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Smart Fiscal Governance: Integrating Artificial Intelligence and Predictive Analytics into Public Budget Management

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Abstract: *Public budget management is increasingly challenged by volatile revenues, complex expenditure portfolios, fraud risks, fragmented data, and demands for faster, more transparent fiscal decisions. This study develops an integrative framework for smart fiscal governance by examining how artificial intelligence and predictive analytics can support budget planning, revenue forecasting, expenditure monitoring, anomaly detection, financial reporting, and public accountability. An integrative literature review synthesized peer-reviewed studies published between 2022 and 2025, prioritizing Scopus-indexed research on artificial intelligence adoption in public administration, machine-learning forecasting, digital government, public financial accountability, and data-driven fiscal management together with relevant Indonesian evidence. Findings indicate that AI can improve forecasting, identify hidden fiscal patterns, automate routine analysis, and strengthen early-warning systems, but benefits depend on data quality, institutional capability, interoperability, explainability, cybersecurity, and human oversight. Predictive analytics is most valuable when embedded in existing financial management information systems and linked to decision rules rather than treated as a standalone technical application. Public organizations also require governance arrangements that balance experimentation with accountability, integrate data-science expertise with budget functions, and document model assumptions and limitations. The proposed framework combines data infrastructure, predictive intelligence, decision augmentation, control mechanisms, and institutional learning. Smart fiscal governance is therefore defined not as automated budgeting but as responsible human-AI collaboration that makes public financial decisions more anticipatory, transparent, evidence-based, and accountable. Accordingly, governments should combine predictive capability with transparent model governance, secure data, institutional learning, and accountable human judgment throughout the public budgeting cycle.*

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INTRODUCTION

Public budget management is moving from periodic, retrospective control toward continuous, data-intensive fiscal governance. Governments increasingly manage high-frequency revenue data, complex procurement systems, digital payments, program-performance information, and rapidly changing macroeconomic conditions. Artificial intelligence can process these information flows at a scale that conventional administrative

routines cannot easily match. Madan and Ashok (2023) show that AI adoption in public administration involves technological, organizational, and environmental factors as well as absorptive capacity and tensions surrounding public value. This perspective is highly relevant to budgeting because fiscal innovation must improve analytical capacity without weakening legality, accountability, or democratic responsibility.

Predictive analytics offers a practical entry point for AI in public finance. Lahiri and Yang (2022) demonstrate that machine-learning approaches using mixed-frequency information can improve real-time tax-revenue forecasting during abrupt economic change. Revenue forecasting is fundamental to credible budgeting because errors can produce unrealistic expenditure ceilings, financing pressures, and disruptive midyear adjustments. AI-enabled forecasting can incorporate broader indicators and update projections more frequently than traditional annual procedures. However, statistical accuracy alone is insufficient. Forecasts must remain interpretable, reproducible, and integrated with fiscal rules and professional judgment before they can support responsible budget decisions.

Indonesia already provides evidence of machine learning in public revenue administration. Febriminanto and Wasesa (2022) develop predictive analytics for identifying tax-revenue potential using taxpayer trigger data and machine-learning techniques. Their study illustrates how administrative big data can be transformed into decision support rather than stored passively. For public budgeting, this capability can improve revenue baselines, compliance targeting, and scenario development. It also highlights governance requirements: data definitions must be reliable, access controlled, models validated, and analytical outputs connected with accountable decisions. Smart fiscal governance therefore requires both technical analytics and institutional arrangements that determine how predictions are used.

AI adoption in government is organizational as well as technological. Selten and Klievink (2024) find that public organizations navigate AI adoption by separating data-science teams to strengthen technical expertise or integrating them into operational units to improve process alignment. Budget agencies face the same choice. Centralized analytics units can develop advanced models and standards, while embedded analysts can understand expenditure programs, accounting rules, and fiscal calendars more deeply. Effective smart fiscal governance may therefore require hybrid structures that combine specialist capability with close integration into budget preparation, execution, reporting, and audit processes.

Managerial acceptance also shapes implementation. Research on public-sector managers indicates that perceived usefulness and perceived impact significantly influence attitudes and intentions toward AI adoption (Ahn & Chen, 2024). In budgeting, users must trust analytical systems enough to consider their recommendations while remaining willing to challenge outputs that conflict with contextual knowledge or legal constraints. Adoption strategies should therefore combine technical deployment with training, explainability, documented accountability, and opportunities for users to evaluate model performance. This human-centered approach reduces the risk that predictive tools become either ignored or followed mechanically.

AI can also strengthen public financial accountability. Aldemir and Uçma Uysal (2025) identify predictive analytics, fraud detection, and automated reporting as important applications for financial governance, while emphasizing transparency, ethics, and institutional capability. These functions connect directly with budget execution, where governments must monitor commitments, detect unusual transactions, control

expenditure, and report performance. Predictive models can prioritize high-risk cases for review and identify emerging deviations earlier than retrospective audits. Nevertheless, automated detection should complement rather than replace professional investigation because anomalies can reflect legitimate program characteristics as well as misuse.

The growing role of AI in public financial management is also recognized in international policy practice. OECD (2025) reports that AI applications in public financial management generally extend existing capabilities in analytics, business intelligence, automation, and financial information systems rather than completely replacing established processes. This evolutionary pattern is important for implementation. Governments can obtain value by embedding AI into existing budget architectures, improving forecasting and monitoring incrementally, and strengthening governance as analytical sophistication increases. Such integration may be more sustainable than creating disconnected experimental tools with limited institutional ownership.

Despite growing interest, research often separates AI adoption, predictive forecasting, financial accountability, and public budgeting. A coherent smart fiscal governance framework remains underdeveloped, particularly regarding how predictive models should connect with institutional decision processes and accountability safeguards. This study addresses that gap by integrating evidence from 2022–2025 around five dimensions: data infrastructure, predictive intelligence, decision augmentation, governance controls, and institutional learning. The framework conceptualizes AI as an analytical partner within public budget management rather than an autonomous fiscal decision maker.

THEORETICAL FOUNDATION

The theoretical framework combines data-driven public management, dynamic capabilities, and public accountability. Data-driven management explains how administrative information can be converted into evidence for planning and control. Dynamic-capabilities reasoning emphasizes the ability of public organizations to sense fiscal risks, seize analytical opportunities, and reconfigure routines as technology changes. Public-accountability theory requires fiscal decisions to remain explainable, auditable, lawful, and attributable to authorized officials. Within this framework, AI and predictive analytics generate value when they improve anticipatory capacity while preserving institutional responsibility. Smart fiscal governance therefore depends on the interaction between analytical intelligence and governance architecture rather than on algorithmic sophistication alone.

Five capabilities structure the proposed model. Data infrastructure provides integrated, timely, secure, and sufficiently granular fiscal information. Predictive intelligence transforms data into forecasts, classifications, anomaly signals, and scenarios. Decision augmentation connects analytical outputs with budget formulation, execution, monitoring, and evaluation. Governance controls provide explainability, validation, access management, privacy, cybersecurity, audit trails, and human approval. Institutional learning enables agencies to recalibrate models, update skills, compare predicted and realized outcomes, and revise procedures. These capabilities jointly determine whether AI improves fiscal performance or merely adds technological complexity to existing budget systems.

RESEARCH METHODS

This study employed an integrative literature review and conceptual synthesis to develop a framework for smart fiscal governance. Peer-reviewed studies published between 2022 and 2025 were prioritized, with emphasis on Scopus-indexed research in artificial

intelligence, public administration, digital government, forecasting, public financial management, accountability, and predictive analytics together with relevant Indonesian evidence. Search concepts included artificial intelligence, predictive analytics, public budgeting, public financial management, tax forecasting, government expenditure, fiscal governance, anomaly detection, financial reporting, and AI adoption. The qualitative synthesis followed data reduction, categorization, interpretation, and conclusion-development principles described by Sugiyono (2022).

The analysis proceeded through three stages. First, studies were coded for technical functions, including revenue forecasting, expenditure prediction, classification, anomaly detection, automated reporting, and decision support. Second, evidence was coded for organizational requirements, including data capability, specialist expertise, managerial acceptance, process integration, interoperability, and institutional learning. Third, governance requirements were synthesized around transparency, explainability, fairness, cybersecurity, privacy, auditability, and human oversight. No fabricated primary dataset was introduced; the framework integrates published empirical and conceptual evidence and formulates propositions for future testing in public-budget organizations.

Source quality was assessed through publication recency, peer-review status, relevance, journal credibility, and DOI traceability. International findings were triangulated with Indonesian public-finance evidence to improve contextual relevance. Future empirical research can operationalize data readiness through completeness, interoperability, timeliness, and quality; predictive capability through forecast accuracy and anomaly-detection performance; governance through explainability, documentation, oversight, and security; and fiscal outcomes through forecast error, budget variance, execution quality, irregularity detection, reporting timeliness, and decision satisfaction. Longitudinal case studies, forecasting competitions, quasi-experiments, process mining, and structural equation modeling are suitable approaches for validating the framework.

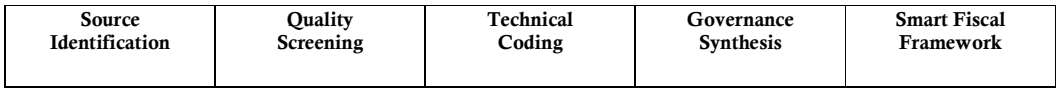


Figure 1. Integrative Review and Smart Fiscal Governance Framework Development

RESULT AND DISCUSSION

The first finding is that public-sector AI adoption should be understood as an organizational innovation process. Madan and Ashok (2023) identify technology, organization, environment, and absorptive capacity as important factors shaping adoption and diffusion, while also highlighting tensions that affect public value. In budget management, this means that purchasing analytical software does not create smart fiscal governance by itself. Agencies need data capability, skilled staff, leadership support, legal clarity, and routines for translating analytical outputs into decisions. Adoption should therefore be evaluated across the entire fiscal process, from data generation to model use and accountability. Consequently, smart fiscal governance requires organizational capacity that connects technical innovation with fiscal rules, public value, professional expertise, and accountable decision processes in practice across.

Second, machine learning can improve fiscal forecasting when governments exploit timely, high-frequency information. Lahiri and Yang (2022) use mixed-frequency data and boosting techniques to forecast New York tax revenues during the COVID-19 disruption and show the value of real-time updating under structural change. This evidence is directly relevant to public budgeting because revenue forecasts determine expenditure ceilings and

financing plans. Predictive systems can update fiscal expectations as new macroeconomic signals arrive, reducing dependence on static annual assumptions. Yet model performance should be compared against transparent benchmarks and monitored over time. Accordingly, predictive revenue systems should combine frequent data updates, transparent benchmarks, uncertainty reporting, professional interpretation, and predefined fiscal responses to meaningful forecast revisions throughout budget execution in practice across the.

Third, Indonesian evidence demonstrates the feasibility of machine-learning decision support in tax administration. Febriminanto and Wasesa (2022) apply predictive analytics to taxpayer trigger data to identify potential tax revenue using decision trees, random forests, and logistic regression. Their work illustrates how large administrative datasets can support revenue mobilization and risk prioritization. For smart fiscal governance, similar methods can strengthen revenue baselines and identify emerging collection opportunities. However, predictive scores should guide professional attention rather than automatically determine enforcement or budget assumptions. Data quality, model validation, access controls, and documentation are essential because errors can propagate into fiscal planning and taxpayer treatment. This approach can strengthen revenue intelligence while preserving fairness, auditability, and responsible professional judgment in tax administration in practice.

Fourth, the organizational placement of AI expertise affects implementation quality. Selten and Klievink (2024) find that separated data teams can strengthen technical expertise, whereas integrated teams improve alignment with primary public-sector processes. Budget organizations need both advantages. Central analytics units can establish common architectures, validation protocols, and reusable models, while embedded analysts can translate fiscal rules and program realities into appropriate model specifications. A hybrid operating model may therefore be particularly suitable for smart fiscal governance. It allows technical standards to remain consistent while ensuring that predictive tools address actual budget decisions rather than abstract analytical problems. Such structures can combine methodological rigor with operational relevance, allowing predictive tools to address real fiscal problems while maintaining common governance standards in.

Fifth, managerial acceptance depends on more than technological performance. Ahn and Chen (2024) find that perceived usefulness and perceived impact influence public-sector managers' attitudes and intentions toward AI adoption. Budget officers may resist models they do not understand, while excessive trust can create automation bias. Implementation should therefore combine training with interpretable outputs, confidence intervals, scenario explanations, and clear statements of model limitations. Managers should be able to trace how predictions inform recommendations and retain authority to override them with documented reasons. This design supports calibrated trust, where analytical evidence improves judgment without displacing professional responsibility. This balance supports calibrated trust, enabling managers to benefit from predictive evidence while preserving critical review, contextual interpretation, and accountable fiscal judgment in practice.

Sixth, AI can strengthen financial accountability through predictive monitoring, fraud detection, and automated reporting. Aldemir and Uçma Uysal (2025) show that these applications can improve efficiency, transparency, and decision making, while also identifying ethical and governance challenges. Public-budget systems can use anomaly models to prioritize transactions, suppliers, programs, or agencies for additional review.

This can shorten detection lags and allocate scarce audit resources more strategically. Nevertheless, anomalies are signals rather than proof of wrongdoing. Smart fiscal governance should combine algorithmic triage with human investigation, documented evidence, appeal mechanisms, and periodic evaluation of false positives and false negatives. These safeguards allow predictive monitoring to accelerate oversight while preserving due process, professional investigation, and accountable decisions about public financial irregularities in practice.

Seventh, AI adoption requires institutional enablers that extend beyond individual projects. Tomaževič et al. (2024) synthesize organizational factors affecting AI adoption in public institutions and emphasize the need for coordinated managerial and employee capabilities. Budget agencies should build governance structures that clarify ownership of data, models, decisions, and risks. Cross-functional teams should include budget specialists, accountants, data scientists, IT professionals, auditors, legal experts, and program managers. This multidisciplinary structure can prevent technically strong models from failing because they ignore fiscal rules or operational realities. Organizational readiness is therefore a core component of predictive capability. Accordingly, agencies should develop cross-functional governance that combines technical expertise, fiscal knowledge, legal oversight, security, audit capability, and executive responsibility for AI-enabled decisions in practice across.

Eighth, public administration research emphasizes that AI creates both opportunities and governance challenges. David (2024) maps conceptual approaches to AI in public administration and highlights the need for public-interest-oriented technology policy. For budgeting, the public interest requires more than efficiency. AI-supported allocation and monitoring must respect transparency, fairness, legality, privacy, and democratic accountability. Agencies should publish appropriate information about model purposes, data sources, validation, and oversight without exposing sensitive security details. Responsible transparency can help legislators, auditors, and citizens understand how analytics influence fiscal decisions and where human authority remains decisive. Public-interest AI therefore requires governance arrangements that make analytical purposes, limitations, responsibilities, and review mechanisms understandable to relevant oversight institutions and affected stakeholders in practice across the budget cycle.

Ninth, digital tools can alter administrative discretion rather than simply automate it. Marienfeldt (2024) shows that digitalization can curtail, enable, or continue street-level decision-making depending on design and context. The same principle applies to budget officials. Predictive systems may narrow discretion by ranking risks, but they can also expand analytical capacity by revealing patterns that humans would otherwise miss. Smart fiscal governance should therefore explicitly design the relationship between algorithmic recommendations and professional discretion. Decision logs, override rules, and review procedures can make this relationship visible and auditable instead of allowing hidden automation to reshape fiscal authority. Explicitly governing this relationship can preserve legitimate discretion while making algorithmic influence visible, reviewable, and consistent with administrative law and fiscal accountability requirements.

Tenth, empirical public-organization research shows that AI adoption benefits from alignment with institutional objectives. Guedes and Oliveira Júnior (2024) identify multiple factors influencing AI adoption in a public organization and emphasize multidisciplinary governance and oversight. Public financial management similarly requires a clear problem definition before model development. Agencies should begin with concrete fiscal questions, such as reducing revenue forecast error, identifying execution

bottlenecks, detecting anomalous payments, or improving cash planning. Technology should follow the decision need. This problem-driven approach reduces the risk of expensive systems that generate impressive analytics without improving budget outcomes. Problem-driven implementation therefore links investment in AI directly to measurable fiscal outcomes, operational needs, user capability, and institutional accountability rather than technological novelty in practice across the.

Eleventh, recent public-expenditure research extends AI applications directly into financial analysis. Amri et al. (2025) review AI for public expenditure analysis in low-income countries and identify opportunities in budget prediction, anomaly detection, auditing, and expenditure efficiency alongside infrastructural and institutional constraints. This evidence is especially relevant for governments with limited analytical capacity. AI may help prioritize scarce oversight resources, but weak data infrastructure can undermine model reliability. Smart fiscal governance should therefore sequence investment: strengthen financial data standards and interoperability first, then expand predictive applications, and finally institutionalize advanced analytics through governance and workforce development. For resource-constrained governments, sequencing data modernization, analytical capability, governance, and workforce development is essential for converting AI potential into credible improvements in expenditure management in.

Twelfth, AI is increasingly linked with local-government financial reporting. Kurniawan et al. (2025) review applications of machine learning and expert systems for fraud detection, financial prediction, and reporting accuracy and identify infrastructure, regulation, and system integration as persistent constraints. Budget management and financial reporting should not be treated as separate digital domains because execution data feeds future forecasts and accountability. Integrated architectures can allow models to compare plans, commitments, payments, outputs, and financial statements. Such integration supports continuous fiscal learning while reducing duplicate data pipelines. It also increases the importance of consistent classifications, master data, and audit trails. Integrated financial architectures can therefore improve learning across budget cycles while strengthening data consistency, traceability, reporting accuracy, and institutional accountability in practice.

Thirteenth, predictive analytics can strengthen expenditure oversight by shifting control from retrospective inspection toward risk-based monitoring. Otim et al. (2025) develop an analytics framework for government expenditure that uses anomaly detection and governance mechanisms to support financial oversight. Their approach demonstrates how predictive scores can triage transactions for closer attention and complement conventional audit. Budget agencies can similarly monitor procurement, commitments, payment timing, and program execution for unusual patterns. To remain accountable, risk models should be documented, periodically recalibrated, and assessed for fairness and measurement error. Predictive oversight is strongest when it accelerates investigation without replacing evidentiary standards. Used responsibly, predictive oversight can shorten detection delays, focus scarce control resources, and strengthen financial accountability without lowering evidentiary or procedural standards.

Fourteenth, national budgeting platforms can support forward-looking fiscal management when AI is integrated into the underlying data ecosystem. Azmi et al. (2025) discuss predictive analytics for national budgeting and expenditure using AI and machine learning within an integrated public financial management environment. Their framework highlights forecasting, fiscal simulation, explainability, and digital-twin concepts. The broader implication is that predictive capability should be built into financial-management

architecture rather than added as disconnected dashboards. Integrated systems can update forecasts, simulate policy alternatives, and connect results with execution data. Explainable AI is particularly important because budget decisions require justification to executives, legislatures, auditors, and citizens. This supports responsible predictive fiscal governance through transparent human oversight secure data institutional learning and accountable public budget decisions.

Fifteenth, the combined evidence supports a smart fiscal governance model based on responsible human-AI collaboration. Iskandar and Usman (2025) map the growing public-finance AI literature and identify transparency, efficiency, decision-making, and emerging research themes, reinforcing the field's movement toward data-intensive fiscal governance. The synthesis in this study extends that trajectory by linking five capabilities: reliable data infrastructure, predictive intelligence, decision augmentation, governance controls, and institutional learning. Governments should judge success not by the number of AI systems deployed but by measurable improvements in forecast accuracy, budget execution, anomaly detection, reporting, and accountability. Success should ultimately be measured by better fiscal outcomes and stronger accountability, not by automation itself, ensuring technology remains subordinate to legitimate public financial governance in practice across.

Table 1. Smart Fiscal Governance Capability Framework

Capability	Core function	Governance safeguard	Budget outcome
Data infrastructure	Integrated fiscal data and interoperability	Quality, access, security	Reliable analytical foundation
Predictive intelligence	Forecasting, anomaly detection, simulation	Validation and uncertainty reporting	Earlier fiscal signals
Decision augmentation	Link analytics to formulation and execution	Human approval and override rules	Evidence-based decisions
Governance controls	Explainability, audit trails, cybersecurity	Accountability and periodic review	Trusted AI use
Institutional learning	Skills, recalibration, outcome comparison	Cross-functional ownership	Adaptive fiscal capability

CONCLUSION

This study concludes that smart fiscal governance emerges when artificial intelligence and predictive analytics are embedded within the institutional architecture of public budget management. AI can strengthen revenue forecasting, expenditure monitoring, anomaly detection, reporting, and scenario analysis, but analytical accuracy alone does not create public value. Reliable data, process integration, skilled personnel, explainability, cybersecurity, auditability, and human oversight determine whether predictive intelligence improves fiscal decisions. The appropriate objective is therefore augmented budgeting: algorithms expand analytical capacity while authorized officials retain responsibility for interpreting evidence and making accountable decisions.

The proposed framework integrates five mutually reinforcing capabilities: data infrastructure, predictive intelligence, decision augmentation, governance controls, and institutional learning. Governments should begin with clearly defined fiscal problems, establish interoperable data foundations, validate models against transparent benchmarks, and connect predictions with explicit decision rules. Organizational design should combine centralized analytical expertise with embedded budget knowledge. Risk-based monitoring should complement audits rather than replace them, and model outputs should be accompanied by documentation, uncertainty information, override procedures, and periodic recalibration. These safeguards can reduce automation bias while increasing trust and practical adoption.

Future research should test the framework across national and subnational budget systems using real administrative data. Comparative studies can measure whether AI

reduces revenue forecast errors, improves cash planning, accelerates detection of irregular expenditure, or strengthens budget execution. Longitudinal research should examine how model performance changes during shocks and how organizations learn from prediction errors. Experiments can compare human-only, AI-only, and human-AI decision arrangements, while process mining can identify where analytics produce the greatest operational value. Research should also investigate fairness, explainability, cybersecurity, procurement, data sovereignty, and legislative oversight so that technological innovation remains compatible with democratic fiscal accountability.

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