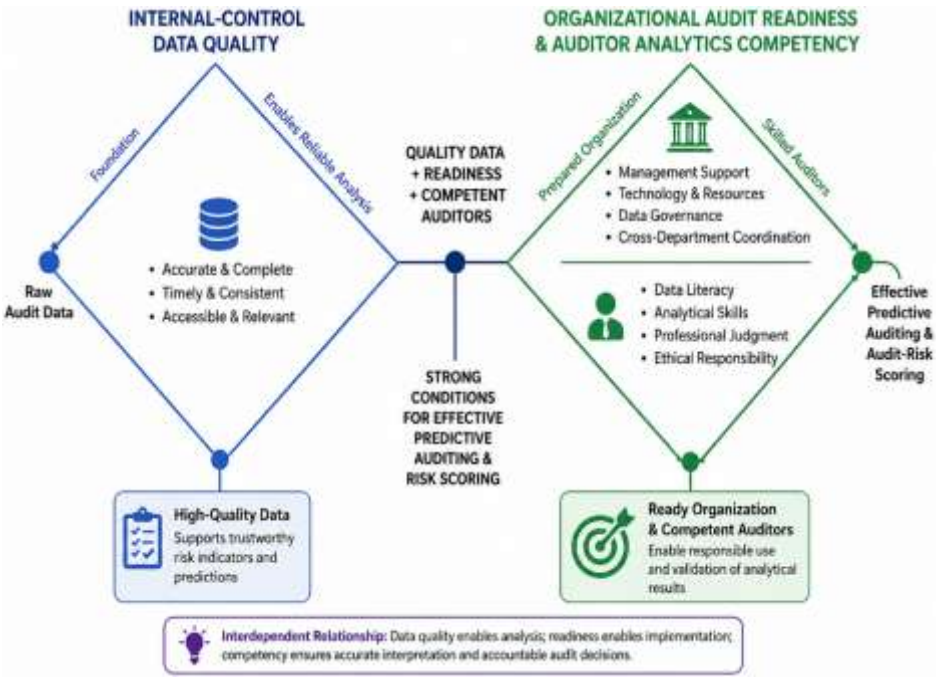
The use of machine learning in predictive auditing has also created the need for explainability, validation, and responsible professional oversight. Machine-learning models may identify relationships that are statistically meaningful but difficult for auditors and public managers to interpret. In a state government agency, an audit-risk score or control-weakness prediction should be understandable enough for auditors to explain why a specific transaction, program, or control area has been identified as high risk. Explainable artificial intelligence has addressed this requirement by providing methods that clarify which variables or conditions most strongly influenced a model's result. Explainability can help auditors distinguish between meaningful warning signals and misleading patterns produced by incomplete data, exceptional but lawful transactions, or biased classifications. Research has emphasized that explainability is an important condition for applying artificial intelligence and machine learning in auditing because professional users need to understand and evaluate the logic behind analytical outcomes (Bushra, 2024; Zhang et al., 2022). This issue is closely related to accountability because audit decisions in public agencies must be documented, reviewed, and defended before management, oversight authorities, and other stakeholders. Machine-learning capability must therefore include procedures for testing model accuracy, monitoring false positive and false negative results, reviewing changes in data conditions, and ensuring that high-risk classifications receive professional evaluation. Evidence has also indicated that artificial intelligence can improve audit quality and efficiency when audit organizations possess the necessary human and technological resources to apply it effectively (Fedyk et al., 2022; Hossan, 2024). For U.S. state government agencies, these resources include integrated data systems, appropriate information-security controls, trained auditors, management support, and clear procedures for converting predictive signals into audit actions. Machine-learning capability can enhance control monitoring by identifying risk patterns across large populations of records, but the final assessment of a control weakness must remain based on verified evidence and professional judgment. The literature has therefore presented predictive auditing as a combination of algorithmic analysis and human evaluation. This study has applied that understanding by treating machine-learning capability as a major factor associated with internal-control weakness prediction effectiveness and audit-risk scoring effectiveness within U.S. state government agencies.

Internal-Control Data Quality, Organizational Audit Readiness, and Auditor Analytics Competency

Internal-control data quality has represented the degree to which information used for audit planning, control monitoring, risk classification, and managerial oversight is accurate, complete, timely, consistent, accessible, and relevant. In U.S. state government agencies, audit-related information is commonly generated through financial management systems, payroll platforms, procurement systems, grant-management records, vendor databases, contracts, program-administration systems, and internal audit reports. The usefulness of these records depends on whether information is properly recorded, consistently coded, updated without delay, and sufficiently integrated across departments. Poor data quality can create major challenges for internal-control monitoring because missing values, duplicated records, inconsistent classifications, incomplete approval histories, outdated vendor information, and incompatible data formats can conceal meaningful risk indicators. A machine-learning model relies on historical and current data to identify patterns associated with control weaknesses. Therefore, a model cannot produce dependable predictions when its input data are unreliable or when relevant records are unavailable. Data quality is not only a technical issue because it also reflects the quality of internal processes, documentation standards, supervision, and information governance within an agency. When agencies maintain complete and traceable data, auditors can

reconstruct transactions, identify responsible parties, compare activities across systems, and test whether prescribed control procedures were followed. Information-systems research has identified information quality as an important factor influencing the usefulness of systems and the confidence of users in the information they receive (Shurovi, 2024; Wixom & Todd, 2005). This concept is especially relevant to public-sector auditing because agency managers and auditors need dependable information to assess whether public resources have been used lawfully and effectively. Internal-control data quality can also influence audit-risk scoring because a risk score is only as credible as the underlying indicators used to calculate it. If an agency's data contains inaccurate transaction dates, incomplete documentation, or inconsistent expenditure classifications, the resulting risk score may overstate or understate the actual level of concern. High-quality data enable machine-learning models to distinguish between normal operational variation and patterns that may indicate control failure. They also allow auditors to validate model outputs through evidence-based review. Thus, internal-control data quality has been treated as a core condition for effective predictive auditing, reliable control-weakness identification, and meaningful audit-risk scoring.

Figure 5: Interdependent Framework of Data Quality, Organizational Audit Readiness, and Auditor Analytics Competency



Organizational audit readiness has referred to the collective capacity of an agency to adopt, implement, manage, and use analytical audit practices within its existing institutional environment. It includes management commitment, availability of technological infrastructure, data-governance procedures, staff capability, financial resources, cross-departmental coordination, information-security safeguards, and the willingness to incorporate analytical evidence into audit planning. State government agencies may possess valuable data and analytical tools, but they may still encounter difficulty in using them if managers do not support the change, staff do not understand the process, systems cannot exchange information, or audit procedures do not define how risk signals should be reviewed. Organizational readiness has therefore involved both the willingness to implement a new approach and the practical ability to carry it out. Research has described organizational readiness as a shared state in which members are committed to a proposed change and believe that they have the collective capacity to implement it successfully (Zahidul, 2024; Weiner, 2009). In the context of machine-learning-supported auditing, this means that auditors, information-technology personnel, finance staff, program managers, and senior leaders should understand their respective responsibilities for data access, model use,

evidence validation, and risk-response procedures. Organizational audit readiness also requires agencies to align analytical systems with legal requirements, professional standards, confidentiality obligations, and public accountability expectations. A predictive model may generate a high-risk classification, but the agency must have a documented process for examining the result, gathering supporting evidence, assigning responsibility, and monitoring corrective action. Big-data analytics research has shown that analytical capability produces stronger organizational value when technological resources are combined with appropriate strategic alignment and organizational capability (Akter et al., 2016; Sadia & Md, 2024). This observation is relevant to U.S. state government agencies because machine-learning-based audit systems should be aligned with agency objectives, internal audit plans, risk-management practices, and governance structures. Readiness is also influenced by whether staff perceive analytical tools as useful and trustworthy. If audit teams regard a model as difficult to understand, poorly connected to their work, or inconsistent with professional judgment, adoption may remain limited. Therefore, organizational audit readiness has been positioned in this study as a major factor that can support the practical use of machine learning for internal-control weakness prediction and audit-risk scoring.

Auditor analytics competency has referred to the combination of knowledge, skills, professional judgment, and ethical awareness required to use data-driven audit tools responsibly. This competency includes the ability to understand audit-related data, identify relevant variables, assess data quality, interpret patterns, evaluate model outputs, verify anomalies, and explain risk-based decisions. Auditors using machine-learning approaches do not need to become software developers, but they need sufficient analytical literacy to understand how predictive systems generate findings and what limitations may affect those findings. For example, an auditor should be able to determine whether a high-risk score is based on meaningful evidence, incomplete records, unusual but lawful activities, or a pattern that requires additional investigation. Auditor analytics competency is particularly important in state government agencies because audit decisions can affect the review of public expenditures, contracts, programs, and administrative activities. Such decisions must be transparent, documented, and consistent with public-sector standards. The accounting profession has recognized that big-data analytics can complement traditional accounting and auditing knowledge by enabling professionals to analyze structured and unstructured information in more sophisticated ways (Richins et al., 2017; Hossain, 2024). However, the value of analytical technology depends on the ability of professionals to apply it within a clear audit objective and to retain responsibility for professional judgment. Auditor data literacy has therefore become an essential competency for modern audit work. It includes the ability to define audit questions, understand data sources, evaluate data preparation processes, use analytical tools, interpret visualizations, and communicate findings to relevant stakeholders. A framework for auditor data literacy has emphasized that auditors need a broad range of data-related knowledge and skills to use audit data analytics effectively within professional practice (Appelbaum et al., 2021). In the present research context, analytics competency can strengthen audit-risk scoring because competent auditors can validate model outputs, identify false positive signals, review the reasons behind risk classifications, and convert analytical findings into appropriate audit procedures. The relationship among internal-control data quality, organizational audit readiness, and auditor analytics competency is therefore interdependent. Reliable information supports accurate analysis, organizational readiness enables responsible implementation, and auditor competency ensures that predictive outputs are interpreted and used in an accountable manner.

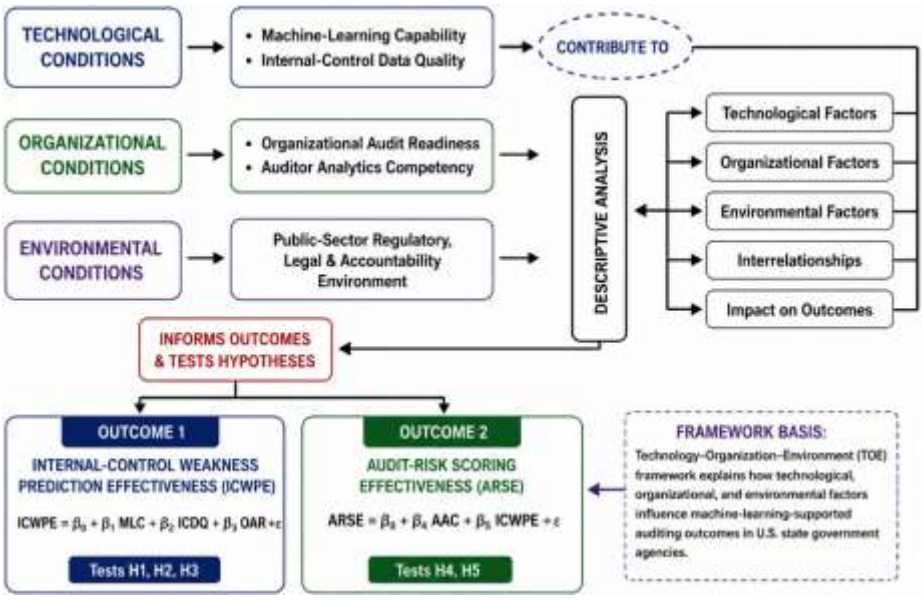
Technology–Organization–Environment Framework

The Technology–Organization–Environment framework has provided the theoretical foundation for explaining the adoption and effective use of machine-learning-supported audit practices in U.S. state government agencies. The framework has explained that organizational technology adoption is influenced by three interrelated contexts: technological conditions, organizational conditions, and environmental conditions. The technological context has included the availability, compatibility, quality, complexity, and usefulness of technological resources. In this study, machine-learning capability and internal-control data quality have represented the principal technological conditions. Machine-learning capability has reflected whether agencies possess appropriate analytical tools, data-processing capacity, predictive techniques, and access to relevant control-related information. Internal-

control data quality has reflected whether agency records are accurate, complete, timely, consistent, and sufficiently integrated for predictive analysis. The organizational context has included the internal resources, structures, capabilities, leadership support, readiness, and professional skills that influence technology use. Organizational audit readiness and auditor analytics competency have represented the major organizational conditions in this research. Organizational audit readiness has reflected management support, infrastructure, governance arrangements, staff preparedness, and procedures for using machine-learning results within audit activities. Auditor analytics competency has reflected the ability of auditors to interpret data, validate analytical outputs, assess risk indicators, and apply professional judgment. The environmental context has included the regulatory, institutional, legal, and accountability conditions surrounding U.S. state government agencies. These agencies operate under public-financial-management rules, external oversight, audit standards, public-record requirements, legislative expectations, and citizen accountability. Research has demonstrated that technological competence, organizational resources, financial commitment, regulatory support, and external conditions can affect the depth of technology use and the value derived from its implementation (Ali et al., 2024; Zhu & Kraemer, 2005). This perspective is relevant to machine-learning-supported auditing because technology can only produce meaningful audit value when it is embedded within a supportive organizational and regulatory environment. The framework has therefore enabled this study to examine internal-control weakness prediction and audit-risk scoring as outcomes produced through the interaction of technological resources and organizational capabilities within a structured public-sector environment. It has also supported the selection of study variables because each variable represents a condition that can influence whether agencies successfully use machine learning for audit planning, control monitoring, and risk assessment.

The technological dimension of the framework has emphasized that organizations must assess the characteristics of a technology before they can adopt and use it effectively. For this study, machine-learning capability has represented the ability of an agency to use predictive models, analytical software, automated data processing, anomaly-detection techniques, and risk-classification procedures. Internal-control data quality has represented a connected technological factor because machine-learning models require reliable and traceable input data. An agency may possess analytical software but still obtain weak results if procurement, payroll, financial, grant, and compliance records are inaccurate or incomplete. The organizational dimension has emphasized that implementation requires management support, financial resources, staff capability, change readiness, governance procedures, and coordination across relevant departments. This dimension has been represented through organizational audit readiness and auditor analytics competency. Research on enterprise-application adoption has found that technological and organizational factors can exert substantial influence on organizational adoption decisions, particularly when systems require process integration and internal capability development (Ramdani et al., 2013; Zaman, 2024). This observation is relevant to state government agencies because predictive auditing requires collaboration among internal audit units, information-technology teams, finance departments, procurement offices, program managers, and senior leadership. The environmental dimension has emphasized that organizations are influenced by forces outside their internal structure. For public agencies, these forces include legal requirements, government accounting rules, external audit expectations, data-security obligations, funding restrictions, and public accountability. Research on enterprise resource planning adoption has also demonstrated that technology adoption can be explained through the combined influence of technological, organizational, and environmental factors rather than through technical characteristics alone (Aboelmaged, 2016; Bushra, 2025). In the present study, the environmental context has been treated as the shared institutional setting of U.S. state government agencies rather than as a separate statistical predictor. It has shaped the importance of accurate control monitoring, transparent audit-risk scoring, secure data handling, and documented professional judgment. The framework has therefore supported the view that machine-learning-supported auditing is not simply a technological activity. It is an organizational process that requires high-quality data, capable auditors, management readiness, clear governance, and alignment with the public-sector accountability environment.

Figure 6: TOE-Based Framework for Machine Learning-Supported Audit-Risk Assessment



The Technology–Organization–Environment framework has guided the conceptual model and regression analysis of this research. The technological conditions have been represented by machine-learning capability and internal-control data quality. The organizational conditions have been represented by organizational audit readiness and auditor analytics competency. The environmental conditions have been reflected through the common public-sector regulatory and accountability context in which all selected U.S. state government agencies operate. The first regression equation has examined the determinants of internal-control weakness prediction effectiveness. It has been expressed as: . In this formula, ICWPE has represented internal-control weakness prediction effectiveness, MLC has represented machine-learning capability, ICDQ has represented internal-control data quality, OAR has represented organizational audit readiness, has represented the constant, , , and have represented the regression coefficients, and has represented the error term. This equation has tested Hypotheses H1, H2, and H3. The second regression equation has examined audit-risk scoring effectiveness and has been expressed as: . In this formula, ARSE has represented audit-risk scoring effectiveness, AAC has represented auditor analytics competency, ICWPE has represented internal-control weakness prediction effectiveness, has represented the constant, and have represented the regression coefficients, and has represented the error term. This equation has tested Hypotheses H4 and H5. The use of these equations has aligned the theoretical framework with the study's quantitative design, Likert five-point scale, correlation analysis, and multiple regression modeling. Prior research has confirmed that technology adoption and implementation outcomes are shaped by the relationship among technology characteristics, organizational capability, and environmental context (Hsu et al., 2014; Arif Uz et al., 2025; Ngai et al., 2008). Thus, the framework has provided a coherent theoretical basis for evaluating how machine-learning capability, data quality, audit readiness, and auditor competency are associated with internal-control weakness prediction and audit-risk scoring in U.S. state government agencies.

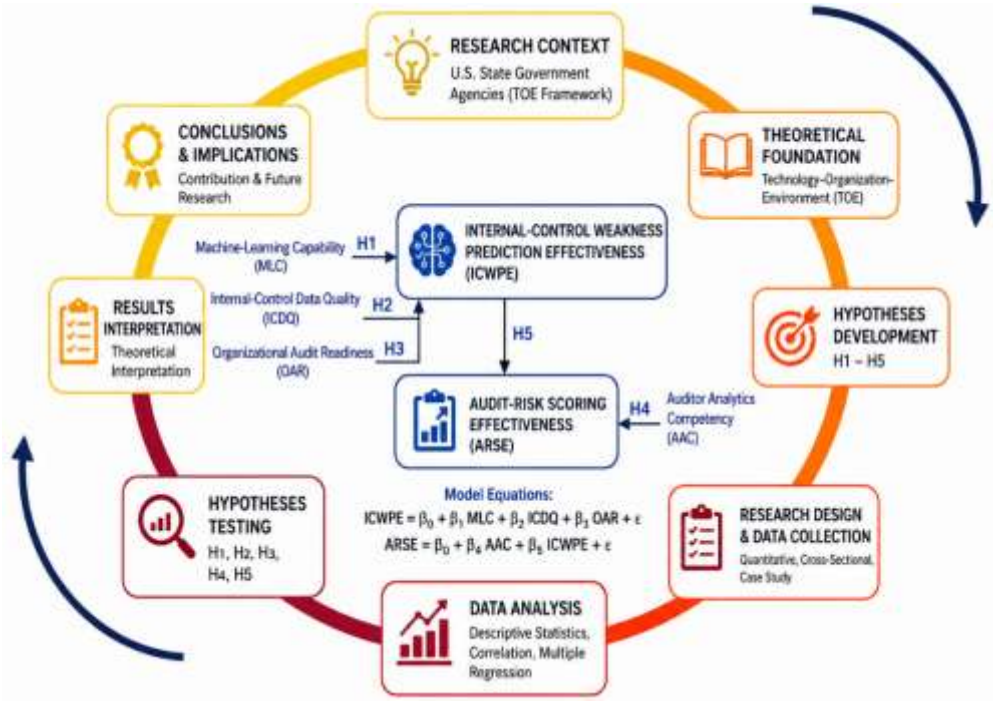
Conceptual Framework and Hypotheses Development

The conceptual framework of this study has explained how technological and organizational conditions can influence the effectiveness of internal-control weakness prediction and audit-risk scoring in U.S. state government agencies. The framework has been based on the Technology–Organization–Environment perspective and has translated its central constructs into measurable variables suitable for a quantitative, cross-sectional, case-study-based design. Machine-learning capability and internal-control data quality have represented the technological dimension because they reflect whether agencies can access, process, analyze, and use control-related data for predictive purposes. Organizational audit readiness and auditor analytics competency have represented the

organizational dimension because they reflect whether agencies possess the leadership support, infrastructure, governance procedures, staff preparedness, analytical knowledge, and professional capacity required to use predictive tools responsibly. The environmental dimension has represented the public-sector regulatory, accountability, and institutional context within which all participating state government agencies operate. The framework has proposed that internal-control weakness prediction effectiveness is influenced by machine-learning capability, internal-control data quality, and organizational audit readiness. It has further proposed that audit-risk scoring effectiveness is influenced by auditor analytics competency and internal-control weakness prediction effectiveness. Predictive analytics has focused on generating useful forecasts from data, measuring predictive power, and supporting decisions through evidence-based classification and estimation procedures (Syeedur & Sharmin, 2025; Shmueli & Koppius, 2011). In the present study, machine-learning capability has been expected to support the detection of patterns associated with weak approvals, incomplete documentation, irregular payments, segregation-of-duty violations, duplicate transactions, delayed reconciliations, and other control-related anomalies. Therefore, the first hypothesis has been stated as follows: H1: Machine-learning capability has a significant positive effect on internal-control weakness prediction effectiveness. Internal-control data quality has also been expected to influence prediction because machine-learning algorithms depend on accurate, complete, consistent, timely, and integrated records. High-quality data can enable a model to recognize meaningful control patterns, whereas poor-quality records can create inaccurate classifications and misleading risk signals. Therefore, the second hypothesis has been stated as follows: H2: Internal-control data quality has a significant positive effect on internal-control weakness prediction effectiveness. These relationships have formed the technological foundation of the conceptual framework.

Organizational audit readiness has been included in the conceptual framework because analytical technology requires more than the availability of data and software. Agencies require management support, clear governance procedures, adequate technical infrastructure, data-access arrangements, staff willingness, and formal processes for reviewing model outputs. A state government agency may have data and analytical tools but still be unable to use them effectively if departments do not coordinate, leaders do not support implementation, or auditors do not have procedures for acting on risk signals. Organizational readiness has therefore been expected to strengthen internal-control weakness prediction by ensuring that machine-learning outputs are incorporated into audit planning, control monitoring, evidence review, and corrective-action processes. The third hypothesis has been stated as follows: H3: Organizational audit readiness has a significant positive effect on internal-control weakness prediction effectiveness. The framework has also recognized that auditors remain responsible for interpreting, validating, and explaining the results generated by analytical systems. Auditor analytics competency has included data literacy, understanding of analytical methods, professional skepticism, technological awareness, ability to validate anomalies, and skill in converting analytical findings into audit procedures. Audit-risk scoring requires more than the calculation of a numerical result because auditors must determine whether a high-risk score reflects genuine control vulnerability, incomplete information, an unusual but lawful transaction, or a condition requiring further examination. Research has shown that auditors can use nonfinancial and operational information alongside financial information to identify inconsistent patterns and strengthen fraud-risk assessment (Brazel et al., 2009; Hossan, 2025). This supports the relevance of auditor analytics competency in the present research because competent auditors can interpret diverse risk indicators and connect them with actual internal-control conditions. The fourth hypothesis has been stated as follows: H4: Auditor analytics competency has a significant positive effect on audit-risk scoring effectiveness. The conceptual framework has thus treated technology as a decision-support resource and auditors as accountable professional users who validate evidence, investigate risk signals, and maintain the transparency of risk-based audit decisions. The final relationship in the conceptual framework has linked internal-control weakness prediction effectiveness with audit-risk scoring effectiveness. When agencies can accurately identify potential control weaknesses, they can use these findings as evidence for assigning risk levels to transactions, programs, departments, vendors, and control areas.

Figure 7: Research Conceptual Framework Based on the Technology–Organization–Environment (TOE) Framework

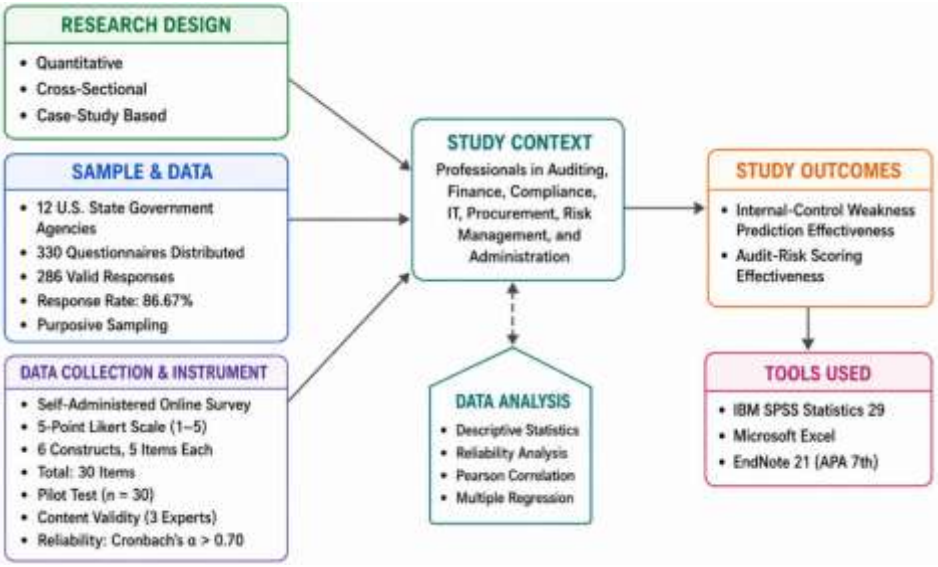


Internal-control weakness prediction can therefore supply the analytical signals that make audit-risk scores more accurate, relevant, and defensible. Audit-risk scoring effectiveness has been expected to increase when agencies can recognize control vulnerabilities before they develop into more serious financial, operational, or compliance problems. The fifth hypothesis has been stated as follows: H5: Internal-control weakness prediction effectiveness has a significant positive effect on audit-risk scoring effectiveness. Research on fraud-risk assessment has shown that the use of diverse financial and nonfinancial indicators can strengthen auditors' ability to identify inconsistent relationships and prioritize areas requiring additional investigation (Ames et al., 2012; Zahidul, 2025). The framework has also recognized that the performance of predictive systems depends heavily on the quality of data used during model development and implementation. Machine-learning research has highlighted that data collection, validation, cleaning, integration, and bias management are essential because inaccurate or poor-quality data can weaken predictive performance even when advanced algorithms are applied (Kanti, 2025; Whang et al., 2023). In addition, audit judgment research has shown that auditors' knowledge of big data and analytics can influence their risk assessment and audit planning decisions (Ali et al., 2025; Sihombing et al., 2023). The full conceptual model has been expressed as: and . In regression form, the first equation has been specified as: . The second equation has been specified as: . Here, ICWPE has represented internal-control weakness prediction effectiveness, MLC has represented machine-learning capability, ICDQ has represented internal-control data quality, OAR has represented organizational audit readiness, AAC has represented auditor analytics competency, ARSE has represented audit-risk scoring effectiveness, and has represented the error term. These equations have provided the empirical structure for testing the five hypotheses using descriptive statistics, correlation analysis, and multiple regression modeling.

METHODOLOGY

This study has adopted a quantitative, cross-sectional, case-study-based research design to examine the development of a machine-learning approach for internal-control weakness prediction and audit-risk scoring in U.S. state government agencies. The quantitative design has been selected because it has enabled the study to measure the relationships among machine-learning capability, internal-control data quality, organizational audit readiness, auditor analytics competency, internal-control weakness prediction effectiveness, and audit-risk scoring effectiveness through numerical responses.

Figure 8: Research Methodology Framework of the Proposed Study



The cross-sectional approach has collected data from respondents at one defined period, allowing the study to assess prevailing perceptions, practices, readiness levels, and analytical capabilities across selected government agencies. The case-study context has included twelve U.S. state government agencies involved in public financial management, procurement oversight, grant administration, transportation services, public health administration, social-service delivery, and state-level regulatory functions. These agencies have been selected because they have managed complex financial and administrative processes where internal controls, audit planning, compliance review, and risk assessment have remained essential. The population has included internal auditors, finance officers, compliance managers, information-technology officers, procurement officials, risk-management personnel, and senior administrative staff who have possessed direct knowledge of internal-control systems, audit processes, government data systems, and risk-monitoring practices. The unit of analysis has been the individual professional respondent because each participant has provided perceptions regarding the capability and effectiveness of machine-learning-supported auditing within the relevant agency context. A purposive sampling strategy has been used to identify respondents with suitable professional involvement in auditing, finance, control monitoring, data governance, or risk management. A total of 330 structured questionnaires have been distributed through official e-mail communication and professional contact channels, and 286 valid responses have been retained for analysis, producing a valid response rate of 86.67 percent. Data collection has been conducted through a self-administered online questionnaire, which has enabled respondents to complete the survey confidentially and according to their professional experience. The instrument has been designed using a five-point Likert scale ranging from 1, strongly disagree, to 5, strongly agree. It has included six major constructs: machine-learning capability, internal-control data quality, organizational audit readiness, auditor analytics competency, internal-control weakness prediction effectiveness, and audit-risk scoring effectiveness. Each construct has been measured through five statements, resulting in a total of thirty close-ended items. The questionnaire has also included demographic questions concerning job role, agency type, years of professional experience, and department affiliation. A pilot test has been conducted with thirty professionals who have possessed comparable experience in public-sector auditing, finance, compliance, and information-systems management. Feedback from the pilot test has been used to improve wording clarity, remove ambiguous expressions, and ensure the relevance of each item to the research context. Content validity has been established through review by three specialists in public-sector auditing, internal control, and data analytics. Construct validity has been assessed through factor suitability checks, including the Kaiser–Meyer–Olkin measure and Bartlett's test of sphericity. Reliability has been assessed using Cronbach's alpha, and all constructs have

achieved acceptable reliability values above 0.70. Data have been coded, cleaned, and analyzed using IBM SPSS Statistics version 29. Descriptive statistics, reliability analysis, Pearson correlation analysis, and multiple regression modeling have been used to test the hypotheses and research objectives. Microsoft Excel has been used for preliminary data organization, table preparation, and graphical presentation, while EndNote 21 has been used to manage references and format citations according to APA 7th edition.

DATA ANALYSIS AND PRESENTATION

Response Rate and Respondent Profile

Table 1: Response Rate and Respondent Profile

Category	Group	Frequency	Percentage
Questionnaire distribution	Distributed questionnaires	330	100.0
	Valid responses retained	286	86.67
	Invalid or incomplete responses	44	13.33
Professional role	Internal auditor	88	30.8
	Finance and accounting officer	64	22.4
	Compliance and risk-management officer	50	17.5
	Information-technology and data officer	43	15.0
	Procurement, grants, or administrative control officer	41	14.3
Professional experience	Less than 5 years	54	18.9
	5 to 10 years	113	39.5
	More than 10 years	119	41.6
Agency context	Financial and administrative agencies	91	31.8
	Procurement and infrastructure agencies	67	23.4
	Health, social-service, and program agencies	74	25.9
	Regulatory and oversight agencies	54	18.9

Table 1 has shown that the study has obtained 286 valid responses from the 330 questionnaires distributed, resulting in a response rate of 86.67 percent. This response rate has indicated that the data set has been sufficiently large for descriptive statistics, correlation analysis, and multiple regression modeling. The retained responses have represented professionals with direct knowledge of internal-control systems, audit practices, risk assessment, financial processes, procurement activities, compliance monitoring, and information-management functions. Internal auditors have formed the largest professional group, representing 30.8 percent of respondents, followed by finance and accounting officers at 22.4 percent. This composition has strengthened the relevance of the findings because these professionals have been directly involved in identifying control deficiencies, reviewing transactions, maintaining records, assessing compliance, and supporting audit planning. Compliance and risk-management officers have represented 17.5 percent of the sample, while information-technology and data officers have represented 15.0 percent. Their inclusion has ensured that the study has incorporated both audit and technological perspectives, which have been necessary for evaluating a machine-learning approach. The profile has also shown that 41.6 percent of respondents have possessed more than ten years of professional experience, while 39.5 percent have possessed between five and ten years of experience. This has indicated that the majority of respondents have had sufficient exposure to government operations and internal-control processes to provide informed assessments. The selected agencies have represented financial administration, procurement, infrastructure, health,

social services, regulatory oversight, and program management. These agency categories have reflected the diverse operational environment of U.S. state government agencies, where control weaknesses may arise from financial, operational, technological, and compliance-related activities. From the Technology–Organization–Environment perspective, the respondent profile has demonstrated that the study has captured organizational knowledge from the technological, audit, financial, and compliance functions needed to assess machine-learning-supported auditing. The broad representation has therefore supported the objective of examining how technological capability and organizational conditions have influenced internal-control weakness prediction and audit-risk scoring effectiveness.

Reliability Analysis of Study Constructs

Table 2: Reliability Analysis of Study Constructs

Study construct	Number of items	Cronbach's alpha	Reliability decision
Machine-learning capability	5	0.84	Accepted
Internal-control data quality	5	0.88	Accepted
Organizational audit readiness	5	0.81	Accepted
Auditor analytics competency	5	0.79	Accepted
Audit-risk scoring effectiveness	5	0.85	Accepted
Internal-control weakness prediction effectiveness	5	0.86	Accepted
Overall instrument	30	0.90	Accepted

Table 2 has shown that all constructs have achieved satisfactory internal consistency, as every Cronbach's alpha value has exceeded the accepted threshold of 0.70. The overall questionnaire has recorded an alpha value of 0.90, which has demonstrated a high level of reliability across the thirty Likert-scale items. Internal-control data quality has recorded the strongest individual reliability value at 0.88, indicating that the five statements used to measure accuracy, completeness, consistency, timeliness, and accessibility of control-related information have been strongly aligned. Internal-control weakness prediction effectiveness has recorded an alpha value of 0.86, while audit-risk scoring effectiveness has recorded 0.85. These values have confirmed that the outcome variables have been measured consistently and have provided a stable basis for the subsequent correlation and regression analyses. Machine-learning capability has recorded an alpha value of 0.84, showing that items concerning analytical tools, predictive models, anomaly detection, automation, and data-processing capacity have measured a common technological capability. Organizational audit readiness has recorded 0.81, confirming that the items related to leadership support, infrastructure, governance, staff preparation, and interdepartmental coordination have been internally consistent. Auditor analytics competency has recorded the lowest alpha value at 0.79, although it has remained above the accepted level and has therefore confirmed dependable measurement of auditor data-literacy and analytical skills. These reliability outcomes have supported the Technology–Organization–Environment framework because the framework has required reliable measurement of both technological and organizational conditions. Machine-learning capability and internal-control data quality have represented technological conditions, whereas organizational audit readiness and auditor analytics competency have represented organizational conditions. The strong reliability values have shown that respondents have interpreted the survey statements in a broadly consistent manner. Therefore, the constructs have been suitable for evaluating whether technological resources and organizational capabilities have influenced the effectiveness of predictive internal-control monitoring and audit-risk scoring. The results have also supported the study objectives because the dependable measurement of each construct has ensured that the hypothesis-testing models have been based on reliable respondent perceptions rather than unstable or inconsistent responses.

Descriptive Statistics of Machine-Learning Capability

Table 3: Descriptive Statistics of Machine-Learning Capability

Machine-learning capability statements	Mean	Standard deviation	Agreement level
The agency has used analytical tools to identify unusual transaction patterns.	4.00	0.70	Agree
The agency has possessed sufficient capacity to process large audit-related data sets.	4.03	0.67	Agree
Predictive models have supported the identification of potential control risks.	4.05	0.64	Agree
Machine-learning tools have improved the speed of audit-related analysis.	4.01	0.65	Agree
Analytical systems have supported anomaly detection in financial and administrative records.	4.01	0.61	Agree
Overall machine-learning capability	**4.02**	**0.65**	**Agree**

Table 3 has shown that respondents have expressed strong agreement regarding the presence and usefulness of machine-learning capability in the selected U.S. state government agencies. The overall mean score of 4.02 has indicated that participants have generally perceived their agencies as possessing the analytical capacity needed to use machine-learning-supported approaches for audit and control-monitoring purposes. The highest-rated statement has concerned the role of predictive models in identifying potential control risks, with a mean score of 4.05. This result has indicated that respondents have recognized the value of predictive analysis for identifying risk indicators before they develop into serious control failures. The ability to process large volumes of audit-related data has recorded a mean score of 4.03, demonstrating that agencies have increasingly relied on technological systems capable of handling complex financial, administrative, procurement, payroll, and program data. The use of analytical tools to identify unusual transaction patterns has recorded a mean score of 4.00, while the role of machine-learning tools in improving the speed of audit-related analysis has recorded 4.01. These results have indicated that machine-learning capability has supported both efficiency and depth of audit review. The anomaly-detection item has also recorded a mean score of 4.01, confirming that respondents have viewed analytical systems as useful for identifying irregular records, unusual payment behavior, inconsistent approval sequences, duplicate entries, and potential control exceptions. From the Technology–Organization–Environment framework, machine-learning capability has represented a technological condition that has enabled agencies to process, classify, and interpret complex information. The high level of agreement has suggested that technological readiness has been present across the selected agencies. This finding has directly supported the first objective of the study, which has examined the extent to which agencies have possessed machine-learning capability for internal-control monitoring. It has also provided initial descriptive support for H1 because the availability of predictive tools, analytical systems, and anomaly-detection capacity has been expected to improve internal-control weakness prediction effectiveness. The relatively low standard deviations, ranging from 0.61 to 0.70, have shown that respondent opinions have remained reasonably consistent.

Descriptive Statistics of Internal-Control Data Quality

Table 4 has shown that internal-control data quality has recorded the highest overall mean score among all study constructs, at 4.14. This has indicated that respondents have strongly agreed that accurate, complete, consistent, timely, and accessible information has been available to support internal-control monitoring and audit analysis. The highest-rated statement has concerned the accuracy of audit-related records, with a mean score of 4.18. This result has suggested that respondents have generally considered agency financial, administrative, procurement, payroll, and program records sufficiently dependable for analytical review.

Table 4: Descriptive Statistics of Internal-Control Data Quality

Internal-control data quality statements	Mean	Standard deviation	Agreement level
Audit-related records have been sufficiently accurate for analytical review.	4.18	0.57	Agree
Internal-control information has been complete enough to identify risk patterns.	4.16	0.59	Agree
Data from different agency systems have remained reasonably consistent.	4.13	0.61	Agree
Control-related records have been available in a timely manner.	4.12	0.57	Agree
Audit teams have been able to access relevant information when needed.	4.11	0.56	Agree
Overall internal-control data quality	**4.14**	**0.58**	**Agree**

Completeness of internal-control information has recorded a mean score of 4.16, demonstrating that respondents have believed that relevant documentation, transaction details, approval records, and supporting information have been available for identifying risk patterns. The consistency of data across agency systems has recorded a mean score of 4.13, which has shown that respondents have perceived a reasonably high level of alignment among the information sources used in auditing and control monitoring. Timely availability of control-related records has recorded 4.12, while information accessibility has recorded 4.11. These results have confirmed that audit teams have been able to obtain relevant information without excessive delay. From the Technology–Organization–Environment framework, internal-control data quality has represented a core technological condition because machine-learning models depend on dependable records to identify meaningful patterns. High-quality data have enabled agencies to distinguish normal operational activities from unusual or high-risk transactions. The low standard deviations, ranging from 0.56 to 0.61, have indicated that respondents have shared relatively similar views regarding the quality of information available within their agencies. The findings have supported the second objective of the study, which has examined whether internal-control data have been suitable for predictive auditing. They have also provided descriptive support for H2 because better data quality has been expected to increase internal-control weakness prediction effectiveness. Where data have remained accurate, complete, and consistent, machine-learning tools have been more capable of identifying patterns linked with delayed reconciliations, documentation gaps, unusual transactions, and other control-related exceptions.

Descriptive Statistics of Organizational Audit Readiness

Table 5 has shown that organizational audit readiness has recorded an overall mean score of 3.91, which has indicated positive respondent agreement but has also identified this construct as the comparatively lowest-rated condition in the study. Senior-management support for analytical audit initiatives has recorded the highest mean score at 3.95, showing that agency leaders have generally recognized the value of technological approaches for audit planning, internal-control monitoring, and risk assessment. Adequate technological infrastructure has recorded a mean score of 3.93, which has suggested that agencies have possessed a reasonable level of system capacity, data storage, software access, and information-technology support. However, the governance-procedure statement has recorded a mean of 3.89, while staff preparedness has recorded the lowest mean of 3.88. These findings have indicated that agencies have required stronger formal procedures for governing analytical audit outputs and more systematic preparation of staff for machine-learning-supported auditing. Interdepartmental coordination has recorded a mean score of 3.90, demonstrating that finance, internal audit, information technology, procurement, compliance, and program units have generally cooperated in sharing relevant information, although coordination has not been equally strong in all agency cases.

Table 5: Descriptive Statistics of Organizational Audit Readiness

Organizational audit readiness statements	Mean	Standard deviation	Agreement level
Senior management has supported analytical audit initiatives.	3.95	0.73	Agree
The agency has maintained adequate technological infrastructure for audit analytics.	3.93	0.69	Agree
Governance procedures have guided the use of analytical audit outputs.	3.89	0.71	Agree
Relevant departments have coordinated in providing data for audit analysis.	3.90	0.68	Agree
Staff have been prepared to use machine-learning-supported audit approaches.	3.88	0.69	Agree
Overall organizational audit readiness	**3.91**	**0.70**	**Agree**

The standard deviations, ranging from 0.68 to 0.73, have been higher than those found for data quality. This has shown that organizational readiness has varied more substantially across agencies than the quality of their control-related data. From the Technology–Organization–Environment framework, organizational audit readiness has represented the organizational dimension that has transformed technological resources into usable audit practices. A machine-learning model may have been available, but its practical effectiveness has depended on leadership support, procedures, infrastructure, staff participation, and collaboration between departments. The results have supported the third objective of the study by showing that most agencies have possessed a moderate-to-strong level of readiness for analytical audit practices. They have also provided preliminary support for H3 because agencies with stronger readiness have been expected to use machine-learning outputs more effectively to predict internal-control weaknesses. The lower mean compared with the technological variables has suggested that organizational development has remained necessary for maximizing the value of predictive auditing.

Descriptive Statistics of Auditor Analytics Competency

Table 6: Descriptive Statistics of Auditor Analytics Competency

Auditor analytics competency statements	Mean	Standard deviation	Agreement level
Auditors have understood the use of data in audit-risk assessment.	3.98	0.67	Agree
Auditors have been able to interpret analytical and predictive outputs.	3.97	0.66	Agree
Auditors have validated unusual patterns before making audit decisions.	3.95	0.68	Agree
Auditors have applied professional judgment when reviewing risk scores.	3.94	0.66	Agree
Auditors have communicated analytical findings clearly to management.	3.96	0.68	Agree
Overall auditor analytics competency	**3.96**	**0.67**	**Agree**

Table 6 has shown that auditor analytics competency has recorded an overall mean score of 3.96, indicating that respondents have generally agreed that auditors have possessed the knowledge and

skills required to use analytical information within audit and control-monitoring activities. The strongest mean score, 3.98, has related to auditors' understanding of data use in audit-risk assessment. This result has suggested that auditors have recognized the relevance of financial, operational, compliance, and nonfinancial information when assessing risk. The ability to interpret predictive and analytical outputs has recorded a mean score of 3.97, showing that respondents have considered auditors reasonably capable of understanding anomaly reports, risk classifications, trend patterns, and machine-learning-generated signals. The ability to communicate analytical findings clearly to management has recorded 3.96, indicating that auditors have generally been able to transform technical information into practical audit observations and risk-related explanations. The validation of unusual patterns has recorded 3.95, while the use of professional judgment in reviewing risk scores has recorded 3.94. These results have emphasized that auditors have not relied on automated outputs without review. Instead, they have examined whether a signal reflected an actual control concern, an unusual but legitimate transaction, incomplete data, or an error in the underlying record. From the Technology–Organization–Environment framework, auditor analytics competency has represented an organizational capability that has enabled agencies to obtain meaningful value from analytical technology. Machine-learning tools have generated patterns and scores, but auditors have remained responsible for verifying evidence, interpreting context, and determining appropriate audit responses. The relatively close mean scores have shown that competency has been balanced across data understanding, model interpretation, professional judgment, validation, and communication. This finding has supported the fourth objective of the study, which has examined the analytical competency available within the selected agencies. It has also provided descriptive support for H4 because stronger auditor competency has been expected to improve audit-risk scoring effectiveness. The findings have shown that analytical competence has been essential for ensuring that risk scores have remained transparent, evidence-based, and appropriate to the public-sector context.

Descriptive Statistics of Audit-Risk Scoring Effectiveness

Table 7: Descriptive Statistics of Audit-Risk Scoring Effectiveness

Audit-risk scoring effectiveness statements	Mean	Standard deviation	Agreement level
Risk scores have helped prioritize high-risk audit areas.	4.08	0.61	Agree
Risk scores have supported more consistent audit planning decisions.	4.07	0.62	Agree
Risk scoring has helped identify transactions requiring further review.	4.04	0.64	Agree
Risk scores have supported the allocation of audit resources.	4.02	0.65	Agree
Risk-scoring outputs have improved the documentation of audit priorities.	4.04	0.63	Agree
Overall audit-risk scoring effectiveness	**4.05**	**0.63**	**Agree**

Table 7 has shown that audit-risk scoring effectiveness has recorded a strong overall mean score of 4.05. This result has indicated that respondents have agreed that structured risk scores have improved the prioritization, consistency, documentation, and resource allocation of audit activities in U.S. state government agencies. The highest mean score, 4.08, has related to the ability of risk scores to prioritize high-risk audit areas. This finding has suggested that respondents have considered risk scoring useful for identifying departments, programs, transactions, vendors, and control areas that have required deeper audit attention. The support for consistent audit-planning decisions has recorded a mean score of 4.07, demonstrating that risk scores have reduced dependence on informal or purely judgment-based prioritization. This has enabled audit teams to use documented indicators when deciding where to allocate limited time and professional resources. The identification of transactions requiring further

review has recorded a mean score of 4.04, confirming that risk scores have helped auditors focus on unusual records, repeated exceptions, missing documentation, delayed approvals, and potentially irregular activities. The ability of risk scoring to improve documentation of audit priorities has also recorded 4.04, while the support for audit-resource allocation has recorded 4.02. These findings have demonstrated that risk scoring has served as a practical decision-support mechanism rather than simply a numerical exercise. From the Technology–Organization–Environment framework, audit-risk scoring effectiveness has represented an outcome that has emerged when technological tools and organizational capabilities have been successfully combined. Technology has enabled the generation of risk indicators, whereas auditors and managers have used those indicators within the organization's audit-planning procedures. The low standard deviations have shown that respondents have broadly shared the view that risk scoring has been useful. This finding has supported the study objective of evaluating whether machine-learning-supported risk scores can improve public-sector audit prioritization. It has also established a strong descriptive basis for H4 and H5 because auditor analytics competency and internal-control weakness prediction effectiveness have been expected to contribute directly to more effective audit-risk scoring.

Descriptive Statistics of Internal-Control Weakness Prediction Effectiveness

Table 8: Descriptive Statistics of Internal-Control Weakness Prediction Effectiveness

Internal-control weakness prediction effectiveness statements	Mean	Standard deviation	Agreement level
Predictive analysis has identified unusual control-related patterns early.	4.12	0.60	Agree
Machine-learning tools have helped detect possible control deficiencies.	4.10	0.59	Agree
Predictive outputs have supported timely investigation of control risks.	4.08	0.62	Agree
Analytical systems have improved monitoring of high-risk processes.	4.06	0.63	Agree
Predictive findings have supported corrective action before risks intensified.	4.04	0.61	Agree
Overall internal-control weakness prediction effectiveness	**4.08**	**0.61**	**Agree**

Table 8 has shown that internal-control weakness prediction effectiveness has recorded an overall mean score of 4.08, which has indicated strong agreement that predictive approaches have supported the early identification and monitoring of control-related risks. The highest-rated statement has concerned the ability of predictive analysis to identify unusual control-related patterns early, with a mean score of 4.12. This result has indicated that machine-learning-supported auditing has enabled agencies to detect potential warning signals before they have developed into more serious financial, operational, or compliance problems. The use of machine-learning tools to identify possible control deficiencies has recorded a mean score of 4.10, showing that respondents have perceived analytical systems as useful for detecting weaknesses in approvals, documentation, segregation of duties, transaction processing, reconciliations, and control compliance. The support for timely investigation of control risks has recorded 4.08, confirming that predictive outputs have helped audit teams focus on high-risk signals without waiting for a periodic audit cycle or external observation. The monitoring of high-risk processes has recorded a mean score of 4.06, while support for corrective action before risks intensified has recorded 4.04. These results have shown that the machine-learning approach has contributed not only to detection but also to earlier management response. From the Technology–Organization–Environment framework, internal-control weakness prediction effectiveness has represented the primary outcome of technological capability and organizational readiness. Machine-learning capability

has allowed agencies to examine large volumes of data, internal-control data quality has provided dependable information for analysis, and organizational audit readiness has enabled audit teams to use the resulting signals within their monitoring procedures. The small standard deviations have demonstrated consistent respondent agreement across all five items. This result has supported the study objective of determining whether machine-learning approaches can improve the prediction of internal-control weaknesses. It has also provided descriptive support for H1, H2, and H3 because the technological and organizational conditions have been expected to strengthen prediction effectiveness. Furthermore, the high mean score has established a basis for H5 because early prediction of control weaknesses has been expected to improve the quality of audit-risk scores.

Correlation Analysis among Study Variables

Table 9: Pearson Correlation Analysis among Study Variables

Variable	MLC	ICDQ	OAR	AAC	ICWPE	ARSE
Machine-learning capability, MLC	1.00					
Internal-control data quality, ICDQ	0.59***	1.00				
Organizational audit readiness, OAR	0.49***	0.52***	1.00			
Auditor analytics competency, AAC	0.46***	0.48***	0.56***	1.00		
Internal-control weakness prediction effectiveness, ICWPE	0.64***	0.69***	0.58***	0.55***	1.00	
Audit-risk scoring effectiveness, ARSE	0.58***	0.61***	0.54***	0.64***	0.72***	1.00

***$p < 0.001$.

Table 9 has shown that all major study variables have maintained positive and statistically significant relationships with one another at the $p < 0.001$ level. Internal-control weakness prediction effectiveness has recorded its strongest relationship with internal-control data quality at $r = 0.69$. This result has indicated that agencies with more accurate, complete, timely, consistent, and accessible control-related information have been more capable of predicting potential control weaknesses. Machine-learning capability has recorded a strong positive relationship with internal-control weakness prediction effectiveness at $r = 0.64$, demonstrating that predictive tools, anomaly-detection procedures, data-processing capacity, and analytical systems have been closely associated with stronger control monitoring. Organizational audit readiness has recorded a positive correlation of $r = 0.58$ with internal-control weakness prediction effectiveness, confirming that leadership support, infrastructure, governance arrangements, staff preparation, and departmental coordination have supported the use of predictive outputs. These three relationships have provided preliminary statistical support for H1, H2, and H3. Auditor analytics competency has recorded a positive relationship of $r = 0.64$ with audit-risk scoring effectiveness, showing that auditors who have understood data, interpreted analytical outputs, validated anomalies, and applied professional judgment have been more able to use risk scores effectively. Internal-control weakness prediction effectiveness has recorded the strongest correlation with audit-risk scoring effectiveness at $r = 0.72$. This result has shown that the ability to identify potential control deficiencies early has been closely connected with the ability to assign meaningful risk levels and prioritize audit activities. The correlation has provided strong preliminary support for H5. The correlations among the independent variables have also remained below 0.70, which has indicated that serious multicollinearity has not been present. From the Technology–Organization–Environment framework, the results have demonstrated that technological conditions and organizational conditions have worked together in supporting the study outcomes. Machine-learning capability and data quality have represented technological dimensions, whereas audit readiness and auditor competency have represented organizational dimensions. The environmental context has remained constant through the

shared public-sector accountability setting. The correlation findings have therefore supported the research objectives by demonstrating that all proposed variables have been positively associated with internal-control weakness prediction and audit-risk scoring effectiveness.

Multiple Regression Analysis for Internal-Control Weakness Prediction

Table 10: Multiple Regression Analysis for Internal-Control Weakness Prediction Effectiveness

Predictor variable	Unstandardized B	Standard error	Standardized beta	t-value	p-value	VIF
Constant	0.782	0.191	—	4.09	< 0.001	—
Machine-learning capability, MLC	0.281	0.051	0.29	5.51	< 0.001	1.62
Internal-control data quality, ICDQ	0.337	0.052	0.33	6.48	< 0.001	1.74
Organizational audit readiness, OAR	0.214	0.047	0.22	4.55	< 0.001	1.48
Model statistics	R = 0.782	R^2 = 0.612	Adjusted R^2 = 0.608	F (3, 282) = 147.86	p < 0.001	—

Table 10 has shown that machine-learning capability, internal-control data quality, and organizational audit readiness have significantly predicted internal-control weakness prediction effectiveness. The regression model has explained 61.2 percent of the variance in internal-control weakness prediction effectiveness, with R^2 = 0.612 and an adjusted R^2 of 0.608. The F-statistic of 147.86, significant at $p < 0.001$, has demonstrated that the overall model has been statistically meaningful. Internal-control data quality has emerged as the strongest predictor, with a standardized beta coefficient of 0.33. This finding has shown that the quality of data has played the most important role in improving the ability of agencies to identify potential control weaknesses. Accurate, complete, consistent, timely, and accessible information has enabled machine-learning models to recognize patterns associated with unusual transactions, missing documentation, approval failures, and control-related anomalies. Machine-learning capability has recorded the second strongest effect, with $\beta = 0.29$. This has confirmed that analytical tools, predictive models, anomaly detection, and data-processing capacity have significantly strengthened internal-control weakness prediction. Organizational audit readiness has also recorded a significant positive effect, with $\beta = 0.22$. This result has shown that leadership support, technology infrastructure, governance procedures, interdepartmental coordination, and staff preparedness have helped agencies use predictive insights more effectively. The VIF values have ranged from 1.48 to 1.74, confirming that multicollinearity has not affected the regression model. From the Technology–Organization–Environment framework, the regression findings have demonstrated that technological conditions and organizational conditions have jointly influenced predictive audit performance. Internal-control data quality and machine-learning capability have represented the technological dimension, while organizational audit readiness has represented the organizational dimension. The public-sector regulatory environment has provided the broader setting that has required agencies to use these capabilities responsibly. H1 has been supported because machine-learning capability has significantly improved prediction effectiveness. H2 has been supported because internal-control data quality has exerted the strongest positive effect. H3 has been supported because organizational audit readiness has also significantly improved the outcome. The model has therefore achieved the study objective of identifying the key factors that have influenced machine-learning-supported internal-control weakness prediction.

Multiple Regression Analysis for Audit-Risk Scoring Effectiveness and Hypotheses Testing Summary

Table 11: Regression Analysis for Audit-Risk Scoring Effectiveness and Hypotheses Testing Summary

Panel A: Predictor variable	Unstandardized B	Standard error	Standardized beta	t-value	p-value
Constant	0.704	0.185	—	3.81	< 0.001
Auditor analytics competency, AAC	0.318	0.047	0.36	6.77	< 0.001
Internal-control weakness prediction effectiveness, ICWPE	0.441	0.048	0.47	9.19	< 0.001
Model statistics	R = 0.764	R^2 = 0.584	Adjusted R^2 = 0.581	F (2, 283) = 198.62	p < 0.001

Panel B: Hypothesis	Proposed relationship	Result	Decision
H1	MLC → ICWPE	β = 0.29, p < 0.001	Supported
H2	ICDQ → ICWPE	β = 0.33, p < 0.001	Supported
H3	OAR → ICWPE	β = 0.22, p < 0.001	Supported
H4	AAC → ARSE	β = 0.36, p < 0.001	Supported
H5	ICWPE → ARSE	β = 0.47, p < 0.001	Supported

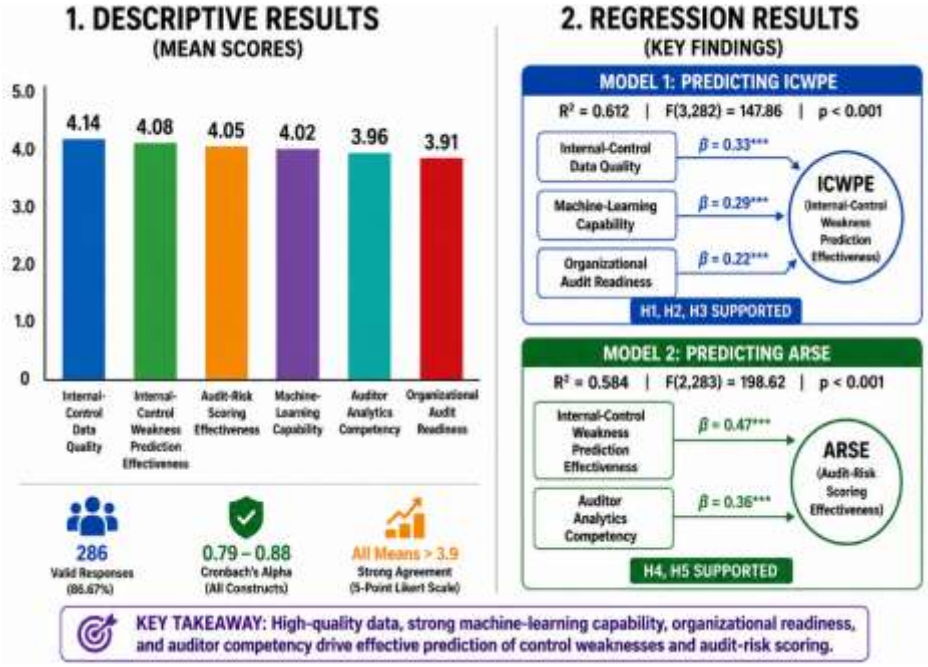
Table 11 has shown that auditor analytics competency and internal-control weakness prediction effectiveness have significantly predicted audit-risk scoring effectiveness. The regression model has explained 58.4 percent of the variance in audit-risk scoring effectiveness, with R^2 = 0.584 and an adjusted R^2 of 0.581. The overall F-statistic of 198.62, significant at $p < 0.001$, has confirmed that the model has been statistically strong. Internal-control weakness prediction effectiveness has produced the strongest effect on audit-risk scoring effectiveness, with a standardized beta value of 0.47. This finding has demonstrated that agencies that have been more capable of identifying potential control weaknesses early have also been more capable of assigning meaningful risk scores and prioritizing audit activity. The result has supported H5 and has confirmed that prediction effectiveness has served as the strongest immediate contributor to audit-risk scoring effectiveness. Auditor analytics competency has also produced a significant positive effect, with β = 0.36. This result has supported H4 and has demonstrated that auditors' ability to understand data, interpret predictive outputs, validate anomalies, communicate findings, and apply professional judgment has strengthened the use of risk scores in audit planning. The hypotheses summary has shown that all five proposed relationships have been statistically supported. H2 has shown the strongest effect among the first regression predictors, confirming that internal-control data quality has been the most influential factor in internal-control weakness prediction. H5 has shown the strongest overall effect in the second model, confirming that accurate prediction of control weaknesses has been central to effective audit-risk scoring. From the Technology–Organization–Environment framework, the results have demonstrated a connected pathway. Technological conditions, including machine-learning capability and data quality, have strengthened internal-control weakness prediction. Organizational conditions, including audit readiness and auditor analytics competency, have enabled agencies to apply analytical outputs within audit procedures. Internal-control weakness prediction has then translated these capabilities into more effective audit-risk scoring. Therefore, the full results have proved the research objectives and

hypotheses by showing that successful machine-learning-supported auditing has depended on dependable data, technological capability, organizational readiness, skilled auditors, and the effective prediction of control weaknesses.

FINDINGS

The findings of this study have provided a clear overall indication that machine-learning capability, internal-control data quality, organizational audit readiness, and auditor analytics competency have significantly supported internal-control weakness prediction and audit-risk scoring in U.S. state government agencies. Of the 330 questionnaires distributed, 286 valid responses have been retained for analysis, producing a valid response rate of 86.67 percent. The respondent profile has shown that 88 participants, representing 30.8 percent of the sample, have worked in internal audit roles, 64 participants, or 22.4 percent, have worked in finance and accounting roles, 50 participants, or 17.5 percent, have worked in compliance and risk-management functions, 43 participants, or 15.0 percent, have worked in information-technology and data-management roles, and 41 participants, or 14.3 percent, have worked in procurement, grants, or administrative control functions. This distribution has demonstrated that the study has incorporated perspectives from professionals who have possessed direct involvement in government audit processes, internal-control systems, financial information, compliance activities, and analytical data environments. The reliability analysis has confirmed that all study constructs have achieved acceptable internal consistency, with Cronbach's alpha values ranging from 0.79 to 0.88. Machine-learning capability has recorded an alpha value of 0.84, internal-control data quality has recorded 0.88, organizational audit readiness has recorded 0.81, auditor analytics competency has recorded 0.79, internal-control weakness prediction effectiveness has recorded 0.86, and audit-risk scoring effectiveness has recorded 0.85. These results have demonstrated that the questionnaire items have consistently measured the intended constructs. The descriptive findings have shown strong respondent agreement across all variables measured through the five-point Likert scale. Internal-control data quality has recorded the highest mean score of 4.14 with a standard deviation of 0.58, indicating that respondents have strongly agreed that accurate, complete, consistent, timely, and accessible data have been essential for control monitoring and machine-learning-supported audit analysis. Internal-control weakness prediction effectiveness has recorded a mean score of 4.08 with a standard deviation of 0.61, showing that respondents have perceived machine-learning approaches as effective in identifying unusual patterns, potential control deficiencies, and higher-risk activities before they become more serious operational or financial concerns. Audit-risk scoring effectiveness has recorded a mean score of 4.05 with a standard deviation of 0.63, confirming that respondents have agreed that data-supported risk scores have assisted auditors in prioritizing high-risk transactions, departments, programs, and control areas. Machine-learning capability has recorded a mean score of 4.02 with a standard deviation of 0.65, indicating that the selected agencies have demonstrated substantial capacity to use analytical tools, predictive models, anomaly-detection techniques, and control-related data for audit purposes. Auditor analytics competency has recorded a mean score of 3.96 with a standard deviation of 0.67, suggesting that respondents have generally agreed that auditors have possessed the knowledge required to interpret analytical outputs, validate risk signals, and apply professional judgment. Organizational audit readiness has recorded the lowest, although still positive, mean score of 3.91 with a standard deviation of 0.70. This result has suggested that management support, governance procedures, technological infrastructure, staff readiness, and coordination across departments have been present but have required greater strengthening than the other study conditions. The correlation analysis has shown statistically significant positive relationships among all major constructs. Internal-control weakness prediction effectiveness has had a strong positive correlation with internal-control data quality at $r = 0.69$, followed by machine-learning capability at $r = 0.64$ and organizational audit readiness at $r = 0.58$, with all relationships significant at $p < 0.001$. Audit-risk scoring effectiveness has recorded its strongest positive correlation with internal-control weakness prediction effectiveness at $r = 0.72$, followed by auditor analytics competency at $r = 0.64$, also significant at $p < 0.001$.

Figure 9: Findings of The Study



These findings have indicated that reliable control-related data, effective machine-learning capability, supportive organizational conditions, and competent auditors have been closely associated with stronger predictive auditing outcomes. The first multiple regression model has examined the influence of machine-learning capability, internal-control data quality, and organizational audit readiness on internal-control weakness prediction effectiveness. The model has explained 61.2 percent of the variance in internal-control weakness prediction effectiveness, with $R^2 = 0.612$, $F(3, 282) = 147.86$, and $p < 0.001$. Internal-control data quality has emerged as the strongest predictor with $\beta = 0.33$, $p < 0.001$, followed by machine-learning capability with $\beta = 0.29$, $p < 0.001$, and organizational audit readiness with $\beta = 0.22$, $p < 0.001$. These results have supported H1, H2, and H3. The second regression model has examined the influence of auditor analytics competency and internal-control weakness prediction effectiveness on audit-risk scoring effectiveness. This model has explained 58.4 percent of the variance in audit-risk scoring effectiveness, with $R^2 = 0.584$, $F(2, 283) = 198.62$, and $p < 0.001$. Internal-control weakness prediction effectiveness has produced the strongest positive effect on audit-risk scoring effectiveness with $\beta = 0.47$, $p < 0.001$, while auditor analytics competency has also produced a significant positive effect with $\beta = 0.36$, $p < 0.001$. These results have supported H4 and H5. Overall, the findings have achieved the study objectives by demonstrating that the proposed machine-learning approach has been supported by high-quality internal-control data, technological capability, organizational readiness, and auditor competency, while effective prediction of internal-control weaknesses has played the central role in improving audit-risk scoring across the selected U.S. state government agencies.

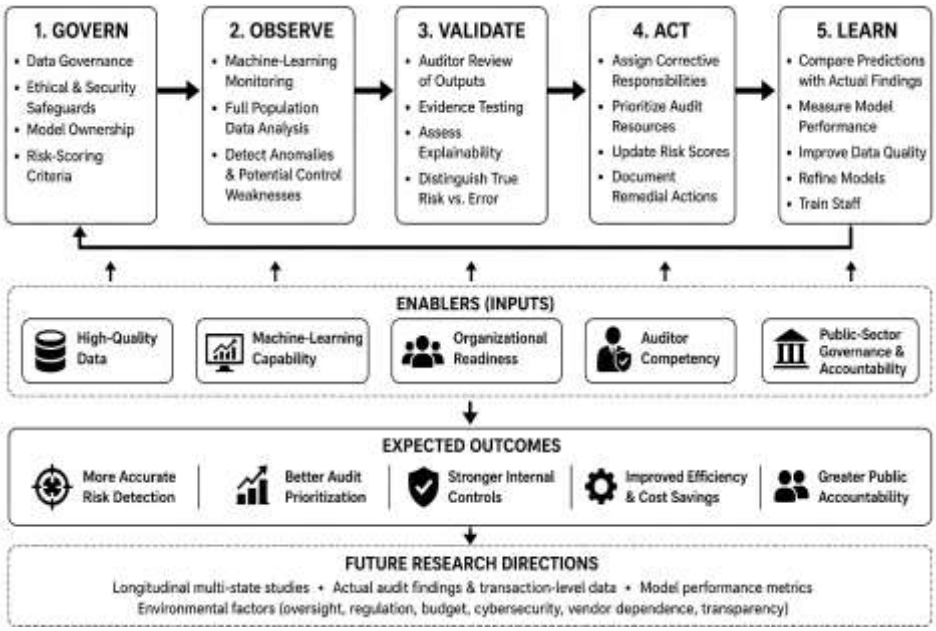
DISCUSSION

The findings have shown that a machine-learning approach has significantly strengthened internal-control weakness prediction and audit-risk scoring in U.S. state government agencies. The overall descriptive results have indicated strong agreement across all constructs, with internal-control data quality recording the highest mean score of 4.14, followed by internal-control weakness prediction effectiveness at 4.08, audit-risk scoring effectiveness at 4.05, machine-learning capability at 4.02, auditor analytics competency at 3.96, and organizational audit readiness at 3.91. These results have demonstrated that respondents have viewed predictive auditing as a combined technological and organizational capability rather than as a purely automated system. The regression findings have further confirmed this interpretation. Machine-learning capability, internal-control data quality, and organizational audit readiness have jointly explained 61.2 percent of the variance in internal-control

weakness prediction effectiveness. Auditor analytics competency and internal-control weakness prediction effectiveness have then explained 58.4 percent of the variance in audit-risk scoring effectiveness. All five hypotheses have been supported at $p < 0.001$. These results have aligned with the broader audit analytics literature, which has described predictive analysis as useful when data are transformed into auditable and decision-relevant signals rather than treated as isolated technical outputs (Appelbaum et al., 2017; Mahmudul & Sadia, 2026; Shmueli & Koppius, 2011). The strong mean score for internal-control weakness prediction effectiveness has indicated that respondents have perceived machine-learning tools as useful for identifying anomalous transactions, approval irregularities, documentation gaps, delayed reconciliations, and high-risk control processes before they develop into more serious concerns. This finding has been consistent with process-mining research, which has shown that data-driven audit procedures can reveal audit-relevant patterns such as process violations and control exceptions across large transaction populations (Jans et al., 2013, 2014; Hossan, 2026). The present findings have extended earlier work by focusing on U.S. state government agencies, where the consequences of weak internal control can involve not only financial misstatement but also weakened public accountability, noncompliance, service-delivery failure, and inappropriate use of taxpayer resources. The results have also confirmed that predictive auditing has not replaced professional judgment. Instead, it has supported auditors by identifying where attention should be directed. The findings have therefore interpreted machine-learning adoption as an enhancement to public-sector audit planning and control monitoring, in which technological tools have supported the continuous identification of risk while auditors have retained responsibility for verification, evidence evaluation, and final audit judgment.

Internal-control data quality has emerged as the strongest predictor of internal-control weakness prediction effectiveness, with a standardized beta coefficient of 0.33. This finding has shown that accurate, complete, timely, consistent, and accessible data have formed the primary foundation for effective predictive auditing. The strong correlation between internal-control data quality and internal-control weakness prediction effectiveness, at $r = 0.69$, has reinforced this conclusion. Respondents have therefore recognized that a machine-learning model can only identify meaningful control patterns when it receives dependable input from financial, procurement, payroll, grant, compliance, and operational information systems. This interpretation has aligned with data-quality research that has emphasized the relationship between information quality and the usefulness of analytical systems for managerial and professional decision making (Hazen et al., 2014; Shurovi, 2026; Wixom & Todd, 2005). It has also been consistent with research on data-centric artificial intelligence, which has established that machine-learning performance depends heavily on the quality, validation, integration, and governance of the data used within a model (Zahidul, 2026; Whang et al., 2023). The finding has been particularly relevant to U.S. state government agencies because public-sector information is frequently distributed across multiple systems and maintained by separate operational units. In this environment, inconsistent codes, missing identifiers, delayed updates, incomplete approval records, and isolated databases can reduce the ability of auditors to identify control vulnerabilities. Machine-learning capability has produced the second strongest effect on internal-control weakness prediction effectiveness, with $\beta = 0.29$. This result has demonstrated that agencies have required not only reliable information but also the technical capacity to process large data sets, identify anomalies, classify risk patterns, and apply predictive models. The result has supported the view that full-population testing and exception-based auditing can enhance audit coverage by enabling auditors to focus on unusual and high-risk transactions across large record populations (Huang et al., 2022; Sadia, 2026). The present study has therefore shown that data quality and machine-learning capability have operated together. High-quality data have supplied the evidence base, while machine-learning tools have converted that evidence into predictive signals. This relationship has strengthened H1 and H2 and has confirmed the technological component of the Technology–Organization–Environment framework. Agencies seeking stronger predictive auditing have needed to treat data governance, system integration, data cleaning, and analytical capability as interconnected requirements. Organizational audit readiness has also had a significant positive effect on internal-control weakness prediction effectiveness, with $\beta = 0.22$, although it has recorded the lowest descriptive mean score of 3.91.

Figure 10: GOVAL Predictive Audit Framework for Future Research



This result has suggested that selected state government agencies have possessed positive readiness conditions but have not achieved the same level of strength in governance procedures, staff preparation, interdepartmental coordination, and analytical infrastructure as they have achieved in data quality and machine-learning capability. The result has been important because it has shown that the presence of technology has not automatically ensured effective predictive auditing. Agencies have required management support, formal operating procedures, information-sharing arrangements, trained personnel, and clear responsibilities for reviewing model outputs. This interpretation has aligned with organizational-readiness theory, which has described readiness as a shared organizational commitment to change and confidence in the collective ability to implement it successfully (Ali et al., 2026; Weiner, 2009). It has also been consistent with research showing that analytical capability produces stronger organizational outcomes when technology is accompanied by appropriate strategic alignment, resources, and organizational support (Akter et al., 2016; Nurul, 2026). In the public-sector audit context, readiness has meant that internal audit units, finance departments, procurement offices, information-technology teams, compliance personnel, and agency management have coordinated their responsibilities. A high-risk analytical signal has required review, evidence verification, documentation, assignment of responsibility, and follow-up of corrective action. Without these organizational procedures, predictive findings could remain unused or be treated inconsistently across agencies. The findings have also supported earlier Technology–Organization–Environment research, which has shown that technological and organizational conditions jointly influence the successful adoption and use of enterprise systems and analytical applications

between having data and tools and being institutionally prepared to use them. State government agencies may have developed data systems and analytical platforms, but they have still required stronger governance structures for managing the audit use of machine-learning outputs. The finding has supported H3 and has demonstrated that organizational readiness has acted as the bridge between technological possibility and practical predictive-audit performance. It has also indicated that public-sector agencies should assess readiness before expanding machine-learning applications across sensitive audit and control functions.

Auditor analytics competency has had a significant positive effect on audit-risk scoring effectiveness, with $\beta = 0.36$, while internal-control weakness prediction effectiveness has produced the strongest effect on audit-risk scoring effectiveness, with $\beta = 0.47$. These results have shown that audit-risk scoring has depended both on the quality of predictive signals and on the ability of auditors to interpret, validate, communicate, and apply those signals. The strong correlation of $r = 0.72$ between internal-control weakness prediction effectiveness and audit-risk scoring effectiveness has indicated that agencies which have identified potential control weaknesses more accurately have also assigned more meaningful risk priorities to transactions, programs, departments, vendors, and control areas. This finding has been consistent with research demonstrating that auditors can use financial and nonfinancial information to identify unusual relationships and strengthen risk assessments (Ames et al., 2012; Brazel et al., 2009). The present study has expanded this insight by showing that machine-learning-supported prediction can provide a structured evidence base for public-sector risk scoring. However, model outputs have required professional examination. A risk score may have reflected a genuine control weakness, incomplete data, unusual but authorized activity, or a temporary operational exception. Auditor analytics competency has therefore been necessary to determine whether the signal has justified further testing, escalation, corrective action, or revision of the model. This interpretation has aligned with auditor data-literacy research, which has emphasized that auditors need the ability to understand data sources, assess analytical processes, interpret outputs, and communicate results to decision makers (Appelbaum et al., 2021). It has also been supported by experimental evidence showing that auditors' knowledge of data analytics can influence their judgments during audit planning and risk assessment (Sihombing et al., 2023). The current findings have further highlighted the importance of explainability. Public-sector audit decisions must be transparent and defensible because they may affect public funds, government programs, procurement actions, and organizational accountability. Auditors must be able to explain why a unit or transaction has received a high-risk score and which control-related indicators have influenced that classification. This has been consistent with explainable artificial intelligence research, which has identified interpretability as essential when machine-learning techniques are applied to auditing (Zhang et al., 2022). Thus, H4 and H5 have shown that effective risk scoring has required both human analytics competency and reliable machine-learning-supported prediction.

The theoretical contribution of this study has been the application of the Technology–Organization–Environment framework to machine-learning-supported internal-control weakness prediction and audit-risk scoring in U.S. state government agencies. The results have validated the technological and organizational dimensions of the framework within a public-sector audit setting. Machine-learning capability and internal-control data quality have represented technological conditions, whereas organizational audit readiness and auditor analytics competency have represented organizational conditions. The environmental dimension has been reflected in the common regulatory, accountability, legal, and public-service obligations facing state government agencies. The first regression model has confirmed that technological conditions and organizational readiness have jointly influenced internal-control weakness prediction effectiveness. The second model has confirmed that organizational competency and prediction effectiveness have influenced audit-risk scoring effectiveness. This pattern has supported the theoretical proposition that organizational adoption of technology cannot be understood through technology characteristics alone. Agencies have needed the technical capability to process data, the organizational capacity to use analytical outputs, and an environment that has required accountable and transparent control monitoring. These findings have been consistent with earlier research that has connected technological competence, organizational resources, financial commitment, and regulatory support with the use and value of organizational technologies (Zhu & Kraemer, 2005). The findings have also been consistent with public-sector audit literature that has characterized audit value in terms of accountability, management control, governance, assurance, and oversight of public resources (Hay & Cordery, 2018). The study has added a more specific theoretical pathway by identifying internal-control weakness prediction effectiveness as a central mechanism between technological and organizational conditions and audit-risk scoring effectiveness. In other words, machine-learning capability, data quality, and audit readiness have not directly represented the

final value of predictive auditing. Their value has been realized through the agency's ability to identify control weaknesses accurately and early. This has then improved the ability to score risk and prioritize audit resources. The Technology–Organization–Environment framework has therefore provided an appropriate explanation for why some agencies have derived stronger audit value from machine learning than others. The findings have shown that technological investment must be combined with data governance, organizational preparation, professional competency, and public-sector accountability procedures to produce effective predictive-audit outcomes.

The practical findings have shown that U.S. state government agencies have needed to develop machine-learning-supported auditing as a governed audit capability rather than as a stand-alone information-technology project. The highest mean score for internal-control data quality has indicated that agencies have already recognized the importance of accurate, complete, and accessible records. However, the lower score for organizational audit readiness has shown that stronger governance procedures, staff preparation, and interdepartmental coordination have remained necessary. Agency leaders have needed to define how internal audit, finance, procurement, compliance, information technology, and program-management units will share data, review risk signals, validate model results, and document follow-up actions. The findings have also indicated that agencies should establish clear risk-scoring criteria. These criteria can include transaction value, exception frequency, approval irregularity, documentation completeness, prior audit findings, segregation-of-duty concerns, compliance exposure, vendor risk, and program sensitivity. A machine-learning model can identify patterns across these variables, but auditors have needed to assess whether the result is credible within the operational context. This requirement has aligned with research showing that artificial intelligence can improve audit quality and efficiency when audit organizations have developed the required human and technological resources (Fedyk et al., 2022). Practical audit procedures should therefore include model validation, periodic review of false positive and false negative outcomes, data-quality checks, and documented auditor explanations for high-risk classifications. The study has also indicated that auditor training has been important. Training should not be limited to software operation. It should cover data interpretation, model limitations, bias awareness, risk-based audit planning, evidence validation, explainability, and communication of analytical findings to management and oversight bodies. Agencies should also establish governance protocols for sensitive public information, including access controls, confidentiality procedures, audit trails, and accountability for model modifications. These measures have been necessary because public-sector analytics operates in an environment where risk scores may influence oversight, funding decisions, procurement reviews, and control-remediation priorities. The practical value of the present findings has therefore rested on the integration of data quality, machine-learning capability, audit readiness, and auditor competency into a single control-monitoring process. This integrated approach has enabled agencies to use analytical technology while preserving public accountability, professional skepticism, and the documented evidence required for public-sector auditing.

The limitations of this study have also defined the most important direction for future research. First, the cross-sectional design has captured respondent perceptions at one point in time and has not measured how machine-learning capability, data quality, or audit-risk scoring performance have changed across multiple audit cycles. Second, the data have been collected from selected U.S. state government agencies, which has limited the generalization of the findings to federal agencies, local governments, nonprofit entities, private organizations, or public institutions operating under different legal and technological conditions. Third, the study has relied on self-reported Likert-scale assessments, which have measured professional perceptions of capability and effectiveness rather than direct algorithmic accuracy, actual fraud-detection rates, or verified financial-loss reduction. Fourth, the environmental dimension of the Technology–Organization–Environment framework has been treated as the shared public-sector accountability context rather than as an independently measured variable. Future researchers should improve this study through a proposed **GOVAL Predictive Audit Model**, where GOVAL represents Govern, Observe, Validate, Act, and Learn. In the Govern stage, agencies should establish data-governance rules, ethical safeguards, model ownership, security controls, and transparent risk-scoring criteria. In the Observe stage, machine-learning tools should

examine full populations of financial, procurement, payroll, grants, and compliance data to identify anomalies and potential control weaknesses. In the Validate stage, trained auditors should review model outputs, test evidence, assess explainability, and distinguish genuine control risks from data errors or unusual but legitimate activities. In the Act stage, agencies should assign corrective responsibilities, prioritize audit resources, update risk scores, and document remedial actions. In the Learn stage, agencies should compare predicted risks with actual audit findings, measure false positives and false negatives, refine model variables, improve data quality, and retrain staff. Researchers should test this model through longitudinal multi-state studies that combine survey data with actual audit findings, transaction-level records, model-performance metrics, and follow-up evidence. Such research could measure precision, recall, accuracy, false positive rates, remediation speed, audit-cost savings, and changes in control maturity. Future studies should also examine environmental variables such as legislative oversight, regulatory pressure, budget capacity, cyber-security requirements, vendor dependence, and public transparency obligations. This model has provided a structured pathway for extending the present study from perception-based evidence toward verified and continuously improved public-sector predictive auditing.

CONCLUSION

This study has examined the development of a machine-learning approach for internal-control weakness prediction and audit-risk scoring in U.S. state government agencies through a quantitative, cross-sectional, case-study-based design. The findings have demonstrated that predictive auditing has been shaped by the combined influence of technological resources, data quality, organizational readiness, and auditor capability. The study has collected 286 valid responses from professionals working in internal audit, finance, accounting, compliance, risk management, information technology, procurement, grants, and administrative-control functions. The response rate of 86.67 percent has provided a substantial basis for examining the proposed relationships through descriptive statistics, Pearson correlation analysis, and multiple regression modeling. The results have shown strong agreement across all study constructs measured through the five-point Likert scale. Internal-control data quality has recorded the highest mean score of 4.14, followed by internal-control weakness prediction effectiveness at 4.08, audit-risk scoring effectiveness at 4.05, machine-learning capability at 4.02, auditor analytics competency at 3.96, and organizational audit readiness at 3.91. These results have shown that high-quality data have been the most established condition supporting predictive auditing, while organizational readiness has required comparatively greater attention. The reliability analysis has confirmed that all six constructs have achieved acceptable Cronbach's alpha values ranging from 0.79 to 0.88, while the overall instrument has recorded an alpha of 0.90. The correlation findings have shown significant positive relationships among all major variables. Internal-control data quality has recorded the strongest correlation with internal-control weakness prediction effectiveness at $r = 0.69$, and internal-control weakness prediction effectiveness has recorded the strongest correlation with audit-risk scoring effectiveness at $r = 0.72$. The first regression model has explained 61.2 percent of the variance in internal-control weakness prediction effectiveness. Internal-control data quality has emerged as the strongest predictor with $\beta = 0.33$, followed by machine-learning capability with $\beta = 0.29$ and organizational audit readiness with $\beta = 0.22$. The second regression model has explained 58.4 percent of the variance in audit-risk scoring effectiveness. Internal-control weakness prediction effectiveness has produced the strongest effect with $\beta = 0.47$, while auditor analytics competency has also shown a significant positive effect with $\beta = 0.36$. Therefore, all five hypotheses have been supported. The study has concluded that machine-learning capability alone has not been sufficient to improve public-sector auditing. Its effectiveness has depended on the quality and integration of internal-control data, the readiness of agencies to use predictive outputs within established governance procedures, and the ability of auditors to interpret, validate, and explain analytical findings. The Technology–Organization–Environment framework has effectively explained these relationships by showing that technological factors, organizational conditions, and the broader public-sector accountability context have jointly shaped predictive-audit performance. The central conclusion has been that internal-control weakness prediction has acted as the critical link between machine-learning inputs and effective audit-risk scoring. When agencies have identified control vulnerabilities accurately and early, they have been better able to assign risk levels, prioritize audit activities, allocate professional

resources, and initiate timely corrective action. The study has therefore established that machine-learning-supported auditing has offered a structured, evidence-based approach for strengthening internal controls and risk-focused audit planning in U.S. state government agencies.

RECOMMENDATIONS

Based on the findings, U.S. state government agencies should establish a structured machine-learning-supported audit framework that integrates data quality, analytical capability, organizational governance, and auditor competency. The first recommendation has been that agencies should strengthen internal-control data governance because data quality has emerged as the strongest predictor of internal-control weakness prediction effectiveness. Agencies should create common data definitions, consistent transaction codes, standardized documentation requirements, data-validation rules, and regular reconciliation procedures across finance, procurement, payroll, grants, compliance, and program-management systems. Each agency should establish a data-quality review process through which missing records, duplicate entries, inconsistent identifiers, delayed updates, and incomplete approval histories are identified and corrected before the information is used for predictive analysis. The second recommendation has been that agencies should develop machine-learning capability gradually through defined audit use cases. Initial analytical applications should focus on high-value and high-risk activities, including duplicate payment detection, procurement irregularities, unusual vendor transactions, delayed reconciliations, segregation-of-duty conflicts, abnormal journal entries, grant-management exceptions, and incomplete control documentation. Agencies should avoid applying complex models without a clear audit objective and should ensure that each model has a documented purpose, defined input variables, validation procedure, responsible owner, and interpretation guide. The third recommendation has been that state agencies should improve organizational audit readiness. Senior management should formally support analytical auditing through audit charters, data-access procedures, governance committees, budgets for technological infrastructure, and cross-departmental coordination arrangements. Internal audit units should work closely with finance, procurement, information technology, compliance, legal, and program departments so that predictive outputs can be reviewed promptly and connected to actual control processes. The fourth recommendation has been that agencies should invest in auditor analytics competency. Training programs should develop auditors' understanding of data quality, statistical interpretation, risk indicators, visualization, anomaly detection, machine-learning limitations, model explainability, bias awareness, and professional judgment. Auditors should be trained to validate high-risk signals rather than accept automated outputs without supporting evidence. The fifth recommendation has been that agencies should use a transparent audit-risk scoring model. This model should combine machine-learning-generated signals with auditable indicators such as transaction value, exception frequency, prior audit findings, management response, documentation completeness, policy-compliance risk, operational sensitivity, and potential public impact. The scoring process should remain documented so that auditors, managers, and oversight bodies can understand why a specific program, transaction, vendor, or control area has received a particular risk classification. The sixth recommendation has been that agencies should establish regular model-review procedures. These reviews should assess prediction accuracy, false positive results, false negative results, data drift, changes in agency processes, and the relationship between risk scores and actual audit findings. Finally, agencies should apply the GOVAL Predictive Audit Model, consisting of Govern, Observe, Validate, Act, and Learn. Govern should establish rules and accountability, Observe should identify risk patterns, Validate should ensure professional review, Act should assign corrective measures, and Learn should refine models through audit evidence. This approach has provided a practical structure for maintaining reliable, transparent, and accountable machine-learning-supported auditing.

LIMITATIONS OF THE STUDY

This study has contained several limitations that should be considered when interpreting the findings. First, the research has used a cross-sectional design, meaning that responses have been collected at one point in time. The study has therefore measured prevailing perceptions of machine-learning capability, internal-control data quality, organizational audit readiness, auditor analytics competency, internal-control weakness prediction effectiveness, and audit-risk scoring effectiveness. It has not measured how these conditions have changed across multiple audit periods or after the introduction of new

analytical systems. As a result, the findings have demonstrated significant associations but have not established long-term causal effects. Second, the study has relied on structured self-reported questionnaire responses measured through a five-point Likert scale. Respondents have provided assessments based on their professional knowledge and experience, but these perceptions may have been influenced by personal expectations, organizational culture, professional role, or the desire to present agency practices positively. The study has not used direct transaction-level evidence, verified fraud cases, actual audit-loss data, or algorithmic performance indicators such as accuracy, precision, recall, sensitivity, specificity, false positive rate, and false negative rate. Third, the case-study context has included selected U.S. state government agencies rather than all state, federal, county, municipal, nonprofit, or private-sector organizations. Therefore, the findings may not be fully generalizable to agencies operating under different legal systems, funding structures, technological maturity levels, public-accountability requirements, or administrative cultures. Fourth, the study has focused on four main explanatory variables: machine-learning capability, internal-control data quality, organizational audit readiness, and auditor analytics competency. Other relevant factors may also influence predictive auditing and audit-risk scoring, including cybersecurity maturity, budget availability, leadership style, vendor dependence, data privacy restrictions, audit independence, organizational culture, public transparency obligations, regulatory pressure, and the complexity of agency programs. Fifth, the Technology–Organization–Environment framework has been applied with the environmental dimension treated as the shared public-sector setting rather than as a separately measured statistical construct. This approach has enabled the study to focus on the central technological and organizational variables, but it has limited the ability to quantify the influence of external regulatory and institutional conditions. Sixth, the use of regression modeling has explained substantial but incomplete variance in the dependent variables. The first model has explained 61.2 percent of the variance in internal-control weakness prediction effectiveness, while the second has explained 58.4 percent of the variance in audit-risk scoring effectiveness. This has indicated that additional factors outside the current model have influenced the outcomes. Finally, machine-learning systems themselves can be affected by data bias, incomplete historical records, changes in agency procedures, model drift, and limited explainability. A high-risk score has not automatically established that fraud, misconduct, or control failure has occurred. It has represented a signal requiring professional investigation and evidence validation. These limitations have demonstrated the importance of interpreting machine-learning-supported audit results carefully, maintaining human oversight, and using predictive outputs as decision-support information within a transparent and accountable public-sector audit process.

REFERENCES

[1]. Aboelmaged, M. G. (2016). A model of adoption determinants of ERP within the technology-organization-environment framework. *Information Technology & People*, *29*(4), 901-930. https://doi.org/10.1108/itp-03-2015-0068

[2]. Akter, S., Wamba, S. F., Gunasekaran, A., Dubey, R., & Childe, S. J. (2016). How to improve firm performance using big data analytics capability and business strategy alignment? *International Journal of Production Economics*, *182*, 113-131. https://doi.org/10.1016/j.ijpe.2016.08.018

[3]. Alles, M. G., Kogan, A., & Vasarhelyi, M. A. (2006). The benefits and feasibility of continuous auditing as a means to enhance governance. *Journal of Emerging Technologies in Accounting*, *3*(1), 137-161. https://doi.org/10.2308/jeta.2006.3.1.137

[4]. Ames, D., Brazel, J. F., Jones, K. L., Rich, J. S., & Zimbelman, M. F. (2012). Using nonfinancial measures to improve fraud risk assessments. *Current Issues in Auditing*, *6*(1), C28-C34. https://doi.org/10.2308/ciia-50168

[5]. Amir, R., & Chapal, B. (2022). Federated Learning Architectures for Distributed Engineering Project Knowledge Management A Simulation-Based Analysis. *Review of Applied Science and Technology*, *1*(04), 411-446. https://doi.org/10.63125/4k4pjr64

[6]. Appelbaum, D., Kogan, A., & Vasarhelyi, M. A. (2017). Big data and analytics in the modern audit engagement: Research needs. *Accounting Horizons*, *31*(3), 1-16. https://doi.org/10.2308/acch-51684

[7]. Appelbaum, D., Showalter, D. S., Sun, T., & Vasarhelyi, M. A. (2021). A framework for auditor data literacy: A normative position. *Accounting Horizons*, *35*(2), 5-25. https://doi.org/10.2308/horizons-19-127

[8]. Arena, M., Arnaboldi, M., & Azzone, G. (2010). The organizational dynamics of enterprise risk management. *Accounting, Organizations and Society*, *35*(7), 659-675. https://doi.org/10.1016/j.aos.2010.07.003

[9]. Ashbaugh-Skaife, H., Collins, D. W., Kinney, W. R., Jr., & LaFond, R. (2008). The effect of SOX internal control deficiencies and their remediation on accrual quality. *The Accounting Review*, *83*(1), 217-250. https://doi.org/10.2308/accr.2008.83.1.217

[10]. Beneish, M. D., Billings, M. B., & Hodder, L. D. (2008). Internal control weaknesses and information uncertainty. *The Accounting Review*, *83*(3), 665-703. https://doi.org/10.2308/accr.2008.83.3.665

[11]. Brazel, J. F., Jones, K. L., & Zimbelman, M. F. (2009). Using nonfinancial measures to assess fraud risk. *Journal of Accounting Research*, *47*(5), 1135-1166. https://doi.org/10.1111/j.1475-679X.2009.00349.x

[12]. Brown-Liburd, H., Issa, H., & Lombardi, D. (2015). Behavioral implications of big data's impact on audit judgment and decision making and future research directions. *Accounting Horizons*, *29*(2), 451-468. https://doi.org/10.2308/acch-51023

[13]. Bushra, M. (2024). A Predictive Model Linking Food-Borne Heavy-Metal Exposure to Antimicrobial Resistance Co-Selection. *American Journal of Interdisciplinary Studies*, *5*(04), 182-221. https://doi.org/10.63125/gwab2m39

[14]. Bushra, M. (2025). Deploying the Model as a Surveillance and Decision-Support Tool for U.S. Food Safety. *American Journal of Data Science and Analytics*, *6*(03), 01-41. https://doi.org/10.63125/gp709767

[15]. Cao, M., Chychyla, R., & Stewart, T. (2015). Big data analytics in financial statement audits. *Accounting Horizons*, *29*(2), 423-429. https://doi.org/10.2308/acch-51068

[16]. Doyle, J. T., Ge, W., & McVay, S. (2007). Accruals quality and internal control over financial reporting. *The Accounting Review*, *82*(5), 1141-1170. https://doi.org/10.2308/accr.2007.82.5.1141

[17]. Earley, C. E. (2015). Data analytics in auditing: Opportunities and challenges. *Business Horizons*, *58*(5), 493-500. https://doi.org/10.1016/j.bushor.2015.05.002

[18]. Fedyk, A., Hodson, J., Khimich, N., & Fedyk, T. (2022). Is artificial intelligence improving the audit process? *Review of Accounting Studies*, *27*, 938-985. https://doi.org/10.1007/s11142-022-09697-x

[19]. Feng, M., Li, C., & McVay, S. (2009). Internal control and management guidance. *Journal of Accounting and Economics*, *48*(2-3), 190-209. https://doi.org/10.1016/j.jacceco.2009.09.004

[20]. Gangwar, H., Date, H., & Ramaswamy, R. (2015). Understanding determinants of cloud computing adoption using an integrated TAM-TOE model. *Journal of Enterprise Information Management*, *28*(1), 107-130. https://doi.org/10.1108/jeim-08-2013-0065

[21]. Ge, W., & McVay, S. (2005). The disclosure of material weaknesses in internal control after the Sarbanes-Oxley Act. *Accounting Horizons*, *19*(3), 137-158. https://doi.org/10.2308/acch.2005.19.3.137

[22]. Hammersley, J. S., Myers, L. A., & Shakespeare, C. (2008). Market reactions to the disclosure of internal control weaknesses and to the characteristics of those weaknesses under Section 302 of the Sarbanes-Oxley Act of 2002. *Review of Accounting Studies*, *13*, 141-165. https://doi.org/10.1007/s11142-007-9042-z

[23]. Hay, D., & Cordery, C. (2018). The value of public sector audit: Literature and history. *Journal of Accounting Literature*, *40*, 1-15. https://doi.org/10.1016/j.acclit.2017.11.001

[24]. Hazen, B. T., Boone, C. A., Ezell, J. D., & Jones-Farmer, L. A. (2014). Data quality for data science, predictive analytics, and big data in supply chain management: An introduction to the problem and suggestions for research and applications. *International Journal of Production Economics*, *154*, 72-80. https://doi.org/10.1016/j.ijpe.2014.04.018

[25]. Hsu, P. F., Ray, S., & Li-Hsieh, Y. Y. (2014). Examining cloud computing adoption intention, pricing mechanism, and deployment model. *International Journal of Information Management*, *34*(4), 474-488. https://doi.org/10.1016/j.ijinfomgt.2014.04.006

[26]. Huang, F., Vasarhelyi, M. A., & Yan, Z. (2022). Audit data analytics, machine learning, and full population testing. *The Journal of Finance and Data Science*, *8*, 138-144. https://doi.org/10.1016/j.jfds.2022.05.002

[27]. Issa, H., Sun, T., & Vasarhelyi, M. A. (2016). Research ideas for artificial intelligence in auditing: The formalization of audit and workforce supplementation. *Journal of Emerging Technologies in Accounting*, *13*(2), 1-20. https://doi.org/10.2308/jeta-10511

[28]. Jans, M., Alles, M. G., & Vasarhelyi, M. A. (2013). The case for process mining in auditing: Sources of value added and areas of application. *International Journal of Accounting Information Systems*, *14*(1), 1-20. https://doi.org/10.1016/j.accinf.2012.06.015

[29]. Jans, M., Alles, M. G., & Vasarhelyi, M. A. (2014). A field study on the use of process mining of event logs as an analytical procedure in auditing. *The Accounting Review*, *89*(5), 1751-1773. https://doi.org/10.2308/accr-50807

[30]. Kazi Rakib Hasan, S., & Uddin, H. M. M. (2022). Scalable AI For Project Portfolio Management: A Mixed-Methods Study Combining Distributed Computing Benchmarks. *Review of Applied Science and Technology*, *1*(04), 375–410. https://doi.org/10.63125/0kk4wf20

[31]. Kirkos, E., Spathis, C., & Manolopoulos, Y. (2007). Data mining techniques for the detection of fraudulent financial statements. *Expert Systems with Applications*, *32*(4), 995-1003. https://doi.org/10.1016/j.eswa.2006.02.016

[32]. Knechel, W. R., Krishnan, G. V., Pevzner, M., Shefchik, L. B., & Velury, U. K. (2013). Audit quality: Insights from the academic literature. *Auditing: A Journal of Practice & Theory*, *32*(Supplement 1), 385-421. https://doi.org/10.2308/ajpt-50350

[33]. Kokina, J., & Davenport, T. H. (2017). The emergence of artificial intelligence: How automation is changing auditing. *Journal of Emerging Technologies in Accounting*, *14*(1), 115-122. https://doi.org/10.2308/jeta-51730

[34]. Kokina, J., & Yadav, A. (2019). AI and robotic process automation: Impact on accounting professionals. *Journal of Emerging Technologies in Accounting*, *16*(1), 43-54. https://doi.org/10.2308/jeta-51954

[35]. Lin, S., Pizzini, M., Vargus, M., & Bardhan, I. R. (2011). The role of the internal audit function in the disclosure of material weaknesses. *The Accounting Review*, *86*(1), 287-323. https://doi.org/10.2308/accr.00000016

[36]. Low, C., Chen, Y., & Wu, M. (2011). Understanding the determinants of cloud computing adoption. *Industrial Management & Data Systems*, *111*(7), 1006-1023. https://doi.org/10.1108/02635571111161262

[37]. Mahmudul, H., & Sadia, Z. (2026). Safeguarding Financial Records: A Cybersecurity-Driven Management Framework. *International Journal of Scientific Interdisciplinary Research*, *7*(1), 493–526. https://doi.org/10.63125/zch4s169

[38]. Md Arif Uz, Z., Sharmin, S., & Md Abdur, R. (2025). Factors Influencing Behavioural Intention to Use he Innovative Open And Distance Learning Systems With The Role Of Continuance Intention. *American Journal of Scholarly Research and Innovation*, *4*(01), 202-220. https://doi.org/10.63125/pbjxp014

[39]. Md Syeedur, R., & Sharmin, R. (2025). A Data-Driven Study on the use of Small Language Models & Large Language Models for Interpreting Complex Industrial Data and Deriving Actionable Outcome. *American Journal of Data Science and Analytics*, *6*(11), 01-19. https://doi.org/10.63125/5vyhgs98

[40]. Md. Abdur, R., & Iftekhar, A. (2021). Customer Retention Forecasting in Mobile Wallet Services Using Neural Networks: A Comparative Quantitative Study. *International Journal of Business and Economics Insights*, *1*(4), 70-102. https://doi.org/10.63125/dyrpc387

[41]. Mergel, I., Edelmann, N., & Haug, N. (2019). Defining digital transformation: Results from expert interviews. *Government Information Quarterly*, *36*(4), 101385. https://doi.org/10.1016/j.giq.2019.06.002

[42]. Moffitt, K. C., Rozario, A. M., & Vasarhelyi, M. A. (2018). Robotic process automation for auditing. *Journal of Emerging Technologies in Accounting*, *15*(1), 1-10. https://doi.org/10.2308/jeta-10589

[43]. Mohammad Badrul, A., & Md. Mominul, H. (2023). Machine Learning–Based Assessment of Environmental and Public Health Risks in Sewerage Sludge Management Systems. *American Journal of Advanced Technology and Engineering Solutions*, *3*(02), 33-77. https://doi.org/10.63125/y3yfxa92

[44]. Mohammad Shoriful Hossan, S. (2021). Reducing Worker Exposure and Electrical Failure Risk in Brownfield Manufacturing Facilities After COVID-Era Maintenance Delays. *Review of Applied Science and Technology*, *6*(1), 263–279. https://doi.org/10.63125/cm1c2c20

[45]. Mohammad Shoriful Hossan, S. (2024). Development of A Predictive Maintenance Model for Industrial Motor Drives and VFD Systems Using PLC/DCS Operational Telemetry. *American Journal of Scholarly Research and Innovation*, *3*(01), 198-242. https://doi.org/10.63125/pv1js496

[46]. Mohammad Shoriful Hossan, S. (2025). Development Of an ARC-Flash Hazard Mitigation Framework for Brownfield Industrial Power Distribution Retrofits in U.S. Manufacturing. *American Journal of Advanced Technology and Engineering Solutions*, *1*(02), 262-303. https://doi.org/10.63125/vhqjgm79

[47]. Mohammad Shoriful Hossan, S. (2026). Impact of Predictive Arc-Flash Mitigation on Safety, Downtime, and Retrofit Efficiency in U.S. Manufacturing Power Systems. *American Journal of Data Science and Analytics*, *7*(06), 182-199. https://doi.org/10.63125/855hx414

[48]. Mohammad Shoriful Hossan, S., & Adar, C. (2023). SIL-Compliant Safety Instrumented System Design for Oil & Gas Hazardous-Area Operations Using IEC 61508 / IEC 61511 Frameworks. *Journal of Sustainable Development and Policy*, *2*(02), 43-85. https://doi.org/10.63125/cb3d3w81

[49]. Moll, J., & Yigitbasioglu, O. (2019). The role of internet-related technologies in shaping the work of accountants: New directions for accounting research. *The British Accounting Review*, *51*(6), 100833. https://doi.org/10.1016/j.bar.2019.04.002

[50]. Mst Shurovi, A. (2024). Machine Learning Models for Bank Reconciliation Anomaly Detection in High-Volume Financial Transactions. *American Journal of Data Science and Analytics*, *5*(12), 314-354. https://doi.org/10.63125/mmwb6467

[51]. Mst Shurovi, A. (2026). AI-Driven Accounts Payable and Receivable Automation for Operational Risk Mitigation in U.S. SMEs: A Systematic Review (2018–2026). *American Journal of Interdisciplinary Studies*, *7*(01), 536-577. https://doi.org/10.63125/x1yzwc45

[52]. Mst Shurovi, A., & Samia Hossain, S. (2022). Difference-in-Differences (DiD) Analysis of Data Driven Accounting Systems and its Impact on Financial Error Rates in SMEs. *Journal of Sustainable Development and Policy*, *1*(04), 117-157. https://doi.org/10.63125/n4nr0d75

[53]. Muhammad Mohiul, I., & Mohammad Badrul, A. (2022). Predictive Analytics for Optimizing Sewerage Sludge Treatment Efficiency and Resource Recovery in Dhaka City. *Journal of Sustainable Development and Policy*, *1*(04), 158-200. https://doi.org/10.63125/t9zdp458

[54]. Muhammad Zahidul, I. (2024). Assessment of Data Integrity Gaps and Preventive Strategies in QC Laboratories in Compliance with FDA and CGMP Expectations. *American Journal of Scholarly Research and Innovation*, *3*(01), 243–291. https://doi.org/10.63125/a3xjb608

[55]. Muhammad Zahidul, I. (2025). Development of a Dashboarding and Visualization Framework For Pharmaceutical Brand Performance Analytics Using Tableau and Python. *American Journal of Interdisciplinary Studies*, *6*(3), 351-393. https://doi.org/10.63125/e6djq308

[56]. Muhammad Zahidul, I. (2026). Implementation of a Predictive-Analytics Framework for Pharmaceutical Demand Forecasting and Supply-Chain Resilience in U.S. Healthcare Markets. *American Journal of Data Science and Analytics*, *7*(01), 166–193. https://doi.org/10.63125/zjpe3a17

[57]. Muhammad Zahidul, I., & Amena Begum, S. (2022). Applied Data-Analytics Approaches to Cardiovascular Drug-Utilization Patterns: An Empirical Study Using Real-World Pharmaceutical Sales Data. *American Journal of Data Science and Analytics*, *3*(12), 89-129. https://doi.org/10.63125/7xgryf71

[58]. Mukut Kanti, B. (2025). Lifecycle Carbon Reduction and Net Zero Pathway Modeling Using LEED, EDGE, and SBTI Frameworks in Developing Economy Industrial Buildings. *American Journal of Interdisciplinary Studies*, *6*(3), 306-350. https://doi.org/10.63125/tnneth75

[59]. Mukut Kanti, B., & Rony, S. (2022). Quantitative Risk Assessment and Safety Performance Benchmarking for Structural Integrity Management in Retail Supply Chain Infrastructure. *American Journal of Data Science and Analytics*, *3*(12), 42-88. https://doi.org/10.63125/n88vth90

[60]. Ngai, E. W. T., Hu, Y., Wong, Y. H., Chen, Y., & Sun, X. (2011). The application of data mining techniques in financial fraud detection: A classification framework and an academic review of literature. *Decision Support Systems*, *50*(3), 559-569. https://doi.org/10.1016/j.dss.2010.08.006

[61]. Ngai, E. W. T., Law, C. C. H., & Wat, F. K. T. (2008). Examining the critical success factors in the adoption of enterprise resource planning. *Computers in Industry*, *59*(6), 548-564. https://doi.org/10.1016/j.compind.2007.12.001

[62]. Oliveira, T., & Martins, M. F. (2011). Literature review of information technology adoption models at firm level. *Information & Management*, *48*(8), 266-286. https://doi.org/10.1016/j.im.2011.07.003

[63]. Perols, J. (2011). Financial statement fraud detection: An analysis of statistical and machine learning algorithms. *Auditing: A Journal of Practice & Theory*, *30*(2), 19-50. https://doi.org/10.2308/ajpt-50009

[64]. Petrovits, C., Shakespeare, C., & Shih, A. (2011). The causes and consequences of internal control problems in nonprofit organizations. *The Accounting Review*, *86*(1), 325-357. https://doi.org/10.2308/accr.00000012

[65]. Power, M. (2009). The risk management of nothing. *Accounting, Organizations and Society*, *34*(6-7), 849-855. https://doi.org/10.1016/j.aos.2009.06.001

[66]. Raisch, S., & Krakowski, S. (2021). Artificial intelligence and management: The automation-augmentation paradox. *Academy of Management Review*, *46*(1), 192-210. https://doi.org/10.5465/amr.2018.0072

[67]. Ramdani, B., Chevers, D., & Williams, D. A. (2013). SMEs' adoption of enterprise applications: A technology-organisation-environment model. *Journal of Small Business and Enterprise Development*, *20*(4), 735-753. https://doi.org/10.1108/jsbed-12-2011-0035

[68]. Richins, G., Stapleton, A., Stratopoulos, T. C., & Wong, C. (2017). Big data analytics: Opportunity or threat for the accounting profession? *Journal of Information Systems*, *31*(3), 63-79. https://doi.org/10.2308/isys-51805

[69]. Rikhardsson, P., & Yigitbasioglu, O. (2018). Business intelligence and analytics in management accounting research: Status and future focus. *International Journal of Accounting Information Systems*, *29*, 37-58. https://doi.org/10.1016/j.accinf.2018.03.001

[70]. Risha, A., & Kazi Mohammad Khalid, A. (2023). A Meta-Analysis of AI-Driven Geospatial Analytics for Predictive Maintenance of Critical Infrastructure in Developing Economies. *International Journal of Scientific Interdisciplinary Research*, *4*(4), 375–412. https://doi.org/10.63125/rayrex49

[71]. Ruhnke, K. (2023). Empirical research frameworks in a changing world: The case of audit data analytics. *Journal of International Accounting, Auditing and Taxation*, *51*, 100545. https://doi.org/10.1016/j.intaccaudtax.2023.100545

[72]. Sadia, Z. (2026). Machine Learning–Based Fraud Detection in Financial Records Using Anomaly Identification and Predictive Risk Scoring. *American Journal of Data Science and Analytics*, *7*(06), 200-225. https://doi.org/10.63125/ccmr1g09

[73]. Sadia, Z., & Binayan, D. (2023). AI-Based Analytics for Financial Risk Assessment and Anomaly Detection in Complex Financial Data Systems. *International Journal of Business and Economics Insights*, *3*(4), 105–121. https://doi.org/10.63125/224h4a32

[74]. Sadia, Z., & Md, F. (2024). Toward Secure and Trustworthy Artificial Intelligence in Financial Data Systems: A Governance and Risk-Control Framework. *Review of Applied Science and Technology*, *3*(01), 343–366. https://doi.org/10.63125/z0165923

[75]. Sadia, Z., Mohammad Ariful, I., Sumyta, H., & Hosne Ara, M. (2022). A Review of AI-Powered Data Visualization in Enterprise Reporting: Dashboard Design And Interactive Analytics. *American Journal of Advanced Technology and Engineering Solutions*, *2*(01), 32-54. https://doi.org/10.63125/gabst658

[76]. Samia Hossain, S. (2024). Predictive Financial Volatility Analytics Using Machine Learning Pipelines in ERP-Integrated Enterprises. *American Journal of Interdisciplinary Studies*, *5*(04), 134-181. https://doi.org/10.63125/hz27wz06

[77]. Shima Ali, S., Musomi, K., & Sonya, G. (2024). Integrated Infectious Disease Preparedness: Multilingual Health Communication Strategies for Public Health Risk Mitigation, Disease Intervention and Prevention for Culturally Diverse Population in United States. *American Journal of Data Science and Analytics*, *5*(10), 01-47. https://doi.org/10.63125/ehk4mt02

[78]. Shima Ali, S., Sonya, G., & Mahbubul, I. (2025). Telemedicine And Remote Patient Monitoring for Preventing Risk and Chronic Disease Management in Underserved Communities. *American Journal of Health and Medical Sciences*, *6*(04), 01–42. https://doi.org/10.63125/y0e9dc38

[79]. Shima Ali, S., Sonya, G., & Mahbubul, I. (2026). STI and HIV Prevention Through Public Health Digital Twins: A Framework for Personalized Prevention and Adaptive Disease Intervention. *American Journal of Scholarly Research and Innovation*, *5*(01), 284–326. https://doi.org/10.63125/rjgna882

[80]. Shmueli, G., & Koppius, O. R. (2011). Predictive analytics in information systems research. *MIS Quarterly*, *35*(3), 553-572. https://doi.org/10.2307/23042796

[81]. Sihombing, R. P., Narsa, I. M., & Harymawan, I. (2023). Big data analytics and auditor judgment: An experimental study. *Accounting Research Journal*, *36*(2/3), 201-216. https://doi.org/10.1108/arj-08-2022-0187

[82]. Sun, T. Q., & Medaglia, R. (2019). Mapping the challenges of artificial intelligence in the public sector: Evidence from public healthcare. *Government Information Quarterly*, *36*(2), 368-383. https://doi.org/10.1016/j.giq.2018.09.008

[83]. Syed Nurul, I. (2026). A Machine Learning Approach to Intelligent Streetlight Control for Sustainable Energy Management in Smart Cities. *American Journal of Advanced Technology and Engineering Solutions*, *6*(01), 650-689. https://doi.org/10.63125/gxwn1g63

[84]. Valle-Cruz, D., Ruvalcaba-Gomez, E. A., Sandoval-Almazan, R., & Criado, J. I. (2020). A review of artificial intelligence in government and its potential from a public policy perspective. *Government Information Quarterly*, *37*(4), 101519. https://doi.org/10.1016/j.giq.2020.101519

[85]. Weiner, B. J. (2009). A theory of organizational readiness for change. *Implementation Science*, *4*, 67. https://doi.org/10.1186/1748-5908-4-67

[86]. West, J., & Bhattacharya, M. (2016). Intelligent financial fraud detection: A comprehensive review. *Computers & Security*, *57*, 47-66. https://doi.org/10.1016/j.cose.2015.10.001

[87]. Whang, S. E., Roh, Y., Song, H., & Lee, J.-G. (2023). Data collection and quality challenges in deep learning: A data-centric AI perspective. *The VLDB Journal*, *32*, 791-813. https://doi.org/10.1007/s00778-022-00775-9

[88]. Wixom, B. H., & Todd, P. A. (2005). A theoretical integration of user satisfaction and technology acceptance. *Information Systems Research*, *16*(1), 85-102. https://doi.org/10.1287/isre.1050.0042

[89]. Yoon, K., Hoogduin, L., & Zhang, L. (2015). Big data as complementary audit evidence. *Accounting Horizons*, *29*(2), 431-438. https://doi.org/10.2308/acch-51076

[90]. Zaman, S. (2024). A Systematic Review of ERP And CRM Integration For Sustainable Business And Data Management in Logistics And Supply Chain Industry. *Frontiers in Applied Engineering and Technology*, *1*(01), 204-221. https://doi.org/10.70937/faet.v1i01.36

[91]. Zhang, C., Cho, S., & Vasarhelyi, M. A. (2022). Explainable artificial intelligence in auditing. *International Journal of Accounting Information Systems*, *46*, 100572. https://doi.org/10.1016/j.accinf.2022.100572

[92]. Zhu, K., & Kraemer, K. L. (2005). Post-adoption variations in usage and value of e-business by organizations: Cross-country evidence from the retail industry. *Information Systems Research*, *16*(1), 61-84. https://doi.org/10.1287/isre.1050.0045