AI-Driven Integrated Framework for Real-Time Fiscal Impact Analysis in Government Financial Management

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Abstract

A real-time fiscal impact analysis capability would improve the accuracy and transparency of government financial management and enable quicker, evidence-informed decisions in response to dynamic economic conditions. Such capability supports the automatic generation of models and assumptions required to assess the fiscal consequences of policy proposals, anticipated revenue collection, or spending out-turns as well as delivering counterfactual analyses that compare likely trajectories under different scenarios. A theoretically sound architecture defines the supporting integrated data-engineering and computing framework together with a set of analytic methods that encompass the use of economic models, parameterization, scenario generation, counterfactual and policy simulation techniques, and uncertainty quantification.

Governments face an oversight challenge—ensuring that sufficient detail and scrutiny are applied to policies likely to have large fiscal consequences while at the same time being able to act quickly when economic conditions require a timely response. Such crises can demand changes to existing policies or the introduction of new measures. The desire for a more rapid assessment of government policies and a demand for more transparency have rekindled a conversation within governments about improving the quality of fiscal transparency and providing real-time advice on the potential future impacts of policies and decisions.

Keywords : AI-driven integrated framework; real-time analysis; fiscal impact; government finance management; machine learning; scenario analysis; policy simulation; uncertainty quantification.

1. Introduction

People and companies constantly adapt their plans based on upcoming events. Such constant change also applies to a country, and fine-tuning its course of action and decisions to achieve more-efficient resource allocation is part of the role of government. Therefore, every government needs a mechanism that provides decision-makers with the expected fiscal impact of policy proposals as they arise in a fast-evolving economic context. Addressing this point constitutes one of the main objectives of the work. The analytical capacity in this type of real-time analysis should be part of the data-analytic ecosystem surrounding governments. Just as countries and organizations have well-implemented systems to calculate flows and balances with the past quickly, the analysis of fiscal impacts on the future should adapt to an economy in flux.

Timely fiscal impact assessments can deepen democracy and transparency. Such analyses, which quantify the effect of public budgets in real time, can produce much-needed information when preparing budgets or any other major governmental decision in an election year—in advance of any electoral campaign—and provide insights into appropriate policies during crises, such as the ongoing pandemic and the war in Ukraine. These government decisions can have a cumulative fiscal impact of billions of dollars, and it is still common for six months to pass before their effects on the economy are provided. An analytical solution integrated into the government's continuous management of resources can help respond to current demands more rapidly and efficiently. The quality of the analysis improves when demand comes from the political agenda instead of only at the end of a process by the media or independent organizations.

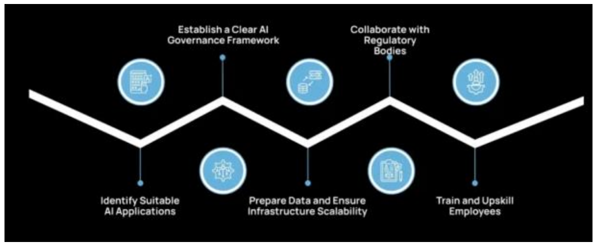


Fig 1: AI-Driven Integrated Framework for Real-Time Fiscal

1.1. Background and Significance Policy development requires timely estimates of the fiscal impact of proposed laws, executive actions, budgets, and other actions that alter government revenue or spending levels. Policymakers must determine how such measures affect the budgetary balance, especially during periods of fiscal pressure. However, existing economic resources are often exhausted by the time proposals are released or are not designed for speed. Without timely estimates, policymakers must frequently rely on internal agency submissions lacking independent validation, guidance, or historical record. As a result, preliminary recommendations are often made without meaningful consideration of their budgetary costs, short-term effect on the deficit, or political viability.

Continuous analysis of economic and budget conditions not only enables timely estimates of the fiscal impact of policy proposals but also provides the information needed to evaluate decisions about spending timelines and assess the short-term budgetary consequences of state and federal fiscal actions. Furthermore, independent tracking, analysis, and probable ranges of outcomes foster transparency, credibility, and accountability—both for those making decisions and those affected by them. The combination of technological advances and expedited data access provides a unique opportunity to build an AI-driven integrated framework that supports real-time analysis of the fiscal impact of the continuously evolving economic environment and of policy decisions taken by local, state, and federal governments.

2. Theoretical Foundations and Context

Four interrelated topics provide a foundation: the economic and computational theories underpinning real-time fiscal impact analysis; the impact of structural budget deficits on fiscal policy choices; the foundations of predictive analytics; and the Syncopated Creative Policy Framework.

The long-standing theory of public expenditure by Musgrave casts fiscal policy into three categories: distribution, stabilization, and allocation. Of these, stabilization has largely fallen to central banks, while fiduciary responsibility for distribution and allocation lies with governments. At the same time, fiscal decisions that remove funds from circulation or encourage private sector expenditure should be carried out at times of economic strength and are thus beyond the executive's normal remit. As a result, most budgetary decisions should reflect the economic conditions at the time of implementation. However, systematic use of structural budget deficit-surplus modelling, together with the economic models of the International Monetary Fund, allows these rules to be refined and liberated from the vagaries of politics, aligning them with economic theory without compromising the practicalities of governance.

Equation 1: Regression-based macro (or sector) model (baseline)

$$y_t = \beta_0 + \beta_1 x_{1t} + \beta_2 x_{2t} + \cdots + \beta_k x_{kt} + \varepsilon_t$$

For the GDP example described in the paper, one concrete mapping is:

- $y_t = \mathrm{GDP}_t$
- $x_{1t} = I_t$(investment)
- $x_{2t} = G_t$(government consumption)
- $x_{3t} = NX_t$(net exports)

- $x_{4t} = D_t$(other final demand components)

So:

$$\mathrm{GDP}_t = \beta_0 + \beta_I I_t + \beta_G G_t + \beta_{NX} NX_t + \beta_D D_t + \varepsilon_t$$

Matrix form (sets up OLS cleanly)

Let:

- $y \in \mathbb{R}^{T\times 1}$be the stacked GDP observations
- $X \in \mathbb{R}^{T\times(k+1)}$be the design matrix with first column all ones (intercept)
- $\beta \in \mathbb{R}^{(k+1)\times 1}$be coefficients

Then:

$$y = X\beta + \varepsilon$$

2.1. Research design An applied research and development methodology is deployed to define and build an integrated framework that enables real-time analytic capabilities for assessing the fiscal impact of major decision-making scenarios. These capabilities support the ability to understand and realize the full implications of government decisions sooner and assist with the design of ex-post evaluative research programs and the design of the specific tools for managing the execution of public policies in a more timely manner. A data-analytic strategy that follows a structured process for defining the requisite analytic methods and ensuring they fulfil user requirements is applied. The applied research and development effort also incorporates a validation component to ensure that the proposed framework and its components meet the desired requirements. Success is defined as achieving the primary objective of developing an integrated framework that enables real-time fiscal impact analytic capabilities, as described in section 2.1.

3. Architectural Overview of the AI-Driven Framework

A high-level diagram offers a comprehensive overview of the AI-driven integrated framework; its major components are outlined and the various data flows are described. The integration of the framework with existing data and IT systems of government enables real-time fiscal impact analysis.

The AI-driven framework forms an integral part of the government's overall digital ecosystem, which connects multiple agencies and departments for service delivery, data sharing, and resource management. The existing government portals, web applications, communication networks, and computing infrastructure will support the data ingestion and integration component of the framework. Administrative and transactional data, geospatial data of the external environment, and media content from various sources will serve as inputs for the framework.

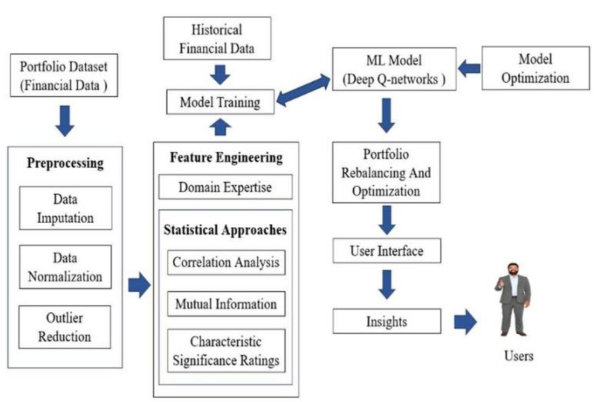
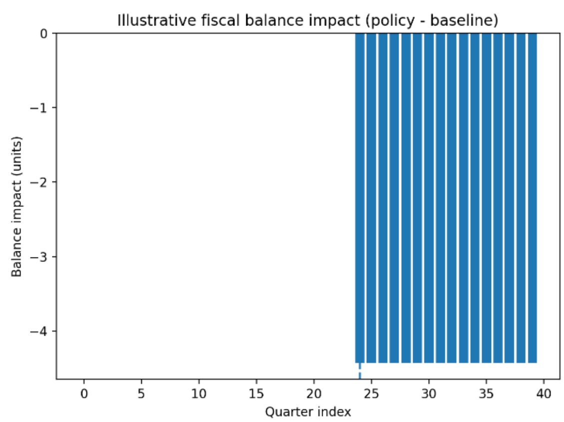


Fig 2: Architecture for AI-Driven Financial Management

3.1. Data Ingestion and Integration A range of public and private data sets can be employed for real-time analysis. External sources may include international organizations, central banks, research institutions, and private firms. Administrative data can be sourced from domestic government institutions and agencies. Data ingestion, both automated and manual for non-containerized domain information, is directed by machine-readable schemas, and providers are responsible for redressing errors prior to ingest. A standardized normalization protocol facilitates data processing for common usage. Data assets are generally linked within the compute cloud environment using Elastic Cloud Storage (ECS) in accordance with the Data Management Platform (DMP) strategy. Fulfilling the DMP and Information Technology for the Government of Canada (ITGC) requirements, all public data are presented following the Open by Default policy. More specifically, they are registered within the Government of Canada Open Data Strategy's connected core, respect the Community Data for Canada engagement framework, and align with the Treasury Board of Canada Secretariat's Open Data Policy, Directive on Open Government, and G7 Charter. Policies concerning privacy, security, access, and disclosure are likewise informed by the same standards.

Real-time analytical pipelines rely on data capture and processing methods that afford minimal latency. Near data storage refers to data processing that takes place as close as possible to the source of generation, ideally at the point where the data are created, allowing devices, networks, and services to process high volumes of data without high costs or delays. Cloud-based technologies, such as Amazon Web Services, Google Cloud Platform, and Microsoft Azure, offer near cloud services for streaming data ingestion and processing. The data mechanism is usually based on data ingestion pipelines to ingest data in real time or near real time. Data streams are the continuously generated data flows, and data capture is the process of extracting the data stream from the data sources. Different pipelines perform different operations on the data captured, all of which require low latency and reliable performance. The generated data must meet specific application criteria and support correct and efficient application development. The various application pipelines must remain well-orchestrated for optimal performance.



3.2. Real-Time Processing and Computational Pipeline The AI-driven integrated framework provides a computational pipeline to support real-time integration, analysis, and interpretation of data prepared by the data ingestion and integration component, illustrated in the left half of Figure 6. Streaming architectures aimed at minimizing latency in data-move-ment and processing are adopted to provide readiness of data for innovative decision-making. Figure 6 shows how the framework will incorporate such streaming architectures into the computational pipeline. Data originating from sources producing time-series data are ingested when emitted from the source or as soon as possible, without incurring any significant delay. Upon ingestion, the streaming architecture ensures that support for innovative business processes is provided with low latency. The focus is on minimizing latency from the creating source of data to when that data is available for consumer applications, rather than on minimizing latency between the reception by a consumer application and reading of that data by business teams within that application. The low-latency processing pipeline performs the logical steps required supporting innovative business demands under minimum latency budgets, even if the activities in the operating environment are outside of real-time activity. The tempo at which time-series data is ingested determines which of those logical steps that processing concentrates on. When the tempo is high, computational activity focuses on producing insights as fast as possible; when the tempo drops, the focus shifts toward producing an up-to-date version of the entire underlying data set for that logical area of demand.

Low-latency processing must be orchestrated over quite a varied set of functions and must permit considerable flexibility of sequence and phase. By easing the need for overall flow control, the notion of a pool of activity zones is introduced: a collection of clusters and pooled sets that support faster flow when pressure builds, permit depth of processing while pressure is lower and provide varied flexibility of sequence and phase, all without needing detailed direction from hard-flow requirements. Within any subsequent logical zone, the area of focus can then be sequenced and phased according to local pressure; and detailed orchestration can concentrate on the sequence and phase of the interaction between distinct clusters and pools. For quite a varied range of innovative demands on support, data appears at minimum latency and is reasonably well tuned for quality and depth of analysis.

3.3. Explainability, Governance, and Accountability The explainability of algorithmic decisions is a fundamental requirement for public sector data initiatives. Automated inputs to fiscal impact analysis can be enormous, and these may persist through the system and combined in unexpected ways. Information asymmetries weaken accountability and increased complexity calls for enhanced interpretability, as decision-makers must remain politically accountable. Public sector organizations must be in a position to demonstrate how AI systems are constructed and operate and be able to justify system outcomes. It must be possible to re-create and validate specific model decisions. Furthermore, it is essential to preserve audit trails for all decisions and actions, including in the decomposition of final results. Roles and responsibilities around system development, usage, and monitoring must be clearly defined.

Explaining decisions accurately and clearly is highly complex; AI systems are very complex knowledge systems and the synthesis of all knowledge is itself complex. Institutional arrangements must incorporate related governance principles while recognising the impossibility of perfect disclosure. Bias, fairness, and discrimination testing must be ongoing, with specified tests being conducted regularly and results disclosed publicly. AI transparency principles must strive to disclose enough information for others to assess trustworthiness, balance this against not overwhelming users with information, and ensure that vulnerabilities are also reported.

4. Methods for Real-Time Fiscal Impact Analysis

Answering real-time questions about the fiscal effects of government decisions, such as those related to tax policy, spending programs, and the business cycle, requires the capacity and tools for real-time fiscal policy analysis. Several aspects of the fiscal impact evaluation can be addressed using techniques to build an economic model of the country, explore its properties, supply its parameters, and design policy scenarios and couterfactuals. Once the model is built and the first analyses are performed, the demand for using the model for real-time fiscal impact evaluation poses challenges that may justify an alternative specific approach for the analysis.

Challenging interpretability requirements can be satisfied by the application of various explainable artificial intelligence (XAI) techniques for model-agnostic interpretable machine learning. Detecting, assessing, and tackling the risk associated with economic and financial decisions demands probabilistic forecasting, risk sensitivity analysis, quantile estimates of the response, value-at-risk estimates for the treated odds of success, and the measure of extreme risk degree. The integration of the capacity of estimating possible responses under uncertainty with counterfactual analysis allows gaining insight on the economic shock resiliency evaluation in processes of altering data generation and policy rules and exploring mitigation strategies adaptable in function of how the national economic system dynamics react to exogenous shocks.

4.1. Economic Modeling and Scenario Analysis Two approaches to modeling the economic impact of government policies are proposed. The first combines a macro-level economic model with micro-level econometric models of key sectors; outputs from the macro model inform the micro models. The resulting models are then employed to project economic growth across sectors under different fiscal policy scenarios.

The second approach is a macro-econometric model that estimates the dynamic relationship among GDP, fiscal balance, political cycle and other major influential explanatory variables. This approach enables the fiscal impact of the policy scenario to be simulated.

Equation 2: Step-by-step OLS derivation (parameter estimation)

$$\min_{\beta} \; S(\beta) = (y - X\beta)^{\top}(y - X\beta)$$

Expand:

$$S(\beta) = y^{\top}y - 2\beta^{\top}X^{\top}y + \beta^{\top}X^{\top}X\beta$$

Take gradient w.r.t. β:

$$\nabla_{\beta}S(\beta) = -2X^{\top}y + 2X^{\top}X\beta$$

Set to zero:

$$-2X^{\top}y + 2X^{\top}X\beta = 0$$
$$X^{\top}X\beta = X^{\top}y$$

If $X^{\top}X$is invertible:

$$\hat{\beta} = (X^{\top}X)^{-1}X^{\top}y$$

Residuals:

$$\hat{\varepsilon} = y - X\hat{\beta}$$

Error variance estimate:

$$\hat{\sigma}^2 = \frac{\hat{\varepsilon}^{\top}\hat{\varepsilon}}{T - (k+1)}$$

Coefficient covariance (classic OLS):

$$\widehat{\mathrm{Var}}(\hat{\beta}) = \hat{\sigma}^2(X^{\top}X)^{-1}$$

4.2. Counterfactual and Policy Simulation Techniques Counterfactual analyses permit estimation of likely outcomes under alternative policies or with different timing. Core components include selection of a target variable or metric, exogenous drivers, a suitable regression model linking the drivers to the target, and estimation of the model’s parameters. For instance, a regression for gross domestic product could rely on investment, government consumption, other final demand components, and net exports as explanatory variables, while a model for inflation might use demand and supply side pressures. Policy simulation entails applying the fitted model to impose designated counterfactual paths for the exogenous drivers, derived from an alternate policy scenario or another modelling framework. Comparison of the model outcomes for the baseline and stimulated scenarios isolates the impact of the respective policy measure.

Key usage of these functions includes modelling phase lags and/or nonlinearities in the response of fiscal aggregates to changes in policy. Counterfactual techniques can provide probability density functions for the projected variables when variability in the regression parameters or fitted structure is incorporated via a draw from the associated parameter distribution from Monte Carlo simulation. Sensitivity assessments yield comparable information for specified changes in the model inputs. Regular reporting of fiscal forecasts that cover several years ahead can allow the economic modelling group to generate periodic assessments of the effects on those forecasts of different paths for specific policy variables or for fiscal policy in general.

4.3. Uncertainty Quantification and Risk Assessment Timely fiscal impact analysis requires not only precise but also probabilistic forecasts. Uncertainty quantification techniques, such as Monte Carlo or Markov Chain Monte Carlo methods, may therefore be used to specify ranges of likely outcomes that reflect the uncertainty surrounding the input data and estimates. As input variables are probabilistically characterized, the frequency distributions of policy impacts may then be computed using standard risk analysis software. This allows sensitivity analyses to assess which variables are most responsible for the range of possible outcomes. It may also be useful to explicitly model tail events and report risk indices (e.g. Value-at-Risk and Expected Shortfall) using other techniques, such as Extreme Value Theory.

Formalised uncertainty quantification, coupled with these other quantitative risk reporting approaches, provides a concise and transparent statement about the likely range of effects from a range of future external influences. These insights are useful for identifying headline indicators that may signal extreme events in quasi-Real Time Monitoring Mode or signalling the likelihood of extreme outcomes in Policy Monitoring Mode. In Pragmatic Decision-Making Mode, they assist in focusing attention on the risks associated with various policy options.

5. Data Sources, Quality, and Privacy Considerations

Government data assets represent a key input supply for the integrated framework. This section identifies the major taxonomies of data underpinning the framework, how issues of data quality and data provenance are controlled, and how privacy regulations are adhered to throughout the integrated pipeline.

Public and administrative data sources are classified according to their characteristics, potential uses, and metadata requirements. These sources are combined with private sector data that range from voluntary, consent-based to proprietary commercial data. The entire spectrum of sources includes accommodation data recorded by various agencies within the Ministry of Finance, public sector banks, the Reserve Bank of India, the Ministry of Corporate Affairs, and the Ministry of Health and Family Welfare; public economic indicators from the Office of the Chief Economic Adviser; the Composite Insurance and Investment Index from the Insurance Regulatory and Development Authority of India (IRDAI); GST returns; financial accounts provided by the National Statistical Office (NSO); labour market information from state governments; corporate financial accounts provided by the Ministry of Corporate Affairs; accommodation-level Census data; price data from the Consumer Price Index-Industry (CPI-IW); real estate transactions published by the revenue department of Maharashtra; data from McKinsey and Company, National Council of Applied Economic Research, Oxford Economics, and PricewaterhouseCoopers; and input-output tables published by the NSO. Sourcing information for private data sets remains a challenge. Solutions include acquiring confidential records for consultancy agencies and exploring partnerships with data-rich entities such as WhatsApp and Facebook. Overall, data selection is taxonomised according to specific categories, sources, and metadata attributes.

In addition to public data supply, issues of data quality and privacy are addressed. Data provenance and a clearly defined data lineage —that is, the process of tracking the origin, movement, and transformation of data from source to destination—ensure that the data feeding the integrated pipeline remain reliable and valid for further inspection and assessment. Various techniques such as data audits, redundant checks, and conflict resolution help identify noise in the data and ensure a high level of data quality. Once integrated within a suitable, authoritative computational pipeline, the information flows automatically but needs to be checked for basic accuracy, quality, and format. While it is impractical to conduct an exhaustive verification due to the high volumes involved, and many aspects are automatically controlled by quality procedures for the administrative datasets, deviations can be managed through focused procedures over key data, such as real-time government revenue bulletins, or on days before important events like elections. Data recognizably in poor conditions as a result of this check can then at least advise caution when using products built upon them without holding back their dissemination.

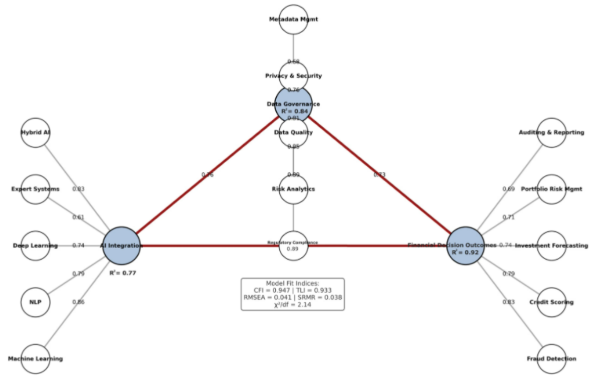


Fig 3: Data Sources, Quality, and Privacy Considerations

5.1. Public and Administrative Data Taxonomies Public and private sector activities generate vast amounts of data. Some are easily accessible offline and online, including information on country demographics and geography, macroeconomic performance, growth forecasts, external trade, job creation, inflation, domestic consumption, production, fiscal and monetary measures, company accounts, and financial indicators of companies. Non-administrative sources like economic indicators, election results, and surveys of public contingents can supplement these when needed. These data can serve as input to formats such as Excel and SPSS, databases (from SQLite to Microsoft SQL Server) for empirical analysis using econometric methods, and programming languages like R for time-series forecasting. In addition, streaming structured and unstructured data from different domains can support detection of change, and unsupervised and supervised machine learning methods can support timely processes.

Government financial management departments also generate large volumes of administrative data as a by-product of their day-to-day activities, either at the local, provincial or center level. Primary enterprise-level master data generation, data about citizens engaging in primary civic processes (like tax collection, crime commission, subsidy utilization, and related beneficiaries), and secondary enterprise-level master data generation (file closures with respect to tax collection) are significant data-generating domains. Data on the operations of the offices of the district collectors, industry, federal reserve banks, pension funds, and social sector schemes are also crucial sources. However, not all of this data is leveraged for comprehensive and timely real-time impact analysis of policies or program implementation, due to challenges in data consolidation and dissemination on a common platform.

5.2. Data Provenance, Lineage, and Quality Assurance Provenance tracking enhances reliability by confirming the role and influence of each data asset, while assurance for cleanliness, format, and trustworthiness boosts computational integrity. Streamlined verification prevents undesired outcomes and policy harms.

Describing and managing the provenance of information ingested are crucial for effective fiscal impact assessment. Tracking at least the source and extraction specification (e.g. dataset name and reading script) within every piece of data enables users to correlate results in the decision-making process with their originating bases and to gauge the effects of their modifications upon the outputs. For statistical modelling and forecasting exercises, allowing users to easily explore the data contained inside the AssessorRegistry in particular is highly desirable too. Fundamental for reliable inferences, specifying a complete provenance has far-reaching implications.

5.3. Privacy, Security, and Compliance Strategies Strong controls safeguard sensitive information in real-time fiscal impact analysis while ensuring compliance with laws governing data privacy and protection. Privacy and security of citizen data take first priority without impairing data sharing and reuse. Controls follow internationally recognized frameworks such as the United Nations Guidelines for the Regulation of Computerized Personal Data Files and the OECD Guidelines on the Protection of Privacy and Transborder Flows of Personal Data. Technology for encryption in transit and at rest, full anonymization during analysis, masking of sensitive features for modeling, compartmentalized access to particular processing pipelines, and strict authentication and authorization are employed. Pursuant to the European Union's General Data Protection Regulation, data subjects are permitted to exercise their rights to restrict, delete, and gain access to stored data.

Research employing models and analytical tools using data from any government department, agency, or public enterprise is governed by the Copyright Act of South Africa, the Promotion of Access to Information Act, and the Protection of Personal Information Act. All uses of the AI-driven framework are bound by conditions outlined in the policy document of the National Cybersecurity Hub of the Republic of South Africa. The establishment of the South African National Data and Cloud Policy and the associated strategic principles is a key step in achieving data security and integrity within the context of a more integrated approach to data protection.

6. Governance, Ethics, and Legal Implications

Organizational and normative aspects constraining or directing framework activities shape its utility. Decision rights and accountabilities define how committee recommendations are considered. Recognizing that public servants may be held accountable for any decision, these governance roles also include a degree of sign-off for machine-generated answers. Involving supervisory decision-makers during planning gives guidance on their requirements.

To ensure norms against bias, unfairness, and lack of transparency are respected, mechanisms for automated detection and reporting are essential, together with interpretation of any analytical result that is used in public decision-making. Subsequently, detection and required action become the responsibility of the governing committees. Political debate, legislation, and community consultation can identify other relevant ethical considerations.

Various laws, such as data protection and privacy legislation governing the collection, storage, and use of personal and business data, apply to the use of AI in the decision-making process; it is critical that these rules remain top of mind and form part of the operational check list of the board responsible for the development phase of the system.

Equation 3: Uncertainty quantification (Monte Carlo / MCMC) + risk metrics (VaR / ES)

1. Fit OLS → get $\hat{\beta}$and $\widehat{\mathrm{Var}}(\hat{\beta})$
2. Approximate:

$$\beta \sim \mathcal{N}\left(\hat{\beta}, \widehat{\mathrm{Var}}(\hat{\beta})\right)$$

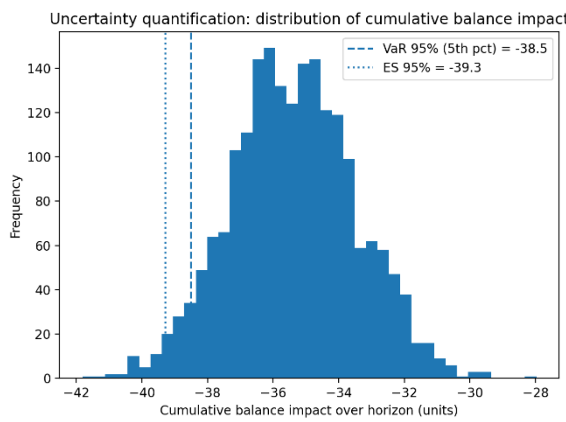
3. For $m = 1..M$:
    - draw $\beta^{(m)}$
    - compute baseline and policy forecasts $\hat{y}^{(0,m)}, \hat{y}^{(1,m)}$
    - compute $\Delta B^{(m)}$(or any fiscal metric)
4. Use the sample $\{\Delta B^{(m)}\}$to form:
    - intervals (e.g., 5th–95th percentile)
    - probabilities of exceeding thresholds
    - VaR / ES

6.1. Institutional Roles and Responsibilities Government agencies that collect and maintain relevant data are expected to play a significant role in owning, establishing and meeting requirements for the analytical framework. These include major domestic economic and revenue forecasters – the Treasury Department's Office of Economic Policy and Office of Tax Analysis, the Council of Economic Advisers, the Federal Reserve Board, and the Congressional Budget Office – which will ensure that the proposed model setups and other underlying analysis can be easily incorporated into their standard procedures. In addition, the Bureau of Economic Analysis, Bureau of Labor Statistics, Federal Reserve Board, and other agencies maintain important survey and other data collections that support federal, state, and local economic modeling efforts.

A Government Executives Committee made up of senior officials from the principal policy formulation agencies and possibly additional bodies, such as the U.S. Agency for International Development, Office of Management and Budget, Office of Science and Technology Policy, and Office of National Drug Control Policy, would oversee the analytical framework's operations and set priorities for what policies should be analyzed. A Technology Advisory Committee would help to ensure that the framework's architecture remains state of the art and explore ways in which private sector technology can be leveraged more effectively. An Academic Advisory Committee would be composed of leading economic modelers and applied economists from the nation's research universities.

6.2. Bias, Fairness, and Transparency Prescribed processes and controls will detect and mitigate bias and fairness concerns, while decision-making transparency will be maintained. The joint initiative will build procedures and metadata templates to detect bias, assess fairness, and enrich data documentation. Ongoing analytical work will profile current data quality, heritage, and usage — including for algorithm training, automatic decision-making, and sensibly predicting which subsectors and demographic groups are computationally interrogated — to design and execute quality improvement projects. The initial focus will be on machine-learning models running potentially harmful decisions, those queries receiving substantial media attention, and popular datasets. Any detected bias will lead to a targeted fairness-preserving intervention.

Considerable effort will also steadily engender follow-on procedures for assessment and articulation of issues implied in Algorithmic Transparency Frameworks. A first draft Model Risk Management Framework will define when a government activity falls under such considerations, which models and algorithms will thus be subjected to testing and reporting, and how such tests will be structured and validated. Relevant governing bodies will be engaged early in this process for buy-in and further enhancement of the drafting work.



6.3. Regulatory and Legal Frameworks Applicable laws and norms relevant to the AI-driven integrated framework for real-time fiscal impact analysis are listed. These include the Data Privacy Act of 2012, E.O. 2 (s. 2016), Government Auditing Code of the Philippines, E.O. 292 (s. 2000), E.O. 10037 (s. 2022), Anti-Red Tape Act (Republic Act 9485, as amended), Digital Governance Act (Republic Act 11032), Cybersecurity Act (Republic Act 10173), Freedom of Information Act (Republic Act 9470), and Privacy of Communications Act (Presidential Decree 1210). Compliance mechanisms must be established to align with these regulations.

Conformance to these laws is imperative and will be facilitated through cooperation between all stakeholders appropriately involved in the planning, development, testing, and operationalization of the integrated framework. Compliance monitoring and management, and regulatory oversight of the planned framework, will be undertaken through established Agency Structures, ORG 1, the Inter-Agency Task Force for Digital Transformation and E-Governance, the Information Systems Security Governance Board chaired by the Cybercrime Investigation and Coordinating Center, and OPAPP and other relevant Inter-Agency Committee-Supervisory and Policy-Making Bodies.

7. Implementation Roadmap and Change Management

An AI-driven integrated framework for real-time fiscal impact analysis in government financial management can be embodied in a roadmap detailing its implementation and the change management process. Use of maturity models enables identification of capability targets—associated with the achievement of specific milestones—and helps understanding how the framework may progressively mature and deliver increasing value to supporting real-time real-sector fiscal impact analysis.

Stakeholder engagement across government is critical for successful adoption and continued operation of the framework. Strong communication and dedicated change management strategies support reskilling and ensure appropriate use, oversight, and governance of the framework. Seemless capability and process interoperability across the broader government ecosystem is achieved through adherence to appropriate standards across data and system interfaces, as determined through relevant data contracts and agencies with the necessary authority.

Fig 4: AI Transformation Roadmap for Financial Institutions

7.1. Maturity Models and Roadmap Phasing A maturity model defines five distinct stages of capability development for implementing a real-time fiscal impact analysis system. Each stage must reach a certain level of performance and address a specific set of maturity indicators before embarking on the next phase. The overview, detailed in the table on the next page, spans all transitions from no capability through to continuous monitoring, supported by an organized change-management strategy. A roadmap indicates the priority sequence of stages, with each tackleable within one year and focused on a readily completable challenge, from the basic extension, through the more complex parallelization, to the platform. Together, these elements provide a practical framework for operationalizing the proposal.

In the first stage of maturity, the architecture is considered a proof-of-concept prototype that enables principal participants to conduct analyses longitudinally without any streaming capabilities. The principal donor agency at the time has an immediate interest for training and coaching leading to the second, baseline-completion stage. In this intervening period, other funders and proposed development partners will leverage the work to support a more integrated platform model. At the third stage, a parallelization maturity model addresses monitoring and guard-railing of actual cash flows, allowing closure of transaction transforms. This supports the development of a complete timeline-mashing capability at the fourth level, enabling sequential hindsight and departmental analogy. Finally, the overall architecture matures into an ecosystem-aware platform for real-time funding impact analysis.

7.2. Stakeholder Engagement and Capacity Building Stakeholder engagement and outreach are critical to managing change and ensuring broad ownership of the built system. During development, regular interactions with both technical and business stakeholders are vital to soliciting input, providing feedback, and managing expectations. Workshops with data-providing agencies will promote increasing data quality, completeness, and ease of access. Communication plans will flag important milestones and occasions to raise awareness of analytical results. Following development, a structured stakeholder engagement program will provide comprehensive training for end users and supporting agencies, clarify expectations around system output and usage, and share knowledge through public outreach.

The success of an AI-driven integrated framework for real-time fiscal impact analysis in government financial management hinges on data-sharing commitments among government agencies, including decisions to conform to specified data contracts. Institutional maturity and capacity complete the list of essential conditions for success. A maturity model with three dimensions

— data capability, analytic capability, and risk assurance — will provide an empirical basis for detecting current capability gaps and establishing an operational roadmap.

7.3. Interoperability and Standards To be adopted throughout the life-cycle approach, interoperability is a key design consideration. All public sector agencies are strongly encouraged to share relevant services and data, thus leading to economies in fiscal impact analysis. Incorporating an interoperability-driven approach, an updated catalog of these shared services and data, along with supporting contracts, can enable streamlined data access to optimize the analytical architecture. As additional services for forecasting, simulation and modelling become available, the maturity of the full life-cycle system will be greatly enhanced. In fact, therefore, enabling absorbent quality assurance to also originate from the users of these services is a core consideration. The use of Artificial Intelligence (AI) technology is accelerating the development of new simulation models that will be required by all government agencies for assessing the fiscal impact of their decisions and thereby fulfil the general, public sector responsibility to act within the fiscal space.

Integrating a maturity model approach to the whole-of-government life-cycle system development will prepare a set of phased, costed stages of work with desired, heavy-weighted capabilities for the future. In addition, the people using the system need to understand it in terms of purpose and operations; they should support system evolution by ensuring that their requirements are regularly considered; and they should possess and apply the necessary technical knowledge through training and workshops in order to detect material failures and abuses in the architecture.

8. Conclusion

Real-time fiscal impact analysis may be a powerful lever for more informed spending and support the realization of rapid, affordable, and responsive governance. Governments juggle myriad priorities for which new public investments are needed yet must remain fast and flexible enough to tackle urgent demands such as pandemics, wars, and natural disasters. Public finance decisions can have significant and often complex near-term effects on the economy and society, but real-time support for analysing the fiscal effects of government priorities is rarely available. Real-time fiscal impact analysis could thus help decision-makers understand potential fiscal effects associated with current policy preferences and thereby support more-transparent governance. Governments and civil servants would no longer be understood to be “fighting fires” after-the-fact without any foresight of what was going to happen. The delay associated with running economic models months down the line to see what Keynesians had said all along and doing so for only a few scenarios would be replaced with more-frequent and faster updates – these analyses would be as baked into the policy pathway as the budget cycle.

The analysis need not change the underlying models and be viewed as “cheap talk” propaganda. Nevertheless, this taxpayer investment in building an integrated stream of real-time support for estimating the near-term fiscal consequences of all key decisions must be explicitly recognised. Success depends on the investment of time, energy, and resources in getting the scenarios that feed into the proper counterfactual, and stakeholder engagement in shaping what-if inquiries and conducting go/no-go testing against the real world as new decisions materialise. It is ultimately about answering the question: what would Keynes (and others) say about this course of action?

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