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Making Cost Data Work for Public Financial Management

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ABSTRACT: Cost accounting can enhance public financial management by strengthening budget credibility, performance-based budgeting, procurement, and accountability. Despite its benefits, it remains underused due to strategic and technical challenges. To address strategic gaps, the paper begins by identifying how cost data supports key PFM functions. To overcome technical barriers, it proposes a standardized, interoperable schema to automate data collection and improve granularity. It also explores machine learning for detecting anomalies and inefficiencies. Drawing on international experiences, the paper offers practical solutions to make financial and administrative data more actionable, even in low-capacity environments.

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WORKING PAPERS

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I. Introduction

Understanding the cost of the goods and services delivered is a cornerstone to achieve value for money in the public sector. When integrated to Public Financial Management (PFM) practices, cost accounting can strengthen budget credibility and serve as a relevant input for efficiency-related indicators within Performance-Based Budgeting (PBB), enabling governments to link resources to outcomes and evaluate cost-effectiveness. Detailed costing can also improve procurement management by informing bid evaluations, enabling life-cycle costing, and ensuring better value in public contracts. Moreover, cost accounting can improve accountability by revealing anomalies that support the detection and prevention of mismanagement and corruption.

Cost accounting has been implemented in a variety of settings across national, sectoral, and subnational levels. Canada and New Zealand use cost data to inform budgeting and resource allocation at the national level, while Croatia, Jordan, Slovenia, and Tanzania have applied it in the health sector, with Croatia also extending its use to regional and local governments (Government of Canada, 2023; National Treasury New Zealand, 2001; Jovanović, 2019; Alqudah & Mohd Salleh, 2023, Mwencha, 2016). National and local initiatives have also taken place in Brazil (Brazil Secretaria do Tesouro Nacional, 2025;) often in connection with broader PFM or administrative reforms. Denmark has used costing approaches to improve efficiency in higher education, energy and other public services (Estevan, Schaefer & Adell, 2018; OECD, 2021). India has institutionalized the Office of the Chief Adviser Cost in the Ministry of Finance to advice ministries and agencies on cost accounting matters and undertakes cost investigation work on their behalf (Department of Expenditure, 2025). Korea and Malaysia have integrated cost accounting practices within their performance budgeting reforms, helping link spending to results (Park 2017; World Bank, 2017). These varied experiences reflect an enduring interest in cost data to support decision-making and improve service delivery.

At the heart of cost accounting is the goal of improving efficiency, and several country initiatives have produced measurable results. For example, in Canada, cost accounting supported comprehensive reviews of the defense portfolio, helping to identify and eliminate low-priority or underperforming activities, with savings totaling CAD 692 million in FY 2013–14 (Canada Department of National Defense, 2015). An analysis of 30 advanced economies between 2000 and 2021 finds that such gains in public sector efficiency can significantly reduce public debt, enhance medium-term sustainability, and boost labor productivity and private investment (Chrysanthakopoulos et al., 2025). Despite these results, cost accounting remains underutilized in PFM. As Premchand (1995) noted decades ago, “in both industrial and developing countries, cost measurement has yet to secure a foothold in the overall accounting system”—a statement that remains largely true today.

Persistent obstacles help explain a pattern of underutilization of cost accounting, which broadly fall into two categories: (i) strategic misalignment and (ii) data and technical implementation challenges. Some cost initiatives have stagnated due to unclear ownership and duplication with other reforms. In several countries, cost accounting and performance measurement frameworks have developed in parallel without coordination, leading to duplication and weak use of both systems (Mohr, 2016). Implementation challenges in Croatia, Denmark and Slovenia underscore the difficulty of gathering granular cost data (Rogošić, 2021; Malmmose & Lydersen, 2021; Jovanović et al., 2019). India faces fragmented information flows across multiple digital systems leading to duplication, inconsistencies, and delayed reporting from service delivery units (eGov, 2024). These conditions have created a negative feedback loop: when data is not timely, accessible, or actionable, policymakers become less inclined to use it and invest in improvements.

Demands for more efficient service delivery and a renewed emphasis on value-for-money are driving interest in cost accounting, including in lower-middle-income economies. Some governments are revisiting earlier efforts, while others are exploring new approaches to expand or establish cost systems. While concerns persist about prioritizing cost accounting before fully developing financial reporting systems, this paper offers an alternative view: practical applications can create momentum for better data use—not just better data collection. A user-centered approach can more effectively uncover classification inconsistencies, data fragmentation, and outdated information flows that might otherwise remain hidden.

Rather than being a competing reform, this paper places cost accounting within the broader context of PFM. When designed with integration in mind, cost accounting can enhance existing systems and help connect relevant data to broader PFM reforms, such as PBB, procurement, and improved fiscal transparency and service delivery. This approach is particularly relevant for countries where reforms have been constrained by siloed systems, underfunded initiatives, or unclear mandates. Cost accounting draws on the same underlying data as financial and administrative or performance reporting but organizes it differently—by cost center, program, or service line—to support operational decisions.[1]

Cost accounting should not be about adding burden—but about giving existing data more purpose. To support this shift, the paper offers a non-country specific data schema to guide the organization of cost data to achieve interoperability across systems, which addressed the above mentioned problems regarding data collection, standardization and granularity. The schema enables governments to consolidate and analyze cost data without duplicating data collection efforts. It is designed as a relatively low-cost solution as it is compatible with existing financial management systems and adaptable to country-specific.

This paper also addresses the persistent underuse of cost accounting data in day-to-day decision-making (Mättö and Sippola, 2016). Even when data exists, traditional methods often fail to extract actionable insights from complex datasets. To bridge this gap, the paper explores how machine learning (ML) models can help detect anomalies, reveal cost patterns, and uncover signals that are difficult to identify manually. While ML applications in PFM remain nascent, they are gaining traction—even in low-income countries—as digital capacity grows. More broadly, the paper encourages designing data structures with future analytical use in mind, laying the groundwork event if not immediately achievable.

The rest of the paper is structured as follows:

- Chapter II provides a brief overview of the evolution of cost accounting;
- Chapter III discusses how cost data can be useful in different PFM functions;
- Chapter IV presents digital enablers to gather and use cost data; and
- Chapter V concludes with a discussion on applicability and next steps.

[1] In the public sector, cost accounting methodologies are typically built by organizing existing financial and administrative data (such as expenditures, inputs, and activity logs) by cost centers, programs, or service delivery units. This data is then structured to allocate direct and indirect costs to specific outputs or services. The methodology often based on the Administrative and Functional budget classifications.

II. Evolution of Cost Accounting

II.1. What is Cost Accounting

Cost accounting (often termed managerial or management accounting) refers to the systematic process of identifying, measuring, analyzing, and reporting the costs associated with delivering goods and services. In the public sector, it focuses on tracing inputs (such as labor, materials, and overhead) to specific activities, programs, or service delivery units, producing granular insights into how resources are consumed. While financial accounting focuses on recording and reporting all financial transactions and balances of public entities in mandated (e.g., national regulations) and (e.g., IPSAS),[2] cost accounting repurposes that same underlying data[3] to support internal decisions—such as evaluating efficiency, comparing delivery models, and identifying areas of overspending or misallocation.

Cost accounting does not follow a standardized, internationally accepted methodology, and national approaches are often intentionally flexible. This flexibility allows managers to select cost drivers and allocation bases that best suit the nature of specific services. However, the absence of standardization can result in significant variation across organizations, limiting comparability unless cost data are clearly reconciled with financial accounts. As a result, countries that apply cost accounting typically develop baseline methodologies[4] to ensure internal consistency[5] and transparency—sometimes including sector-specific guidelines for areas such as health or education.[6]

II.2. Cost Accounting in the Public Sector

Cost accounting has evolved in response to technological advancements in the manufacturing sector. The systematic development of cost accounting began during the industrial revolution, when growing inventories and labor costs called for more detailed accounting measures. The traditional system of management accounting, focusing on identifying areas for improvement and activities with higher returns, had dominated inventory costing. However, innovations in production technology soon made this system obsolete, leading to the emergence of the cost management system. The new system recognizes that labor no longer dominates the manufacturing sector and addresses modern managerial needs by integrating process, activity, and target costing. It improves traceability of costs to objectives, reducing costs and proactively informing decision-making (Premchand, 1995).

Public sector cost accounting systems have different objectives but share common techniques and principles with the private sector. Governments do not operate as profit-maximizing investors like businesses do, but cost remains an important strategic consideration, and cost information can help in effective management and use of public funds. While slight variances exist in cost measurement, fundamental concepts and processes

[2] Government financial accounting systems use a chart of accounts and double-entry bookkeeping (often cash or accrual basis) to record transactions in a central general ledger. The data is aggregated to create entity-wide totals.

[3] Because financial accounting is ideally registered in one integrated database, governments can draw cost information from the same financial ledger to ensure consistency.

[4] A cost accounting methodology generally includes guidance on the classification of costs, cost centers, cost drivers, allocation bases, data sources, frequency of updates, reconciliation procedures with financial data, and documentation requirements.

[5] Jordan's case of hospitals cost accounting highlights the relevance of maintaining consistency across a same sector to enable the ministry's services development team or the operations improvement team in identifying higher cost centers and high-cost activities in order to enhance their delivery processes, which is the purpose of assessing service costs (Alqudah & Salleh, 2023).

[6] For more on terms and country methodologies, see Brazil Secretaria do Tesouro Nacional (2025), Alqudah & Salleh (2023), Jovanović et al. (2019), Chan & Pessoa (2016), New Zealand Treasury (2001), IFAC (2000).

for cost accounting remain unchanged for the public sector. Its application may need adjustments to meet different management objectives. Some examples are provided in Table 1.

Table 1. Commercial and government applications of cost accounting

Method/Tool	Description	Commercial Application	Government Application
Activity-based costing (commonly known as ABC)	Identifies cost factors based on activities.	Accurately determine costs and performance for administrative and manufacturing activities.	Activity classification in performance budgeting (e.g., Jordan, United States).
Lifecycle costing	Identifies all costs throughout the project lifecycle.	Guide product development or project planning and investment decision-making.	Evaluation of public projects or programs over their entire lifespan, especially in public procurement. (e.g., Denmark.)
Process costing	Identifies unit costs for each stage of production or process.	Identify and eliminate non-value-added costs; often used in assembly production of standardized goods.	Programs involving repetitive processes (e.g., entitlement benefits); identifying overheads associated with policy formulation and implementation.
Standard costing	Estimates costs for each component (i.e., material, labor, overhead) based on a per unit basis.	Identify cost variances and opportunities for process improvement or cost savings.	Budgeting and performance evaluation (e.g., Malaysia); appropriate for some operations using process costing.
Target costing	Estimates the target cost, and then cost elements based on the target cost.	Manufacture products within the specified target cost to retain/ enhance market shares or competitiveness.	Expenditure caps/ceilings as the equivalent of target costs.
Cost-driver analysis	Identifies activities that will influence the future cost or performance.	Estimate future cost and improve manufacturing by eliminating defective parts; used with technology accounting.	"Value engineering" to replace expensive items and reduce the costs of specific tasks to increase the ratio of function to cost.
Cost-performance analysis	Relates costs to performance and management objectives.	Determine the efficiency of production and impact of policy/technical changes.	Linking spending to policy objectives and outcomes to assess the cost-effectiveness of public projects.
Cost/budget variance analysis	Compares actual costs to standard/budgeted costs.	Improve cost control and performance measurement.	Identifying where actions could be taken to improve budget credibility (see Box 1).

Source: Authors.

Cost accounting can provide valuable insights into public service operations and support the efficient and effective management of public finances. In an accrual-based system, governments can use historical data on program costs to project future costs and prepare budget estimates. Costs can also act as benchmarks when setting prices and user fees for public goods and services, even when they are subsidized or set at market prices (see example of the Chief Adviser Cost of India). In addition, combining costs with effective performance metrics also enables cost-effectiveness or cost-benefit analysis, informing evaluations and decisions on the authorization, modification, and discontinuation of government programs. Lastly, cost accounting can allow comparisons of costs between different alternatives in economic decisions, thereby enhancing resource allocation and strategic policymaking across various sectors (IFAC, 2000). A recent survey shows that public sector managers recognize the potential of cost accounting data to enhance resource allocation and policy development (Rogošić, 2021).

In the public sector, cost accounting started to gain prominence in the mid-20th century, together with PBB. In the United States, cost accounting influenced the application of PBB at the federal government level in the 1950s. The new approach to accounting required government activities to be classified into cost elements, making costs relevant not only as a potential benchmark for appropriations but also for monitoring and control purposes (Premchand, 1995). Federal government agencies continued to implement cost accounting in recent decades, with nine out of ten agencies having adopted activity-based costing systems as of 2009, six of which were less than ten years old (Miller, 2009). More countries have made efforts to measure the costs of public services, often combined with performance measurements. In 19 European countries, central ministries and agencies with a higher use of cost accounting showed higher use of performance management (Mohr et al., 2018). Adoption of accrual accounting and the “value for money” concept have also led to the increased use of cost accounting in countries such as Australia, Canada, Malaysia, and New Zealand (IFAC, 2000).

Substantial efforts have also reached the local government level, but cost accounting reforms in the public sector have seen limited success. In the United States, local governments first introduced cost accounting and PBB, with adoption dating back to the late 1800s for cost accounting and to the early 1920s for PBB (Rivenbark, 2005). While cost accounting has evolved across different levels of government, challenges in standardization, integration with the general ledger, and alignment with internal management needs have limited its effectiveness (Premchand, 1995). In Brazil, pilots[7] have demonstrated the feasibility and usefulness of applying cost accounting in the state of São Paulo (Uña, 2017), but expansion has slowed due to a lack of financial resources and limited use of the data.

Cost accounting can require substantial resources and be time-consuming, especially when allocation or estimation of costs requires revising the underlying data structure. In most cases of public sector cost accounting systems, the systematization has required the development of specific reporting systems. These systems tend to run in parallel to existing budget execution, accounting, and PBB systems, while facing the same issues with obsolescence and rigidity as other government systems (Rivero del Paso et al., 2023). As a result, governments face several difficulties in deploying and managing cost accounting systems over time. In addition to the initial investment required, the lack of clarity around the use of cost accounting data makes it challenging to secure and maintain a coalition of users and other stakeholders, which helps obtain a return on this investment (Chan & Pessoa, 2016; Rivenbark, 2017).

The lack of robust digital and institutional infrastructure can create a disconnect between the theoretical benefits of cost accounting systems and their practical application in everyday management, presenting a significant challenge to continued success of implementation. In the United States, despite several laws and guidance that emphasize the need for cost management, only three of ten agencies had systems that could routinely provide managers with relevant, reliable data for decision-making; and only two were actively using it (GAO, 2007). In Slovenia and Croatia, inadequate IT support and resources constraints undermine hospital costing systems, leading to skewed cost allocations and reduced decision-making reliability (Jovanovićet al, 2019). In Finland, sophisticated costing tools often devolve into mere formalities, as they are not fully integrated into routine decision processes (Mättö & Sippola, 2016). In Jordan, institutional constraints and limited technical capacity hamper cost accounting initiatives, while in Brazil, a disconnect between the systems and operational needs frequently leads to underutilization of cost data (Alqudah et al., 2022; Ribeiro et al., 2024). These cases underscore that, without robust IT infrastructure and tailored system requirements, even well-designed cost accounting methods can fail to deliver on their promise of improving decision-making in the public sector. Such failure can, in turn, make it difficult to sustain managerial interest for cost accounting initiatives or necessitate costly redesigns (IFAC, 2000).

[7] With support from the Inter-American Development Bank (IADB) and the IMF.

Yet, governments continue to show interest in adopting or renewing cost accounting due to its potential to support various management functions and decision-making. For example, Peru is developing a new cost accounting model within the modernization framework of their financial management system to improve public expenditure management, with a pilot planned for the health sector (IADB, 2024). More recent reforms are recognizing the lesson that efficient cost accounting systems should "exchange information with many existing managerial systems as well as most accounting systems (IFAC, 2000)," drawing from common data sources as other systems supporting PFM (FASAB, 2024). Governments can tailor their approach based on their specific needs for cost information and the existing basis of financial accounting, choosing gradual implementation without a stand-alone system. Even those on a cash basis could develop approximate cost information that can support managerial decisions, using expenditure records and estimates for asset recognition effects.

III. Cost Accounting and Public Financial Management

Cost accounting can offer relevant insights to improve the efficiency and effectiveness of public expenditure, mainly through its interaction with other PFM functions (Robinson, 2007). While expenditure and cost are not always synonymous, they are closely related. Cost accounting helps break down and analyze the actual costs associated with a budgetary program or activity, providing a more accurate and comprehensive understanding of its financial implications. In short, it accumulates data from available sources to measure, analyze, interpret, and report detailed information to support resource planning, control, and accountability (FASAB, 1995). This chapter will discuss budget credibility, PBB, and public procurement as three main functions where cost accounting can improve budgetary decision-making. It will note the advantages as well as the challenges of embedding cost accounting into these functions, offering useful indicators where appropriate. The chapter will also touch on how cost accounting can help detect and deter corruption and mismanagement, which can have impact on different PFM functions.

III.1. Budget credibility

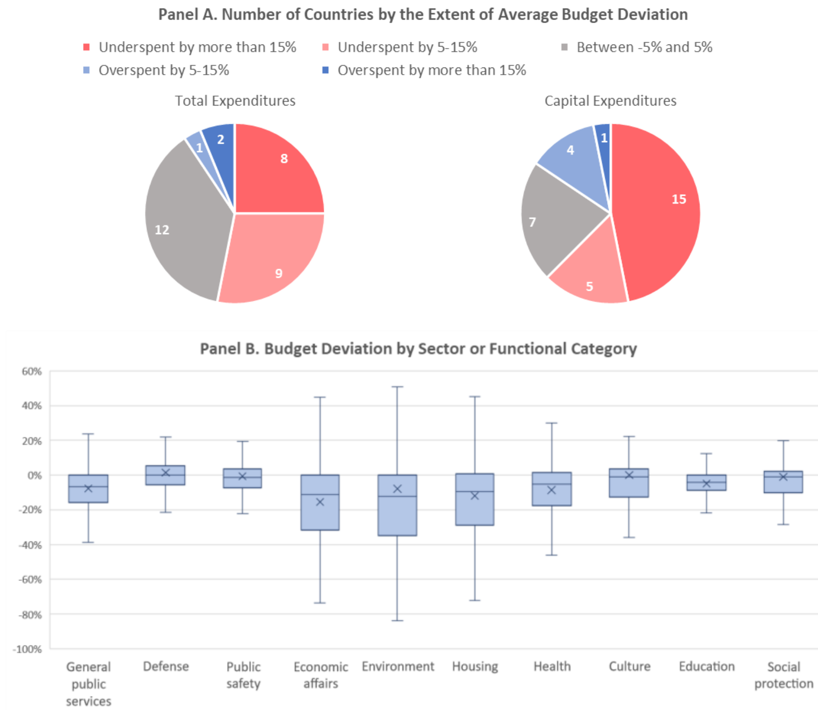
Budget credibility—the extent to which governments meet their expenditure and revenue targets—is an important indicator that can signal sound fiscal management (IBP, 2023; PEFA Secretariat, 2018).[8] While some deviations from original allocations can be justified and necessary[9], large and consistent deviations from the approved budgets can indicate poor practices such as unrealistic, hidden, and deferred budgeting (Mustapha, 2019). Implementing budgets as intended—with minimal deviations in aggregate *and* composition—can also indicate that the government is committed to delivering on its promises, making the achievement of its policy objectives, performance targets, and development goals more likely.

Available data show significant budget credibility challenges in many countries. According to the World Bank's BOOST data covering 32 countries over the period 2010-2022, governments tend to underspend their overall budgets and especially capital budgets (Panel A of Figure 1). PEFA data covering a larger number of countries also show that executed budgets deviated from planned budgets by more than 5 percent in roughly half of the countries, with the share being higher for some regions and income groups (Gurazada et al., 2022). The lack of budget credibility is more prevalent in key sectors, with deviations in the composition of expenditure over the budget cycle. For example, average underspending was over 10 percent in economic affairs such as agriculture and transport, while other sectors showed much smaller deviations (Panel B of Figure 1Figure 1).

[8] Budget credibility is also referred to as budget reliability.

[9] For example, governments may need to spend more than planned to respond to unexpected shocks such as natural disasters.

Figure 1. Budget credibility challenges across countries



Source: Authors using the World Bank's BOOST data.

Note: Pie charts use average budget deviation over the years with available data for each country.
Box plot uses each country-year observation and budget deviation in a given year, excluding outliers.

Cost accounting can support budget credibility by facilitating data-driven decision-making throughout the budget cycle. Its role is especially relevant in the budget formulation stage in helping governments plan budgets that are more realistic. By considering the entire life cycle of projects, cost accounting can also help incorporate longer-term perspectives into budgeting, including setting medium-term expenditure estimates. Cost accounting can produce real-time data during budget execution, helping to monitor and analyze variances while improving transparency. The cycle would repeat itself, with the data collected throughout the fiscal year informing budget preparation for the next year. Specific ways cost accounting can enhance budget credibility include:

- **Cost information can help prevent unrealistic budgeting**. Governments can analyze the data on historical costs, cost drivers, and cost risks[10] associated with specific activities to estimate their future costs, which can be aggregated to guide expenditure ceilings and prevent over or underbudgeting. Accurate cost estimation can also inform allocations for ministries, spending areas (e.g., functions), or individual projects, reducing the likelihood of significant budget deviations in composition.[11]
- **Cost accounting can help align the budget with policy changes**. By integrating cost accounting data into the budgeting process, governments can evaluate and consider in their annual budgets the financial

[10] Historical costs refer to the original costs incurred to acquire or produce an asset or resource. These costs are fixed and based on actual expenditures. Cost drivers refer to the factors that cause or influence the cost of an activity (e.g., labor hours and production volume). Cost risks refer to the potential for cost overruns or uncertainties for unexpected costs to incur. Cost risks can be caused by a variety of factors, such as fluctuations in market conditions or technical issues.

[11] In the U.S., the Department of Veterans Affairs relies on cost estimates for construction programs to make annual funding decisions for their facilities, which are in turn used by the Congress to make annual appropriations decisions (U.S. GAO, 2020).

implications of various options, such as introducing new spending programs. Cost accounting can help estimate not only new costs that will be incurred, but also the impact on any existing costs as well as the costs of supporting services. It can also inform analyses about the affordability and cost-effectiveness of new initiatives, leading to better decision-making (Government of Canada, 2023).

- **Cost accounting can help improve fiscal monitoring and reporting.** By increasing the availability of real-time data, cost accounting can strengthen internal control and encourage adherence to the approved budgets. Accounting systems tend to serve as the most reliable source of information for fiscal monitoring purposes, producing timely, centralized, reconcilable, and comprehensive data (Potter and Diamond, 1999). Cost driver data can also support the development and regular updates of expenditure baselines, which serve as a powerful monitoring tool that can help identify spending pressures, fiscal space, and possible sources of savings (Rahim et al., 2022).
- **Cost accounting can help identify and respond to budget deviations**. Variance analysis using cost accounting data can help to both identify deviations that may negatively impact budget credibility and understand the contributing factors and potential reasons behind those deviations. This can, in turn, support effective cost control, enabling governments to identify and implement appropriate measures (e.g., cost reduction or process improvement).[12] More information, including indicators that may be used in variance analysis, is provided in Box 1.
- **Cost accounting can help enhance fiscal transparency and accountability.** Timely publication of cost accounting data can improve not only internal but also external oversight, informing audits and increasing the visibility of cost control challenges that are contributing to the lack of budget credibility. Proper documentation can ensure that budget deviations are at least communicated and explained to the public, while increased public awareness can pressure governments to address them.

Box 1. Indicators for variance analysis in earned value management

Tracking and analyzing variances can help ensure that execution of a project follows the original plan and budget, while mitigating risks. Comprehensive variance analyses also help identify the root causes and impact of deviations, supporting the application of corrective measures. Integrating and monitoring cost, schedule, and performance data—through earned value management, for example—can enable such analyses, improving financial control and informing future planning in government projects. Measures used in a comprehensive variance analysis may include:

- Cost variance = budgeted cost for work performed (BCWP) - actual cost of work performed (ACWP)
- Schedule variance = BCWP - budgeted cost for work schedule (BCWS)
- Variance at completion = budget at completion (BAC) - estimated cost at completion (EAC)
- Cost performance index (CPI) = BCWP / ACWP
- To complete performance index (TCPI) = (BAC - BCWP) / (EAC - ACWP)

These measures could be disaggregated at the level of cost elements, plotted and examined for trends, compared to each other or against a threshold, and investigated further to identify the cause of variances and test the underlying assumptions. For example, low CPI may indicate cost inefficiency, unanticipated travel, expensive labor, or technical issues, although managers should assess its full meaning to apply corrective measures as appropriate. CPI that is lower than TCPI may also indicate that higher productivity was assumed for the future at the time of budget approval, which may no longer hold and may need to be revisited. Additional indicators which may help identify lack of reliable data, poor project execution, and other issues related to budget credibility include:

[12] Governments may also consider in-year budget adjustments or reallocations as a form of cost control. However, while some flexibility can be necessary and can help with resource optimization, it is important to ensure that clear rules and mechanisms are put in place to prevent in-year adjustments from undermining budget credibility. See PEFA dimensions 18.4 and 21.4 and Herrera and Lakin (2019) for more information.

- Large and frequent cost or schedule variances (either at program or cost element level)
- Significant difference between estimated cost to complete and budget for remaining work
- Insufficient budgets, including management or contingency reserve, for the remaining work
- Program status and schedule that are not comparable to historical data or original plan
- Logic sequence and durations for forecasted work that vary significantly from plan
- Recurring data errors or anomalies (e.g., negative values for actual costs).

Source: Authors, based mainly on U.S. GAO (2020).

While the advantages of cost accounting in ensuring budget credibility are clear in theory, application in practice may be challenging. Not only is the lack of budget credibility a complex issue driven by different factors ranging from inaccurate revenue projections to coordination challenges with donors[13], producing credible cost estimates for budgeting poses a challenge of its own, as it requires: (1) continuous participation of diverse stakeholders, (2) clear understanding of scope, project life cycle, and all relevant cost elements, (3) access to reliable historical data that can serve as the basis, (4) robust risk and sensitivity assessment, (5) sufficient validation, and (6) detailed documentation (Government of Canada, 2023). Its application can further require some judgments and "imagination" about the expected benefits (Chan & Pessoa, 2016).

Quantification of cost risks and uncertainties is particularly crucial in producing credible cost estimates and ensuring realistic budgeting—but is often inadequate (U.S. GAO, 2020). Risk and uncertainty analysis can predict the probability of achieving the estimate and successfully executing the program within its budget, while adding a contingency to provide an acceptable level of confidence. Sensitivity analysis can acknowledge data limitations and show the potential effects of changing assumptions. Yet, countries face various difficulties in conducting objective and comprehensive analyses. The large deviations in capital budgets seem to reflect these challenges across countries. Investment projects are generally susceptible to more cost risks and uncertainties—including those arising from procurement, another area that can be strengthened by cost accounting, as discussed later—and their costs are harder to forecast as a result, making deviations more likely (de Renzio et al., 2019; Simson and Welham, 2014).

Despite the inherent uncertainties involved, governments can adopt good practices to improve the credibility of their cost estimates and thus their budgets. For example, governments can require the update of risk and uncertainty analysis prior to budget submissions and at other key decision points. They can also use past outcomes, similar initiatives, and other benchmarks to validate the cost estimates. Improving the availability and quality of relevant data—from historical and current costs to information about program schedule, data required for normalization (e.g., inflation rates), and more—is especially crucial, for not only validation efforts but also all other steps of the costing process. After all, "data are the foundation of every cost estimate (U.S. GAO, 2020)." Ensuring that available budgetary financial data can be used for estimating costs, through standardizing the necessary accounting adjustments and defining the appropriate level of detail, can help in this regard.[14]

Open data and documentation can also improve the credibility of cost accounting data and help minimize principal-agent problems that can undermine budget credibility. For example, policymakers would be less likely to overstate the costs of an initiative to receive more funding if the actual cost of a similar initiative can be

[13] See for example Addison (2013), Mills (2018), Mustapha (2019), and de Renzio and Cho (2019).

[14] In São Paulo, for example, it was determined that budgetary data at the verification or liquidation stage could be transformed to cost data through the integrated financial administration system (SIAFEM), provided that (1) the classification into service and cost center was included in the chart of accounts and (2) necessary accounting adjustments, for example considering future cash advances, were applied. See Chan and Pessoa (2016) for more information.

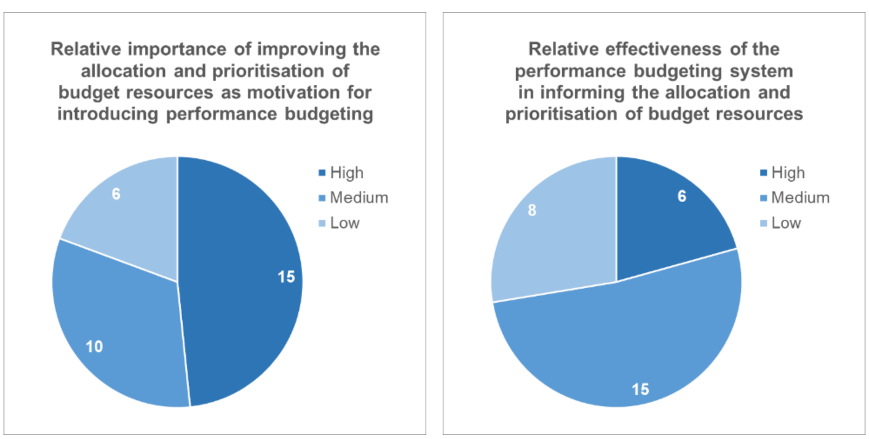
easily verified, or if significant cost variances will be made available for public scrutiny. Cross-country analyses found that greater fiscal transparency—together with more advanced practices in accounting and reporting—is associated with better overall credibility on the expenditure side (de Renzio & Cho, 2020). This finding supports the premise that increased availability and timely reporting of financial information can enable better, real-time control in the use of public resources. Documentation should be done not at the end but throughout the cost accounting process, capturing ground rules and assumptions, methods, data sources, and other key details about the exercise. This would ensure that the data can be understood, traced, used for audits, and later replicated or updated as needed (Government of Canada, 2023).

III.2. Performance-based budgeting

PBB can help improve the efficiency of the production of goods and services by integrating relevant disaggregated data. While there is no universally accepted or fit-for-all model, PBB is generally defined as the "systematic use of performance information to inform budget decisions" (OECD, 2023). Its primary aim is often understood as increasing the focus on the results rather than on internal processes, but stakeholders in the budgetary process can also obtain valuable information from individual transactions. Incorporating this granular information can enhance budgetary decision-making, leading to a more efficient and effective allocation of public resources (Trenovski & Nikolov, 2015).

One of the principal critiques of PBB models is that, despite the significant increase in performance information, there is a notable lack of its application in decision-making (Joyce, 2011). While there has been some improvement in the consolidation of PBB across the world—reflected, for instance, in a 24 percent increase in budget transparency scores since 2008 (IBP, 2023)—performance budgeting has proved less effective as a tool for resource allocation and prioritization, strategic coordination, facilitating evaluation or for setting service delivery targets" (OECD, 2018, p. 12). Even countries with robust PBB technical designs, such as France, or with considerable progress in budgetary reform, such as Uruguay, have extremely rigid budgeting systems that prevent the reallocation of resources based on performance information (Radics & Fernandez, 2019). As Figure 2 shows, while 15 OECD countries (48 percent) indicated that improving the allocation of resources was one of their main drivers for performance budgeting, only six (21 percent) consider a high effectiveness in informing the allocation and prioritization of resources.

Figure 2. Importance of budget allocations for performance budgeting in OECD countries



Source: OECD (2018), OECD Performance Budgeting Survey.

Another important issue is the scarcity of relevant performance indicators that can help compare programs and make budget decisions based on accurate, timely, and detailed information.[15] Gathering more strategic information in terms of number of indicators has been the norm for PBB (Hughes, 2008). However, countries as varied as Chile, France, Italy, Mexico, New Zealand and Norway have reduced their number of performance indicators in budget documents in response to high administrative burden for line ministries and the realization of having lengthy and irrelevant reports (OECD, 2024). In addition, these indicators are generally compiled in aggregate forms (e.g., national averages, averages by gender). This high-level focus, while placing more emphasis on results, tends to miss data on individual-level problems that could inform budgetary decision-making and help achieve those high-level results. An example of this is gathering maternal health indicators at the national level that reveal the overall policy direction but provide little actionable information for budget offices.

Detailed data should allow decision-makers to identify where specific issues lie and make appropriate adjustments. One viable option to increase the relevance of performance information, therefore, is to allow drilling down on such strategic indicators. For instance, as part of a performance review conducted in 2008, Australia defined that outcomes must be more detailed and include a sub-level for performance indicators to be attributable to the responsible entities. Hence, the outcome for primary care, as an example, was revised from "access to high-quality, well-integrated and cost-effective primary care" as originally drafted to "access to comprehensive, community-based healthcare, first point of call services for prevention, diagnosis, and treatment of ill-health, and for ongoing management of chronic disease" (OECD, 2024).

Developing digital solutions that allow drilling down to granular data with a strategic view is a departure on how traditional PBB digital solutions were built over one to two decades ago and continue in operation today. Current PBB systems usually fall under one of three models: (1) systems that capture only strategic indicators (impact and outcome indicators); (2) systems for processes control (outputs[16] and activities indicators); and (3) hybrid systems in which both strategic and control indicators are gathered. In any case, these systems rely on direct reporting of the results of the algorithms behind the indicators, which do not allow identifying the nuances in how results are being achieved. Everyday transactions can build performance indicators by considering information on costs—that is, by not only including data on outcomes or outputs in the numerator but also including costs in the denominator (Behn, 2003)—thus helping to assess the financial implications of different policy options and their trade-offs between costs and benefits.

Cost accounting data can support the construction of relevant performance information. While it does not substitute strategic or lower-level indicators, cost accounting data can act as an input to support PBB objectives. According to Behn (2003), there are eight key functions of performance measures: evaluate, control, budget, motivate, promote, celebrate, learn, and improve. Cost accounting can offer relevant input for all eight functions. One obvious link is with the budget function, where it can help to build efficiency measures (i.e., outputs divided by the cost of inputs to produce them). For example, it can build an indicator regarding the efficiency in the construction of roads (e.g., km of road constructed / costs associated to build that road) or even an indicator that considers costs indirectly (e.g., the number of medical appointments by doctor or health personnel). There are also important links with the other seven functions, especially for the learn and improve functions, based on the detailed benchmarking learning by comparing programs and their costs.

[15] Wholey and Newcome (1997) point out that ¨[p]erformance measurement may be done annually to improve public accountability and policy decision making or done more frequently to improve management and program effectiveness" (p. 98).

[16] Products and services.

There are different methodologies to include costs in performance evaluation (Table 1). According to Chan and Pessoa (2016), one method acknowledges tradeoffs between service and costs. A second method considers as an advantage the reduction of costs, recommending cost cutting without placing much focus on the consequences. A third method is to compare actual costs with standard costs, identifying variations that might be worth understanding. Despite its benefits, integrating cost accounting into PBB presents significant challenges that need to be addressed. Some of the more general hazards include the cost of implementing a detailed cost accounting approach (Thomas, 2006; Robinson, 2007) and not considering or considering arbitrary measures of the indirect or hidden cost (Behn, 2003; Robinson, 2007), especially on a program basis (Breul, 2007). Box 2 shows some specific challenges and advantages of integrating cost accounting into PBB measurements.

Box 2. Advantages and challenges of integrating cost accounting into PBB

Advantages

- **Simple and practical information.** According to Robinson and Last (2009), the biggest challenge in PBB is keeping the information simple, affordable and usable. The use of cost accounting helps to achieve two of those features by simplifying the presentation of complex interactions in simple terms, for instance, by using activity-based costing.
- **Allocation of indirect costs.** According to the OECD's best practices, programs should group all resources used to the achievement of their goals. Yet, it is hard and sometimes impossible to split the contribution of support programs (OECD, 2018). Cost accounting offers tools to allocate indirect costs to products with reasonably accurate mechanisms (Robinson and Last, 2009).
- **Cross-sectional cost benchmarking.** Compare the cost of producing a given output (good or service) with other producers with similar characteristics, in this case, other agencies, programs, or external entities. This offers insights on efficiency and points out strategies to reduce costs (Robinson, 2007).
- **Linkage between funding and results.** Cost accounting can be useful for medium-term expenditure estimates, the formulation of more informed performance targets, and as the basis for formula funding, including the purchaser-provider version (Robinson, 2007).

Challenges

- **Oversimplified unit costs.** The level of production can affect significantly the costs. Oversimplification comes from the fact that average costs can increase or decrease according to the production target. The solution is to use the complete cost function rather than the average, but since it can be quite complex and costly to obtain, it can be substituted by the average variable costs (Robinson, 2007).
- **Differentiated costs based on geographical location.** Costs may vary depending on the location where the goods or services are provided. For instance, schools and hospitals located in rural areas may have considerably higher costs than their metropolitan counterparts (Robinson, 2007).
- **Difficulties with outcome measurement.** Cost accounting information is normally used for outputs more than for outcomes since there are many variables related to an outcome. Thus, applying a cost-based formula to determine the budget can result in highly distorted results (Robinson, 2007).
- **External factors.** Programs with contingency actions, where it is not possible to determine the demand ex ante, introduce complexity in the calculation of prospective costs. For instance, fire services cannot know for sure how many fires they will have to attend, but they need to have the required resources to address any given threats (Robinson, 2007).

Source: Authors, based mainly on Robinson (2007) and Robinson and Last (2009).

Considering the advantages, challenges and contribution to specific PBB functions, cost accounting can contribute primarily to three objectives:

- **Through cost attribution, cost accounting can enable the identification and allocation of costs to specific activities, programs, or projects**. By tracking and attributing costs accurately, governments can assess the actual expenses associated with different performance measures or outcomes. For example, a public university can track its costs associated with generating each class, allowing for better allocations; or a state hospital can track accurately the cost of each surgery, allowing for automatic use of data for cost attribution. Also, costs are important for deciding on user prices and setting fees for the provision of goods and services (Rogošić, 2021). This information helps in aligning resources with priorities and making informed budget decisions based on performance data. As preconditions, the accounting system needs to "record expenditure on a continuing basis by program (as well as by the established economic and administrative classifications)" (Robinson & Last, 2009, p. 6). A possibility for determining the costs is to use the purchaser-provider system approach, where line ministries are paid prices for the services they deliver to the community. However, this approach has only been successful in small, controlled sectors such as hospitals.

The introduction of technology can be especially helpful for enhancing the accuracy and transparency of cost allocation processes. An algorithm could analyze the variations in cost allocations for different cost categories over time using raw data, preferably integrated into an Integrated Financial Management Information System (FMIS).[17] This would allow the identification of sudden or unexplained changes that exceed a predetermined threshold, which may indicate errors, manipulation, or misreporting in cost attribution. The ability to identify significant fluctuations in allocations for specific cost categories offers stakeholders relevant tools for determining amendments to the initial allocations that would otherwise have gone unnoticed. Another possible application of digital solutions is to detect the lack of documentation or inadequate evidence for cost allocations. An algorithm could assess the availability and quality of supporting documentation for cost allocations, issuing warnings when there is a lack of documentation or insufficient evidence to substantiate the basis for cost allocations, which indicates potential weaknesses in the accuracy and reliability of the cost accounting process.

- **Cost accounting provides insights into the cost structure and resource requirements for different programs, allowing governments to allocate resources based on the expected costs of achieving desired outcomes**. However, cost-based analysis and budgeting may be challenging for complex activities with mixed inputs. Allocations based on pre-defined formulas are normally useful to compare programs that produce similar inputs in controlled environments. However, the interaction of different variables affecting program results or even outputs, or political and moral considerations of public policies make it difficult to base allocation decisions solely on reducing costs. On the other hand, cost analysis enables detailed examination of cost drivers, identifying areas of inefficiency and cost-saving opportunities. By linking costs to performance outcomes, governments can assess program cost-effectiveness and make informed decisions on resource allocation, including the definition of expenditure baselines, considering that cost may change even if policies remain constant (Rahim et al., 2022).

  By comparing the costs incurred for similar programs or activities, algorithms can help identify disproportionate cost variances. A benchmarking approach can detect deviations, even with the consideration of a significant threshold. Warnings can be issued whenever costs are significantly higher or lower compared to similar programs, suggesting potential inefficiencies or anomalies. Also, technology can be helpful to detect high levels of overhead costs without clear justifications or impact on performance. In a typical PBB framework, budgetary analysis focuses on the outcomes achieved and includes identifying the reasons for not meeting or exceeding a specific target. Algorithms can help identify cases where the overhead costs are excessively high or low compared to the overall budget program size. Another possible application is to implement cost-effectiveness evaluations.

[17] As explained further in Chapter IV, the algorithm that we propose in this paper is executed in Python. There can be different ways in which Phyton can connect to the FMIS, including the installation of specific packages to connect with SQL and not SQL databases (including " pymysql" or " PyMongo", among others), connect to an API, publish the data in a URL and connect to that data periodically or even manually update a local csv file and use it to run the algorithm in Python.

- **Cost accounting provides a foundation for measuring and monitoring performance against budgeted targets.** It enables the comparison of actual costs incurred with budgeted costs, allowing governments to identify variances and take corrective actions. By integrating cost accounting data with performance indicators, governments can evaluate the efficiency and effectiveness of programs and assess their contribution to desired outcomes and conduct spending reviews, especially program reviews, that are more related to delivering efficiency savings, that is, reducing the costs of delivering services under the program (Doherty & Sayegh, 2022).

  An example of indicator could be a consistent underperformance or failure to achieve targeted performance outcomes despite high costs. The idea is to compare the observed outcomes with the associated costs for each program or activity and identify patterns of underperformance or failure despite significant investment. Additionally, a lack of correlation between cost increases and improvements in performance outcomes can show relevant insights for a more detailed impact evaluation, revealing potential relationship between costs and performance.[18]

III.3. Public procurement

Well-managed public procurement processes are crucial in ensuring the effective use of public funds and successful provision of public services. By incorporating cost accounting to enable informed decision-making, cost control, and contract management, governments can enhance the efficiency and value for money in public procurement (see Box 3). Some forms in which cost accounting can support different stages of the procurement cycle—from planning and tender to award, contract, implementation, and evaluation—include:

- **Cost estimates can serve as the basis for contract budgets, evaluations, and negotiations**. As with budget credibility, cost accounting provides valuable data and insights for cost estimation, helping governments develop more realistic and reliable budgets for goods, services, or infrastructure projects. Accurate cost expectations can also help governments in evaluating vendor proposals and negotiating contracts. For example, an analysis of cost risks and uncertainties may inform negotiations around not only price but also risk-sharing (Government of Canada, 2023).
- **Cost accounting can help governments make informed procurement decisions based on long-term costs and benefits.** By analyzing the total cost of ownership—which includes not only the initial acquisition cost but also maintenance, operation, and disposal costs—governments can compare the procurement options while considering factors such as life-cycle costs, quality, and sustainability. Cost accounting can also help evaluate the value for money offered by different procurement choices and the potential return on investment by supporting cost-benefit analysis.
- **Cost accounting can facilitate the implementation of performance-based contracts.** By integrating performance metrics and costs, governments can link payment to the achievement of agreed-upon targets, ensuring alignment with intended outcomes and value for money in public procurement. Performance-based contracting also offers benefits for suppliers, granting them greater flexibility. Cost

[18] A challenge that could arise for performance measurement is that costs might be calculated in different units than the level of granularity for budgets. While costs are normally calculated at the level of the unit that provides the services (e.g., schools, hospitals), budgets are normally prepared at the services level. A consolidation would be required, which can be addressed through the digital tools presented in the following section of this Working Paper.

analysis plays a crucial role in enabling performance-based contracting, as it supports the development of rates and deliverables that are measurable, realistic, and data driven.[19]

- **Cost accounting data can aid in evaluating and monitoring supplier performance, ensuring adherence to cost commitments and accountability in implementation.** By tracking and analyzing actual costs incurred by suppliers and comparing them to contracted costs, governments can identify any cost overruns, variances, or discrepancies. This helps in assessing supplier performance, managing contract compliance, and taking appropriate actions when necessary.
- **Cost accounting can contribute to risk assessment and mitigation in procurement**. By analyzing cost accounting data, governments can identify potential cost-related risks, such as cost escalation, budget overruns, or inadequate cost controls. This enables proactive risk management and the implementation of measures to mitigate risks associated with procurement activities.

Box 3. Use of cost accounting in public procurement

In **Canada**, cost accounting guides price negotiation and helps to determine contract costs when market-based pricing is not possible. In cost-based pricing, the price is based on the acceptability of actual and/or estimated costs, with a profit margin and added incentives when applicable. Contracting officers should apply professional judgment when considering the desired outcome and risk of a contract, as well as use the Cost Accounting Practices Submission from the contractor, to determine whether cost types are attributable, appropriate, and reasonable.

In **Denmark**, total cost of ownership (TCO) calculation has helped local governments factor energy efficiency into their procurement decisions. In 2012, for example, the government evaluated computer suppliers for 40 municipalities after adding three-year power consumption costs. Total estimated savings for the three-year period were almost 11 million DKK (about 1.6 million USD), 7,250 MWh, and 3,625 tons of CO_2. The Danish Ministry of Environment has since developed a tool that calculates TCO for selected product types, which has been used in other contracts. For example, in a municipality lighting tender, the tool demonstrated that LED bulbs would be six times less expensive than halogen bulbs over 15 years.

In the **United States**, procurement cost and schedule estimates are monitored throughout implementation. For example, U.S. Government Accountability Office (GAO) has reviewed the Department of Defense (DOD)'s F-35 program every year since 2001, reporting on the estimated costs and lengths. Based on GAO recommendations, DOD has made some changes to reduce the likelihood of cost overruns and improve the credibility of cost estimates. Actions taken include: (i) reviewing capability requirements, (ii) conducting an independent cost estimate, (iii) requiring a detailed cost estimate and baseline schedule to be submitted before expending more funds, (iv) submitting a system redesign strategy that identified key risks, and (v) implementing automated tools that provide real-time access to software development metrics.

Source: Public Services and Procurement Canada (2022), Estevan, Schaefer & Adell (2018), U.S. GAO (2023).

As in PBB and budget credibility, cost accounting can help detect anomalies or significant variations in procurement. Actual costs can be compared to market benchmarks, historical costs, or budgeted costs for contracts to flag significant cases of deviations. Disaggregated data can indicate their origins, for example in specific cost elements, helping governments identify areas that may require risk mitigation measures or other interventions. Cost accounting data can also help find discrepancies in pricing, quantities, and other purchase order information, as well as unusual patterns in cash flow. Other related information, such as project schedule and supplier performance, can be analyzed to detect anomalies in procurement activities that may warrant attention. Such analysis can be performed at any time of the procurement cycle to enable governments to

[19] Governments should carefully assess whether it would be appropriate and take into consideration any risks involved. For example, new programs may not have the historical data to inform the negotiation of objective and measurable performance targets. In such cases, governments could consider a hybrid model, to provide time to collect the necessary data. As suppliers also risk incurring non-reimbursable indirect costs (e.g., costs associated with tracking deliverable), governments may need to provide additional assistance to ensure compliance. For more information, see Nonprofit Resiliency Committee (2019).

reschedule or redesign the project, update cost estimates, and take actions to mitigate risks as necessary. To better inform their decisions and interventions, governments may need to further investigate the trends and patterns observed in variance analysis.[20]

III.4. Detection of corruption and mismanagement

Cost accounting offers relevant insights for detecting and deterring various forms of corruption and mismanagement, which can have both direct and indirect impacts on PFM.[21] Acts of corruption can be classified according to different categories, such as bureaucratic or political, cost-reducing or benefit-enhancing, and coercive or collusive (Tanzi, 1998). They can also take or combine different methods, such as bribery, extortion, cronyism, embezzlement, and fraud[22], which vary by factors such as the number of parties involved, the type of benefit provided, and the degree of coercion used. In the budget cycle, corruption can lead to the diversion of spending choices towards activities offering more opportunities for kickbacks and exemption of controls, such as complex defense equipment. During budget execution, it can manifest as the exploitation of weaknesses in the purchase of goods and services, wages and pension payments, as well as off-budget spending encompassing extrabudgetary funds (IMF, 2019).

Regardless of the forms or motivations, cost accounting can strengthen the information available to help prevent corruption. Ways in which cost accounting data can be used with the existing technologies include:

- **Cost accounting data can help define indicators to detect possible cases of corruption.** As the concealed nature of corruption makes it difficult to gather and assess direct evidence, available indicators—such as the Global Corruption Barometer and Corruption Perceptions Index—tend to measure the incidence and perception of corruption through stakeholder surveys. While useful, such information provides limited value for budget and fiscal decision-making. Cost accounting can help fill some gaps by enabling the calculation of the costs of producing a given good or service, which can serve as a benchmark to compare similar providers or activities and identify unexplained cost savings or outliers that may be linked to corruption (Box4).

Box 4. Example of possible red flags in public procurement

The sheer volume of public procurement spending calls for high standards and accountability, but it remains highly vulnerable to corruption (Abdou et al., 2022). According to the Open Contracting Partnership (OCP, 2020), public contracts constitute one-third of government spending, totaling about 13 trillion USD per year on a global scale.[23] However, less than three percent of public contracts are published openly—and key data needed for useful analyses (e.g., contract amount, start and end dates) are made available for an even smaller share. Such lack of transparency has undermined the efforts to increase competition as well as effective oversight, which could have dire consequences on the quality of public goods, works, and services acquired.

Advanced uses of cost accounting data can help improve accountability and outcomes in public procurement by supporting real-time detection of irregularities. Several countries are experimenting or implementing this approach to help enhance integrity and transparency in procurement (e.g., Ukraine, Paraguay, Dominican Republic, Guatemala[24]). OCP[25] and the Inter-American Network of Public Procurement (RICG) of the Organization of American States have published extensive documentation to implement red flags, including the algorithms for their calculation. International experiences illustrate that an alert system requires quality, real-time, and standardized data for calculations.[26] By improving the availability and quality of data, cost accounting can enable the calculations and support the implementation of red flags in public procurement.

Some indicators that could be calculated in an alert system for public procurement include:

- Line-item bids are unreasonably high / low
- Tender value is higher or lower than the category average

- Agents charge excessive fees or overcharge for the work performed
- Small initial purchase from supplier is followed by much larger purchases
- Awarded price is higher than the price of the input under open contract
- Margins on a particular item or category of items is consistently low or high
- There is a large difference between contract award and final contract amount
- Payments of unjustified high prices relative to historical average are made
- Total payments to a contractor exceed total contract or purchase order amounts

In the absence of an alert system, countries could also consider using the Corruption Cost Tracker (Basdevant & Fazekas, 2023), which calculates the Corruption Risk Index based on the frequency of seven red flags—(i) single bidder, (ii) non-open procedures, (iii) lack of publication of call for tenders, (iv) and (v) long or short period for submission and decision, (vi) concentration in bidders, and (vii) share of suppliers with limited transparency—across all available contracts.

Source: Authors based on OCP (2016 & 2020), OCP blogs, RICG (2022), and Basdevant & Fazekas (2023).

- **Cost accounting data can also help uncover disorganization that—whether intentionally or unintentionally—may allow potential corrupt behavior.** For example, significant variations in prices of similar goods or services may indicate a lack of standardized policies or legal compliance. ML algorithms can be useful in identifying these possible cases of disorganization, as they can analyze a huge amount of data to detect inconsistencies or deviation patterns. Additionally, the algorithms can help ensure that all transactions are properly recorded and accounted for, enhancing monitoring of inventory and assets.
- **Data analysis can facilitate the implementation of preventive measures.** ML algorithms can be used to discover accrual manipulation and unusual activities such as unexpected growth in employee productivity or discretionary accruals (Aryal, 2022). Cost accounting can also add value in analyzing trends and deviations in the expected financial outcomes, offering relevant insights for detecting fraud. Analysis of peaks in wages, for example, can help create red flags to be monitored in the future. Such proactive approach not only aids in the early detection but also supports the implementation of measures that can help to deter corruption and mismanagement.

[20] Further investigation may be necessary to detect corruption, for example. To illustrate, an abnormal spike in labor costs could reflect a range of issues, including an overly optimistic assumption about the required amount of labor, a change in the scope of the project, or fraudulent activities (e.g., over-reporting or inflating of labor charges). As another example, selection of suppliers with poor past outcomes could potentially indicate conflicts of interest or other improper practices, but it could also be a result of limited competition and lack of performance-based contracting.

[21] While it does not constitute a PFM function, corruption—defined as the abuse of public office for private gain (IMF, 2024)— has large economic consequences (IMF, 2016) and reduces resources available for conducting expenditures, undermining their impact. Given this close linkage, corruption—together with mismanagement, which may lack the intent but have similar impact and detection methods—is discussed as an area that can benefit from cost accounting.

[22] Fraud is defined in this paper as any act, including omission or misrepresentation of facts, that aims to deceive and induce a party to act to their detriment (World Bank, 2010).

[23] In OECD member countries, public procurement spending was estimated to be 6 trillion EUR (about 7 trillion USD) per year, representing 12 percent of GDP and 29 percent of government expenditure.

[24] Based on the data challenge/ hackathon "From Procurement to Payments" implemented by the Ministry of Finance with support from the FAD of the IMF in 2022.

[25] Cardinal is an open-source solution that makes it easier to calculate common risk indicators of corruption and collusion in procurement that is built on the Red Flags for Integrity Guide. https://www.open-contracting.org/2024/06/12/cardinal-an-open-source-library-to-calculate-public-procurement-red-flags/

[26] For example, four out of 43 identified flags were implemented in Colombia due to data limitations, while 28 were implemented in Paraguay. See RICG (2022) for more information on their experiences.

IV. Digital Enablers to Gather and Use Cost Accounting Data

Although core cost accounting methodologies have remained largely consistent, the digitalization of government over the past 10 to 15 years has transformed the landscape of what is possible. Advances in digital infrastructure, data systems, and analytics have opened new opportunities to generate, process, and use cost data in ways that were previously impractical or impossible.

As highlighted in the preceding examples, technology can help uncover cost patterns and inefficiencies that would otherwise go unnoticed—making cost accounting data significantly more actionable for decision-making. These methods are not without their challenges. Large investment projects, for instance, often have inflated or opaque cost structures that are difficult to compare due to their unique characteristics. Yet, with sufficient data granularity, key elements (such as materials or labor inputs) can be standardized and compared across projects, enhancing visibility and scrutiny.

This chapter explores leveraging automated, standardized cost data collection through interoperability with administrative records and shows how this data can be further analyzed using ML techniques. These approaches are designed to be flexible and practical, allowing countries to adapt them to their specific cost accounting and classification systems while laying the foundation for more sophisticated analysis over time. Although ML applications in PFM are still in the early stages, they are gaining momentum—even in low-income countries—as digital capacity expands. More broadly, the chapter emphasizes the importance of designing data structures with future analytical use in mind

IV.1. Gaining data granularity through interoperability with administrative records

A key limitation in using cost accounting data for public financial management lies in the challenge of collecting high-quality, granular information that supports decision-making. Traditional methods are often labor-intensive, error-prone, and time-consuming, requiring standardized databases and active oversight. Manual consolidation—typically via spreadsheets submitted from line ministries to the Ministry of Finance—frequently results in poor data quality and delays. Centralized systems offer better controls and update alerts but can lead to duplication across administrative platforms, creating inefficiencies and risks of conflicting data sources.

The proliferation of administrative systems in line ministries and agencies requires a different approach that enables automated data flows across different systems (Box 5). For example, São Paulo's Secretariat of Education—with support from the State Data Processing Company—has developed APIs[27] to gather and send the administrative data by program and school cadaster to the cost accounting database, eliminating the need for manual data entry. This new approach using administrative systems is not only technically feasible but can also help address some of the biggest challenges faced by cost accounting initiatives, such as high costs, poor data quality, and limited uses of the data.

Administrative systems, where spending units oversee costs and pricing, have expanded; however, these systems often lack integration with a centralized repository, thereby limiting the ability to compile a comprehensive and comparable overview. Experiences show that standardization of data is essential in

[27] An API aims to expose certain functionalities of a software application in a secure, controlled manner, so that other applications can leverage them without needing to understand the full complexity of the source application. While most everyday users interact with APIs indirectly, those with technical knowledge can interact with them directly to retrieve and analyze data.

leveraging digital innovations to increase the coverage and use of cost accounting data. An example this is a solution developed by eGov Foundation, a non-governmental organization of India, to address the fragmentation in data flows by standardizing transactional data to enable interoperability between service delivery units and local government agencies.[28] Interoperability with administrative systems and standardized protocols for sending and receiving administrative data can expedite the development and ensure the sustainability of cost accounting systems, but this is not the prevalent form of adoption at present. The concepts of interoperability and data linkage are acknowledged as important features of a mature administrative system in the UNICEF's AdaMM, which assesses the existence of national data standards and formats, data dictionary, and unique identifiers, among others (UNICEF, 2021). Aligning cost centers and drivers with budget classifications and performance indicators can enable cost accounting to be easily integrated into the PBB system and support budgetary decision-making.

Box 5. Interoperability mechanisms to collect cost accounting data

- **Data integration**: Interoperability can be developed via APIs to connect administrative systems (e.g., schools and hospitals) with a central cost accounting system. This would enable the exchange of relevant data in a standardized format, ensuring compatibility and consistency.
- **Data retrieval:** A central cost accounting system can request specific data, including personnel expenses, operational costs, facility expenses, and program-specific expenditures, from the administrative systems via APIs.
- **Real-time updates:** Interoperability can enable real-time or scheduled data updates, ensuring that the cost accounting system has the latest administrative records and allowing accurate and up-to-date cost analysis and reporting.
- **Data mapping and transformation:** Through APIs governments can map and transform data from the administrative records into the required data standards for cost accounting purposes.
- **Security and access control:** APIs can incorporate authentication and authorization mechanisms to ensure secure access to the administrative records.
- **Error handling and logging:** APIs can include error handling mechanisms to address data inconsistencies or issues encountered during data retrieval or integration. Additionally, API logs can be generated to track data exchange and identify potential errors or discrepancies.

Source: Authors.

In practice, however, agencies implementing cost accounting often encounter challenges in automating data collection due to variations in the levels of cost centers and services. This typically results in the creation of ad-hoc data structures specific to each ministry, which must subsequently be transformed by the consolidating agency—usually the Ministry of Finance.

To facilitate automated data collection in cost accounting, it is critical to standardize data structures, flows, and concepts. Box 6 presents a data schema that can serve as a blueprint for organizing data across cost centers and services, accommodating varying levels of granularity. APIs can be developed based on this schema to enable the automated and standardized transfer of data from administrative systems to the cost accounting system. To eliminate the need for ad-hoc programming for data exchange, the IT department could issue guidelines for API development and mandate their adoption by both internal and external developers. This approach ensures consistency, reduces redundancy, and streamlines the integration process.

[28] The open-source platform DIGIT has been piloted in some states of India and other countries. https://egov.org.in/digit/

Box 6. Schema to standardize cost centers and services with different levels of data granularity

A cost accounting data schema can be designed to address the challenge of standardizing cost centers and service disaggregation across ministries and agencies with varying levels of granularity. By implementing a hierarchical structure for both cost centers and services, the schema allows for n levels of detail through parent-child relationships, ensuring scalability and flexibility. A mapping table further links cost centers to services, enabling comprehensive allocation and reporting. By harmonizing disparate data structures, this design supports diverse organizational needs while maintaining a consistent framework, making it easier to consolidate data and perform cross-agency analysis.

Advantages of this design include:

- Flexibility: Supports agencies with varying levels of granularity.
- Scalability: Easily accommodates new cost centers or service levels without restructuring the schema.
- Traceability: Maintains hierarchical relationships for comprehensive reporting.
- Integration: Links cost centers and services for cross-dimensional analysis, such as cost allocation and performance tracking.

Key components of the schema are provided below.

1. Cost Center Hierarchy: A single table with a parent-child relationship to represent n levels of cost centers.

Field	Description
Cost_Center_ID	Unique identifier for the cost center.
Cost_Center_Name	Name of the cost center (e.g., Payroll).
Parent_Cost_Center_ID	Identifier for the parent cost center. Use NULL for the top level.
Level	Numerical level of the cost center in the hierarchy (e.g., 1 for top level).
Org_ID	Identifier of the associated organization.
Description	Description of the cost center.

2. Service Disaggregation Hierarchy: A similar structure as the cost center hierarchy but for service breakdowns.

Field	Description
Service_ID	Unique identifier for the service.
Service_Name	Name of the service (e.g., Emergency Care).
Parent_Service_ID	Identifier for the parent service. Use NULL for the top level.
Level	Numerical level of the service in the hierarchy.
Program_ID	Identifier of the associated program or project.
Description	Description of the service.

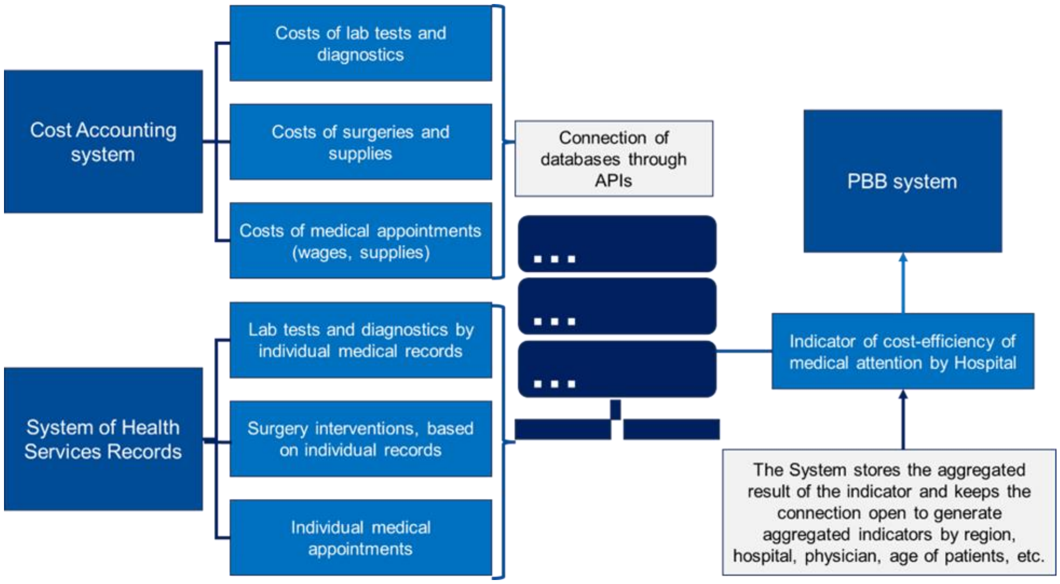
3. **Linking Cost Centers and Services**: A mapping table to enable flexible reporting and analysis.

Field	Description
Mapping_ID	Unique identifier for the mapping.
Cost_Center_ID	Identifier of the associated cost center.
Service_ID	Identifier of the associated service.
Allocation_Percentage	Percentage allocation of the cost center to the service.
Start_Date	Start date of the mapping.
End_Date	End date of the mapping (nullable for ongoing).

Source: Authors.

Implementing interoperability with administrative records can also bring benefits for PBB through the automated calculation of performance indicators. PBB can benefit from the automated calculation of cost related indicators, while also benefiting from non-cost related data to measure strategic performance indicators (Figure 3; Box 7)**.** In both cases, this would allow drilling down for the additional data granularity (e.g., seeing the cost or performance by region or school) needed for decision making.

Figure 3. Cost data for performance indicators via interoperability with administrative systems



Source: Authors.

Box 7. Linking administrative records to measure performance under PBB

Linking administrative records to calculate performance information using cost accounting data requires integrating data from multiple sources, ensuring consistency, and defining performance metrics aligned with administrative data. It is important to bear in mind that performance in the public sector should not be reduced to cost efficiency, and therefore, cost indicators should only be one type of metrics within a broader set of key performance indicators for governments.

The following steps can establish the aforementioned data link between cost accounting and performance measurement:

1. Define performance indicators

Clearly specify the performance indicators that need to be calculated based on administrative data (e.g., efficiency metrics such as cost per service unit and time taken to deliver services).

Each indicator should include:

- Name (e.g., average processing time).
- Definition, including all variables used in formula.
- Baseline and objective.
- Data sources (i.e., administrative records required to compute the metric).

2. Identify administrative data sources

Identify sources that can be integrated, ensuring they are well-documented with metadata (e.g., fields, data types, frequency of updates). Common data sources in public sector organizations include:

- Financial records: For budget utilization and cost metrics.
- Operational records: For tracking activities, outputs, and outcomes.
- HR records: For workforce productivity and capacity utilization.
- Service delivery logs: For service reach and beneficiary data.

3. Establish common identifiers

Create a set of common identifiers across datasets to link records (see Box 6). Examples include:

- Organizational identifiers: Unique codes for ministries, departments, or agencies.
- Program/project codes: Unique identifiers for programs or initiatives.
- Service IDs: Unique codes for specific services delivered.
- Time periods: Standardized fiscal year or monthly timestamps.

4. Integrate data (using data warehouse or data lake)

Develop an integration platform to consolidate and link data:

- Data extraction: Pull relevant data from administrative records.
- Transformation: Standardize formats, clean data, and resolve inconsistencies.
- Load: Store linked datasets in a central repository with clearly defined relationships.

For instance, link financial data to service delivery logs using:

- Program_ID: To associate costs with specific programs.
- Region_ID: To link expenditure and outcomes in geographic areas.
- Time_Period: To align costs and performance metrics over time.

5. Calculate performance metrics

Create workflows or queries to compute metrics. For example: $\text{Cost efficiency} = \frac{\text{Total service units delivered}}{\text{Total cost}}$

Source: Authors.

While the interoperability of FMIS with administrative records of line ministries offers significant benefits, it also raises additional considerations. Usability concerns may arise due to the complexity of integrating various systems, emphasizing the need for clear naming conventions and comprehensive documentation. Developers should also manage the learning curve associated with different systems through proper training and resources. Potential performance issues, such as latency, can be mitigated through optimized system design. Robust authentication and authorization mechanisms should be put in place to ensure security and effective data protection during data exchanges. Additionally, attention should be paid to data privacy, particularly in handling sensitive information such as personal data, across systems. This will help to ensure effective and secure interoperability, as well as compliance with relevant laws and regulations.

IV.2. Machine learning to enhance uses of cost accounting data

Machine learning (ML) models offer advanced capabilities for cost accounting, particularly in detecting patterns and generating automated alerts. Several analytical approaches are available—such as descriptive statistics, Business Intelligence Dashboards (Uña, 2021), Process Mining, Linear and Non-Linear Models, and ML (Annex I). Among these, ML stands out due to its ability to process large, complex datasets and uncover subtle patterns that traditional models may overlook.

While Business Intelligence tools are valuable for visualizing and summarizing cost data, they primarily serve as informative platforms, offering dashboards and reports that support decision-making but do not inherently detect anomalies or learn from data. In contrast, ML models go beyond visualization by adapting to evolving datasets, continuously improving their ability to identify irregularities, inconsistencies, or even fraud. Unlike statistical models, which rely on predefined theoretical frameworks, ML can uncover relationships not previously considered, making it a powerful tool for predictive analysis and risk detection in cost accounting.

To illustrate the integration of ML-based anomaly detection in cost accounting, this section presents alternative models and an example involving an elementary school infrastructure transfers program. Before applying ML techniques, it is essential to ensure data quality through rigorous validation and quality assurance. Poor data—such as errors, inconsistencies, or misclassified costs—can lead ML models to generate false alarms or overlook genuine irregularities. [29]

The first step to apply ML for cost accounting is the model selection. There are four basic types of ML models: supervised, unsupervised, semi-supervised, and reinforcement learning, each of them with different techniques or algorithms (Annex II). Each model and technique have different objectives that respond to the data structure and inputs received, therefore the selection should be guided by the type of data and specific objectives.

Selecting an appropriate ML model for cost accounting requires careful consideration. Ranta, Ylinen, and Järvenpää (2022) reviewed ML applications in management accounting and found the field still in its early stages. Their review highlights progress in three areas: (1) the impact of AI on the accounting profession, (2) text analysis for accounting reports, and (3) predictive methods that reveal complex patterns not defined in advance.

Regarding model types, the authors note that while neural networks—popular supervised models—are widely used, they are better suited for large, unstructured datasets like images, videos, or text. In contrast, most management accounting datasets are structured and modest in size, making other ML architectures more suitable. Ensemble methods, which combine multiple models to improve prediction accuracy, are identified as particularly promising. Brady et al. (2017) provide an example of ensemble methods applied to classify large expenditure datasets, and Barboza et al. (2017) similarly conclude that ensemble approaches offer superior accuracy and efficiency for predictive tasks.

However, ensemble methods can be computationally intensive and are primarily geared toward prediction. For tasks focused on pattern detection or classification, other ML models may be more appropriate depending on the structure and size of the dataset.

Model selection in cost accounting must also consider whether supervised or unsupervised learning is more appropriate. Supervised models require labeled data that defines, in advance, what constitutes mismanagement or corruption risk. While they can be used for anomaly detection through classification algorithms—where the target variable is the risk of fraud—this approach is limited by its reliance on predefined labels and may miss unforeseen patterns. Moreover, the labeling process can introduce human bias: "Some fraud you know about, but other instances of fraud slipped by without your knowledge. You can label the dataset with the fraud instances you are aware of, but the rest of your data will remain unlabeled" (Nielsen, 2020, p. 9).

Unsupervised models offer a valuable alternative for flagging potential mismanagement and corruption in cost accounting data. These models, particularly clustering and classification techniques, can detect anomalies and uncover associations without prior labeling. Their findings can later be refined using supervised learning to improve accuracy. Regardless of the model chosen, domain expertise remains essential to interpret results meaningfully and assess their implications within the context of cost accounting.

Semi-supervised learning offers a promising approach for anomaly detection in cost accounting, especially when labeled data is scarce or biased. In this method, an unsupervised algorithm first identifies patterns and generates pseudo-labels, which are then refined by a supervised model (Bhattacharya & Lindgreen, 2020; Green & Choi, 1997; Kondo et al., 2019). This hybrid approach is particularly useful in cost accounting, where relationships among variables are often undefined and proven cases of mismanagement or corruption are rarely labeled.

[29] Establishing a reliable foundation for AI-driven analysis involves validation exercises like cross-checking cost estimates against historical benchmarks, verifying data completeness, and removing duplicates or misreported entries. These steps help prevent misleading results and support sound decision-making. In this context, ML can flag anomalies that traditional methods might miss, offering a proactive approach to monitoring cost data.

Given the limitations of supervised models—which require pre-labeled datasets and may miss unforeseen interactions—semi-supervised learning combines the strengths of both supervised and unsupervised techniques. It enables the detection of anomalies without relying entirely on prior knowledge, while still benefiting from the structure and precision of supervised refinement.

Reinforcement learning, by contrast, is less suitable in this context, as it focuses on learning through sequences of actions and is typically applied in domains like robotics. Regardless of the model chosen, domain expertise remains critical to interpret results accurately and assess their implications within the cost accounting framework.

IV.2.1. An Illustrative example for practical application

This subsection discusses an example to illustrate how the described process can be applied in practice. It outlines the process of model selection and implementation to flag anomalies in an elementary school infrastructure transfers program, using a synthetically augmented dataset. [30]

To apply the semi-supervised algorithms approach, we need to start by running the unsupervised algorithm and then feed the results into a supervised model. For the unsupervised algorithm, we chose the Isolation Forest, to focus first on the identification of anomalies. For unsupervised anomaly detection, algorithms like Isolation Forest, DBSCAN, or One-Class SVM can be used (Box 8). For this analysis, Isolation Forest was chosen given its advantages in handling large datasets efficiently. [31] Additionally, Isolation Forest is less computationally intensive and requires less parameter tuning compared to One-Class SVM, making it a more robust and adaptable choice for this case.

As seen in the previous section, cost accounting data is fundamentally structured[32] and standardized.[33] Initially, we work with an unlabeled dataset which allows us to employ unsupervised learning techniques for anomaly detection. This dataset considers the main variables in a cost accounting dataset that were identified as related to identifying cost anomalies (see Annex III for the structure of the dataset).[34] The synthetic data augmentation allowed us to gain granularity, which helps create clusters and detect possible relationships among variables. Since we created an ideal dataset,[35] we intentionally avoided including noise in our training data. However, as governments venture into the practical implementation of these models, there are important considerations to keep in mind such as data preprocessing, feature selection, and tuning of hyperparameters. For instance, it is critical to employ cross-validation to gauge the model's performance on unseen data and prevent overfitting (see Box 8 for more details).

[30] The original dataset was augmented using Generative AI.

[31] Its random partitioning technique is adept at detecting diverse anomaly patterns without the need to specify clusters or data density, unlike alternatives like DBSCAN.

[32] Some of the characteristics of structured data, as opposed to unstructured, semi-structured, or metadata, are that it has a well-defined arrangement, conforms to a data model following a highly organized and easily accessed standard order, and is used by an entity or a computer program (Sarker, 2021, p. 3).

[33] Some AI models can also help standardize the data in case necessary, however that is beyond the scope of this paper.

[34] Enhancing the dataset with additional information that further characterizes the transactions can significantly improve the analysis. For instance, adding columns for the unit price of items, payment terms, delivery schedules, or traditional data on the supplier can be beneficial. Additionally, information about the historical performance of the suppliers, any past legal issues, and the competitive landscape at the time of the procurement could also be included. Through these enhancements, ML algorithms can better discern patterns, relationships, and outliers, thereby facilitating more informed decision-making in cost accounting.

[35] The creation of an ideal dataset involves curating data that is free from inconsistencies, errors, and irrelevant information, ensuring that the model is trained under optimal conditions. In practical applications, particularly within governmental contexts, data often contains various forms of noise or irregularities, requiring careful preprocessing to clean and structure the data effectively.

Box 8. Using unsupervised ML to detect anomalies in cost accounting data

Algorithm options:

- **Isolation Forest** is an unsupervised ML algorithm for anomaly detection that builds multiple decision trees or isolation trees with random splits to isolate anomalies. For more details, see Liu and Zhou (2009).
- **DBSCAN** (Density-Based Spatial Clustering of Applications with Noise) is a data clustering algorithm that groups together or clusters data points that are densely packed in a specific area, based on a distance metric and a density threshold (parameter defines the minimum number of points required in a local area to be considered a cluster). Points that lie outside of these dense regions are classified as noise. For further details, see Ester et al. (1996).
- **One-Class SVM** (Support Vector Machine) is an unsupervised anomaly detection algorithm that constructs a boundary around the normal data points, effectively creating a region of normalcy. Points that deviate significantly from this boundary are then considered anomalies or outliers. See, for example, Manevitz and Yousef (2001).

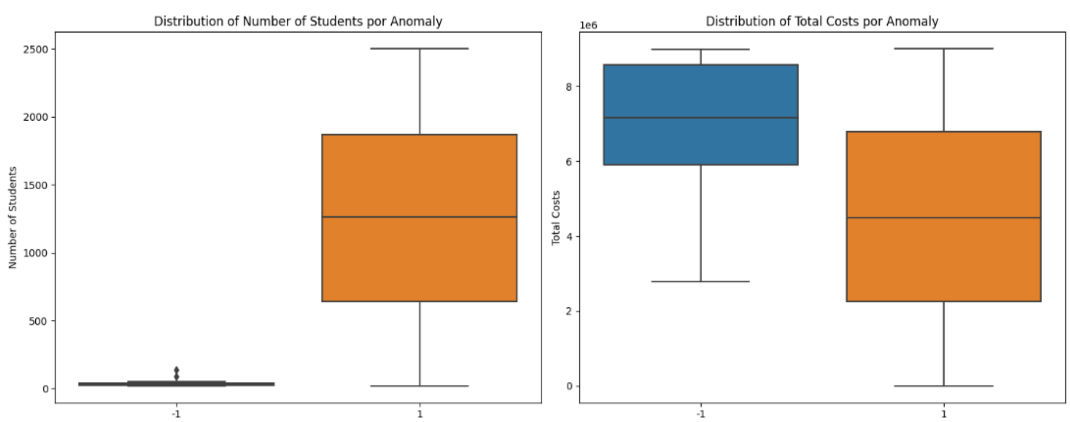
Considerations and processes for implementation:

- **Feature selection** is the process of identifying the most relevant variables that contribute to the predictive power of the model, which can significantly influence its performance.
- **Hyperparameter tuning** involves adjusting the parameters of the model that govern its learning process, aiming to enhance accuracy and efficiency.
- **Cross-validation** is a statistical method used to assess how well the model generalizes to an independent dataset. It partitions the data into subsets and evaluates the model's performance across different combinations of these subsets, thus reducing the risk of overfitting, where the model performs well on training data but fails to generalize to new data.

Source: Authors based on various sources.

The Isolation Forest algorithm was tested with the sample data set showing how it can pinpoint the categories that are more susceptible to irregularities (Annex IV). Upon applying the algorithm to our dataset, we discovered that out of 10,000 records, 20 were identified as potential anomalies. In the dataset, schools labeled as anomalies by the Isolation Forest algorithm are characterized by a significantly smaller student body, averaging around 39 students, in stark contrast to the average of 1,259 students in normal schools. Additionally, despite their smaller size, these anomalous schools incur notably higher total costs, averaging approximately 6.95 million compared to the normal average of 4.50 million. This combination of much lower student numbers and disproportionately higher costs marks them as distinct outliers in the dataset, as shown in Figure 4.

Figure 4. Data distribution (anomalies vs rest of data)



Source: Authors.

Once anomalies are flagged via unsupervised learning, the analysis shifts to supervised learning by incorporating labels. These labels are ideally created based on the results of investigative follow-up, audit findings, or known historic cases of irregularities. These labeled datasets enable the training of supervised models such as Random Forest, XGBoost, or K-Nearest Neighbors, which are suitable for classification tasks with categorical and continuous features. With this approach, a semi-supervised learning pipeline can be implemented:

1. Unsupervised anomaly detection identifies suspicious observations.
2. Domain experts investigate and validate these cases (e.g., audit teams).
3. The results of investigations feed into a labeled dataset.
4. Supervised learning algorithms are trained on this labeled data to generalize detection of future anomalies.

As the supervised model is trained, a confusion matrix[36] can be used to assess the performance (true positives, false positives, etc.) against validated outcomes. This allows for model evaluation and tuning. Over time, the model can become more accurate at identifying systemic anomalies or emerging patterns, improving the effectiveness of public oversight mechanisms.

This pipeline can also be extended using:

- Active Learning, where the model queries for the most informative labels from auditors.
- Semi-supervised ensemble methods, combining weakly-labeled and high-confidence samples for model training.
- Explainable AI (XAI) methods such as SHAP or LIME to interpret model outputs and enhance institutional adoption.

V. Conclusion

This paper has examined the role of cost accounting in PFM, highlighting its potential to improve budget credibility, PBB, public procurement, and the detection of corruption and mismanagement. When properly integrated, cost accounting provides governments with more reliable and granular cost information, enabling more informed decisions and fostering transparency and accountability.

Despite its benefits, cost accounting remains underutilized in many public sector contexts. Implementation challenges—ranging from fragmented data systems to unclear institutional mandates—have often led to isolated or underused systems. Moreover, the perception of cost accounting as resource-intensive has discouraged broader adoption, particularly in low- and middle-income countries.

This paper argues that leveraging existing digital infrastructure—especially interoperability and automation—can help overcome these barriers. The proposed standardized data schema offers a practical solution for integrating cost accounting with administrative records, enabling real-time data flows without requiring major system overhauls. This approach is adaptable to diverse digital environments and can be scaled across sectors and government levels.

Advanced analytical tools, including ML, further expand the utility of cost accounting data. ML models can detect anomalies, uncover hidden patterns, and support predictive analysis, enhancing oversight and

[36] A confusion matrix is a table used to evaluate the performance of a classification model by comparing predicted outcomes with actual outcomes. It shows the number of true positives, false positives, true negatives, and false negatives, helping assess accuracy, precision, recall, and other key metrics.

responsiveness. Semi-supervised learning, in particular, offers a promising path forward in contexts where labeled data is scarce or biased.

Applicability and Next Steps

The applicability of these approaches depends on aligning technical solutions with institutional realities. Governments should begin by assessing their existing data infrastructure, identifying opportunities for interoperability, and mapping cost centers and service lines to administrative records. Pilots in sectors with relatively structured data can help demonstrate value and build momentum.

Implementers should consider three key areas:

1. Institutional Integration: Embed cost accounting into core PFM processes, including budget formulation, procurement planning, and performance reviews. This requires clear mandates, cross-sectoral coordination, and sustained leadership.
2. Capacity Building: Invest in training for both technical staff and decision-makers to ensure that cost data is not only collected but also understood and used.
3. Iterative Implementation: Early wins—such as identifying cost anomalies or improving procurement efficiency—can help build support and justify further investment.

Ultimately, the success of cost accounting reforms lies not in the sophistication of the tools, but in their consistent use to inform decisions. By focusing on practical integration, institutional ownership, and user-centered design, governments can unlock the full potential of cost data to improve public sector efficiency, accountability, and service delivery.

Annex I. Main Analytical Tools for Cost Accounting

Main analytical tools that could be easily implemented for cost accounting analysis include:

- **Descriptive statistics**: as the foundation of data analysis, descriptive statistics organize, summarize, and present data visually to highlight its key characteristics. This includes measures of central tendency, variability, and visual representations like histograms, box plots, and scatter plots. In cost accounting, this can help in understanding the distribution of costs and identifying any unusual data points or trends.
- **BI dashboards**: these tools compile and display data in an interactive and visually engaging way, enabling real-time monitoring and analysis of key performance indicators. In the context of cost accounting, BI dashboards can track costs, performance, revenues, and other financial metrics, helping decision-makers to swiftly react to emerging trends or issues.
- **Process Mining**: a technique that uses event log data to understand how existing processes operate. It can be particularly relevant in the public sector and cost accounting for optimizing processes for efficiency and compliance.
- **Linear models**: a class of statistical models that assume a linear relationship between the dependent variable and one or more independent variables. This is valuable in cost accounting for making predictions and understanding relationships between different financial variables, such as how a change in production volume could affect costs.
- **Non-linear models**: unlike linear models, non-linear models allow for more complex relationships between variables. This flexibility makes them suitable for modeling phenomena where the relationship between variables is not strictly linear, such as economies of scale, diminishing returns, or complex budgetary relationships.
- **ML**: encompasses a wide range of algorithms, both linear and non-linear, that can learn from data and make predictions or decisions. In cost accounting, ML can be used for predictive analytics, anomaly detection, and optimization, among other applications. This can enhance budget forecasting, identify potential fraud or errors, and optimize resource allocation.

Advantages and disadvantages of these tools are discussed in Annex Table 1.

Annex Table 1. Comparison of different methods for analyzing data

Method	Advantages	Disadvantages
Descriptive statistics	• They are helpful for an initial approach to the data. • They can help figure out data distribution and even detect certain anomalies based on the detection of outliers. • Due to their simplicity, they are easy to implement periodically. • They are computationally inexpensive.	• They are limited in their scope. • They cannot analyze the complex relationship between data. • Insights might not be directly actionable, requiring further analysis. • It cannot be used straightforwardly for PFM decision-making.
BI dashboards	• Easy to read by decision-makers. • Allow to compare raw data or more complex indicators. • Easy to share and justify decisions based on graphs and other visual aids.	• The dashboards are limited to presenting a clear course of action. • They require initial setup and configuration which may need expert knowledge. • May not always reflect the real-time state of data as they depend on the frequency of data refresh cycles.
Process Mining	• Enables the discovery, monitoring, and improvement of real processes (not assumed processes) by extracting knowledge from event logs. • Helps in identifying bottlenecks, inefficiencies, and deviations in processes. • Can be used for conformance checking and optimizing process models.	• Requires event log data in a specific format which may not be available in legacy systems. • Interpretation of complex process models can be difficult for non-experts. • May raise privacy and security concerns if sensitive data is involved.
Linear models	• Helpful for detecting patterns by normalizing an observed relationship through a linear equation. • Helpful for predicting outcomes and comparing observed results to predictions.	• Limited to variables that show a linear relationship. • They are based on theoretical approaches, so the model cannot detect patterns not envisioned previously. • Assumptions such as homoscedasticity and normality need to be met which might not always be the case in real-world data.
Non-linear models	• Capable of capturing more complex relationships compared to linear models. • Helpful for predicting outcomes and comparing observed results to predictions.	• Based on theoretical approaches, so the model cannot detect patterns not envisioned previously. • A bit more complex to model and interpret. • May overfit the data if not properly regularized.
ML	• High level of accuracy for detecting relationships and patterns in data. • Self-learning from previous data to improve the results. Can be adapted to different types of data and prediction requirements.	• Requires a considerable amount of data. • In general, the interpretation of results is complex. • Preprocessing and feature engineering can be labor-intensive.

Source: Authors.

Annex II. Types of Machine Learning Algorithms Considered

Learning type	Features	Applications	Types of data/models
Supervised (Task-driven)	- Learn a function that maps an input to an output. - Uses labeled training data and training examples to infer a function. - Useful for training models to generate reasonable predictions of new data. - Gets feedback from humans to learn the relationship of given inputs to a given output.	Text classification: predicting the class label or sentiment of a text	- Classification (target variable is discrete) - Regression (target variable is continuous)
Unsupervised (Data-driven)	- Analyzes unlabeled datasets without the need for human interference. - Useful when you want to explore your data but do not yet have a specific goal or are not sure of the informational content of the data. - The algorithm will explore input data without being given an explicit response variable	- Extracting general features - Identifying meaningful trends and structures - Groupings in results - Exploratory purposes	Unlabeled data: - Clustering - Density estimation, - Feature learning - Dimensionality reduction - Finding association rules - Anomaly detection.
Semi-supervised (Hybrid)	- Combination of supervised and unsupervised methods. - Operates on both labeled and unlabeled data. - Provides a better outcome for prediction than that produced using the labeled data alone from the model. - Uses an extensive unlabeled data set to augment a labeled data set to produce more accurate results.	- Machine translation - Fraud detection - Labeling data - Text classification	Learns from combined data (labeled and unlabeled) -Classification -Clustering
Reinforcement (Environment-driven)	- Enables software agents and machines to automatically evaluate the optimal behavior in a particular context or environment to improve its efficiency. - Based on reward (maximizing it) or penalty (minimizing the risk) - The learning algorithm is not given examples of optimal outputs but must instead discover them through a process of trial and error.	Training AI models that can help increase automation or optimize the operational efficiency of sophisticated systems, such as: - Robotics - Autonomous driving tasks - Manufacturing and supply chain logistics - Not preferable to use it for solving the basic or straightforward problems	- Classification - Control

Source: Sarker (2021) and Nielsen (2020).

Annex III. Sample Data Dictionary of Costs for Anomaly Detection

As the table below shows, this sample dataset considers variables on the administrative, economic, functional, programmatic, and geographical classifications of expenditures. It also includes data regarding relevant features of the school facilities as well as data on costs. While it is recommended to include information on the economic, administrative, functional, geographic, and programmatic classifications, the most relevant categories are the school ID as well as the costs, hence, the model can be applied across different contexts and maturity levels of alignment towards the Government Finance Statistics Manual 2014.

Variable	Type	Example Value
Year	String	"2023"
ID_Ministry	String	"4"
Ministry	String	"Ministry of Education"
ID_School	Integer	12345
School	String	"School_567"
ID_District	Integer	78901
District	String	"District_78901"
ID_COFOG_Division	String	"9"
COFOG_Division	String	"Education"
ID_COFOG_Group	String	"9.3"
COFOG_Group	String	"Post-secondary non-tertiary education"
ID_Class	String	"09.3.0"
Class	String	"Post-secondary non-tertiary education"
ID_Budgetary_Program	String	"3"
Budgetary_Program	String	"Staff Training"
ID_Main_economic	String	"27"
Main_economic_classification	String	"Social benefits"
ID_Economic_sub	String	"272"
Economic_subclassification	String	"Social assistance benefits"
ID_revenue	String	"13"
Source_of_revenue	String	"Grants"
School_size	Integer	750
Number_of_students	Integer	1500
Number_of_rooms	Integer	10
Students_per_room	Float	150.0
Type_of_cost	String	"Fence installation - service"
ID_Agreement_contact	Integer	98765
Total_costs	Integer	4500000
Cost_per_student	Float	3000.0

Source: Authors

The dataset has various columns, some contextual to compare individual units, and others substantial for the analysis. For anomaly detection, particularly in identifying unusual procurement activities which could signify fraud or corrupt practices, the following columns are most relevant:

- ID_School: It may be relevant and useful to group data by purchasing unit, to identify trends or anomalies specific to certain units.
- Type of cost: The type of procedure might be relevant because certain types may be more prone to anomalies or irregularities.
- School characteristics: The size of the schools as well as the number of students might creative different incentives to commit an illegal practice.ID_District: certain regions or municipalities might have different incentives or might be governed by different political forces, impacting on the presence of anomalies.
- Economic classification: Certain type of expenditures might be indicative of anomalies.
- Functional classification: We included some features of the COFOG classification, since there can be corrupt practices in different education levels.

Annex IV. Technical Note on Isolation Forest for Anomaly Detection

The Isolation Forest algorithm, fundamentally, is based on the concept of isolating anomalies instead of profiling normal data points. It is a tree-based model that works on the principle of recursive partitioning. The formalization of the Isolation Forest model can be described as follows:

1. **Tree Construction**: Each tree in the Isolation Forest is constructed by randomly selecting a feature and then randomly selecting a split value between the minimum and maximum values of the selected feature. This process is repeated recursively until the tree is fully constructed. The recursive partitioning continues until an instance is isolated, or a predefined depth limit of the tree is reached.

2. **Path Length Calculation**: The path length $(h(x))$ for a point x is the number of edges that the point traverses in a tree from the root node to the external node. Anomalies will generally have shorter path lengths.

3. **Anomaly Score Calculation**: The path length from the root node to the terminating node is used to calculate the anomaly score. A shorter path length indicates an anomaly, as anomalies are more susceptible to isolation. The anomaly score, $s(x,n)$, for a data point x in a forest of n trees is defined as:
$$s(x,n) = 2\frac{E(hx)}{c(n)}$$
   Where:
   - $E(h(x))$ is the average path length of x across the forest.
   - $c(n)$ is the average path length of an unsuccessful searches in a Binary Search Tree (BST) of size n, and is approximated by:
   $$c(n) \approx 2(\ln(\mathrm{n}-1)+\gamma) - \frac{2(n-1)}{n}$$
   Here, $\gamma \approx 0.5772$ is the Euler–Mascheroni constant, used to approximate the harmonic number $H(n-1)$, which underlies the expected path length in random binary trees.

   This normalization ensures that anomaly scores are comparable across datasets of different sizes. Anomalies tend to have shorter path lengths, making their $s(x,n)$ scores closer to 1, while normal points have scores closer to 0.5 or below.

4. **Model Training and Prediction**: Isolation Forest does not require labeled data and is trained on the entire dataset. Once trained, the algorithm assigns each data point an anomaly score, classifying those with significantly shorter paths as anomalies.

5. **Parameter Tuning**: The primary parameters in an Isolation Forest are the number of trees in the forest and the contamination factor, which is the proportion of outliers in the dataset. These parameters can be adjusted based on the specific characteristics of the dataset.
   - **n_estimators:** Number of trees in the forest,
   - **contamination:** Expected proportion of anomalies in the dataset (used to set the threshold),
   - **max_samples:** Number of samples used to build each tree,
   - **max_features:** Number of features to draw from when looking for the best split.

These can be tuned based on dataset characteristics to optimize performance.

Annex Box 1. Example python code for anomaly detection using isolation forest

```
import pandas as pd
 import numpy as np
 from sklearn.ensemble import IsolationForest
 from sklearn.preprocessing import LabelEncoder

# Read the file and load it into a DataFrame
 file‘path = 'Example Data’et.xlsx'
 data = pd.read_excel(file_path,’engine=’'penpyxl')

# Initialize the Isolation Forest model with a specified contamination parameter
 clf = IsolationForest(contamination=0.002) # The contamination parameter can be adjusted based on the expected
proportion of outliers in the dataset

# Fit the model to the data
 clf.fit(data)

# Predict anomalies in the dataset
 pred = clf.predict(data)

# Add the predictions as a new column to the DataFram‘
 data['Anomaly'] = pred

# Output the DataFrame with the predictions into an Excel file
 data.t‘_excel('Trained_Data’et.xlsx', index=False)
```

6. **Labeling Data for Supervised Learning:** Once anomalies are detected, a supervised learning phase can follow by labeling a subset of the data:

    - **Regulatory flags:** Use known cases identified by audit institutions or anticorruption agencies.
    - **Expert labeling:** Involve a panel of experts to review flagged transactions. To reduce bias, consensus-based decisions should be used, and ambiguous cases excluded.

These labeled examples can then be used to train supervised algorithms like Random Forest, XGBoost, or K-Nearest Neighbors in a semi-supervised pipeline.

References

Abdou, A., Basdevant, O., David-Barrett, E., & Fazekas, M. (2022). Assessing Vulnerabilities to Corruption in Public Procurement and Their Price Impact. *IMF Working Papers, 2022(094).*

Alqudah, O. M. & Mohd Salleh, S. I. (2023). The Realities and Expectations of Calculating Government Service Costs: An Analysis of Jordanian Hospitals. *International Journal of Economics and Financial Issues* 13 (1): 65–72.

Aryal, A. (2022). Embracing Artificial Intelligence in Accounting. *Caldwell University Archives*. https://jstor.org/stable/community.36366721.

Barboza, F., Kimura, H., & Altman, E. (2017). Machine learning models and bankruptcy prediction. *Expert Systems With Applications*, 83, pp. 405-417. https://doi.org/10.1016/j.eswa.2017.04.006.

Basdevant, O. & Fazekas, M. (2023). The Corruption Cost Tracker: An Online Tool to Assess Corruption Risks in Public Procurement. *Technical Notes and Manuals 2023/001*. International Monetary Fund (IMF).

Behn, R. (2003). Why Measure Performance? Different Purposes Require Different Measures. *Public Administration Review*, 63(5), pp. 586-606. https://doi.org/10.1111/1540-6210.00322.

Bhattacharya, I. & Lindgreen, E. R. (2020). A Semi-Supervised ML Approach to Detect Anomalies in Big Accounting Data. *European Conference on Information Systems*.

Brady, E. S., Leider, J. P., Resnick, B. A., Alfonso, Y. N. & Bishai, D. (2017). Machine-Learning Algorithms to Code Public Health Spending Accounts. *Public Health Reports*, 132(3), pp. 350-356. doi.org/10.1177/0033354917700356

Brazil Secretaria do Tesouro Nacional (2025). *Contabilidade de Custos no Setor Público: Experiências e Diretrizes*. Brasília: Ministério da Fazenda. https://sisweb.tesouro.gov.br/apex/f?p=2501:9::::9:P9_ID_PUBLICACAO:51563.

Breul, J. (2007). GPRA—a Foundation for Performance Budgeting. *Public performance & Management Review*, 30(3), pp. 312-331. https://doi.org/10.2753/pmr1530-9576300301.

Canada Department of National Defence. (2015). Department of National Defence- Strategic Review (SR) and Deficit Reduction Action Plan (DRAP) - DPR - 2013-14. https://www.canada.ca/en/department-national-defence/corporate/reports-publications/departmental-performance/2013-14/section-iv-strategic-review-deficit-reduction-action-plan.html

Caplan, D. (1999). Internal Controls and the Detection of Management Fraud. *Journal of Accounting Research*, 37(1), 101–117. https://doi.org/10.2307/2491398.

Chan, J. A. & Pessoa, M. (2016). Finding the Costs of Public Services: The Experience of the State of São Paulo in Implementing a Cost System. In Pessoa, M. & Pimenta, C. (Eds.), *Public Financial Management in Latin America: The Key to Efficiency and Transparency*. Inter-American Development Bank.

Chrysanthakopoulos, C., Bouloumpasis, P., Skotoris, M. & Tagkalakis, A. (2025). "The Macroeconomic Effects of Public Sector Efficiency in Advanced Economies." *International Economics* 182: 100600. https://doi.org/10.1016/j.inteco.2025.100600.

Department of Expenditure, Ministry of Finance, Government of India. (2025). *Office of Chief Adviser Cost*. https://doeaudit.php-staging.com/office-chief-adviser-cost.

De Renzio, P. & Cho, C. (2020). Exploring the Determinants of Budget Credibility. International Budget Partnership (IBP).

De Renzio, P., Lakin, J. & Cho, C. (2019). How Deviations are Affecting Spending on Social Priorities. IBP.

Doherty, L. & Sayegh, A. (2022). How to Design and Institutionalize Spending Reviews. *How to Notes 2022/004.* IMF.

eGov Foundation. (2024). Strategy and Approach to Public Financial management.

Estevan, H., Schaefer, B. & Adell, A. (2018). Life Cycle Costing: State of the Art Report. European Secretariat.

Federal Accounting Standards Advisory Board (FASAB). (2024). *FASAB Handbook of Federal Accounting Standards and Other Pronouncements, as Amended.*

Government of Canada. (2023). *Guide to Costing*. https://www.tbs-sct.canada.ca/pol/doc-eng.aspx?id=32600.

Green, B. P. & Choi, J. H. (1997). Assessing the Risk of Management Fraud through Neural Network Technology. *Auditing: A Journal of Practice and Theory*, 16(1), pp. 14-28.

Gros, J.B., Rivero, L., Aldunate, E., Armijo, M. & Hilal, S. (2021). Quality of Public Expenditures. *Technical Report*. IMF.

Gurazada, S., Kirova, S., Alazmi, N., Rahman, A., & Pirlea, A. F. (2022). Government budget credibility and the impact of COVID-19. https://datatopics.worldbank.org/world-development-indicators/stories/government-budget-credibility-and-the-impact-of-covid-19.html.

IBP. (2023). *Open Budget Survey 2023.* https://internationalbudget.org/open-budget-survey-2023/.

IBP. (2023). *Initiatives – Budget Credibility*. https://internationalbudget.org/initiative/budget-credibility/.

International Federation of Accountants. (2000). *Perspectives on Cost Accounting for Government*.

IMF. (2019). Curbing Corruption. *Fiscal Monitor (April 2019)*.

IMF. (2024). Governand and Anti-Corruption. https://www.imf.org/en/Topics/governance-and-anti-corruption.

Jovanović, T., Dražić Lutilsky, I. & Vašiček, D. (2019). Implementation of cost accounting as the economic pillar of management accounting systems in healthcare: a comparison of Slovenia and Croatia. Economic Research-Ekonomska Istraživanja, Taylor & Francis Journals, vol. 32(1), pages 3754-3772, January.

Joyce, P. (2011). The Obama administration and PBB: building on the legacy of federal performance-informed budgeting? Public Administration Review, 71(3), pp. 356-367. https://doi.org/10.1111/j.1540-6210.2011.02355.x

Kondo, S., Miyakawa, D., Shiraki, K., Suga, M. & Usuki, T. (2019). Using Machine Learning to Detect and Forecast Accounting Fraud. *Discussion papers 19-E-103*, Research Institute of Economy, Trade and Industry (RIETI). https://www.rieti.go.jp/jp/publications/dp/19e103.pdf

Malmmose, M., & Lydersen, J. P. (2021). From centralized DRG costing to decentralized TDABC-assessing the feasibility of hospital cost accounting for decision-making in Denmark. *BMC health services research*, *21*(1), 835. https://doi.org/10.1186/s12913-021-06807-4

Mättö, T. & Sippola, K. (2016). Cost Management in the Public Sector: Legitimation Behaviour and Relevant Decision Making. Financial Accountability & Management, 32(2), 179-201.

Miller, A. D. (2009). Managerial Cost Accounting in the Federal Government: Providing Useful Information for Decision Making. AGA CPAG Research Series: Report No. 22.

Mohr, Z. T. (2016). Performance Measurement and Cost Accounting: Are They Complementary or Competing Systems of Control? *Public Administration Review*, 76(4), pp. 616-625.

Mohr, Z. T., Raudla, R., & Douglas, J. W. (2018). Is Cost Accounting Used with Other NPM Practices? Evidence from European Countries. *Public Performance and Management Review*, 41(4), pp. 696-722.

Mustapha, S. (2019). Budget Credibility, Fiscal Outcomes, and PFM Performance in Fragile and Nonfragile Countries. In Kristensen, J. K., Bowen, M., Long, C., Mustapha, S. & Zrinski, U. (Eds.), *PEFA, Public Financial Management, and Good Governance*. World Bank.

Mwencha, Marasi & Rosen, James. (2016). Better Data Visibility & Data Use Result in Lower Cost and Improved Performance in Medicine Supply Chains. 10.48550/arXiv.1609.09065.

Nestulia, V. (2020). How do you build a network of citizen corruption fighters? Ask Ukraine's revolutionaries. Open Contracting Partnership (OCP). https://www.open-contracting.org/2020/09/14/dozorro-a-network-of-citizen-corruption-fighters/

New Zealand Treasury. (2001). *A Guide to Output Costing*. Wellington: New Zealand. https://www.treasury.govt.nz/publications/guide/output-costing.

Nielsen, S. (2020). Management accounting and the idea of machine learning. Institut for Økonomi, Aarhus Universitet. Economics Working Papers No. 2020-09. https://pure.au.dk/portal/en/publications/management-accounting-and-the-idea-of-machine-learning

Open Contracting Partnership. (2016). Red flags for integrity: Giving the green light to open data solutions. https://www.open-contracting.org/resources/red-flags-integrity-giving-green-light-open-data-solutions/

Open Contracting Partnership. (2020). How governments spend: Opening up the value of global public procurement. Open Contracting Partnership and Spend Network.

Organisation for Economic Co-operation and Development (OECD). (2018). OECD Best Practices for Performance Budgeting. *Public Governance Committee Working Party of Senior Budget Officials GOV/PGC/SBO(2018)7. https://one.oecd.org/document/GOV/PGC/SBO(2018)7/en/pdf*.

OECD. (2018). Performance Budgeting Survey.

OECD (2021). *Resourcing Higher Education in Denmark*. Paris: OECD Publishing. https://www.oecd.org/content/dam/oecd/en/publications/reports/2021/12/resourcing-higher-education-in-denmark_6dab4b07/c8217325-en.pdf

OECD. (2023). OECD Performance Budgeting Framework. *Public Governance Directorate Committee of Senior Budget Officials* GOV/SBO(2023)*1. https://one.oecd.org/document/GOV/SBO(2023)1/en/pdf*.

OECD. (2024). Fiscal Sustainability of Health Systems: How to Finance More Resilient Health Systems When Money Is Tight? OECD Publishing. Paris, https://doi.org/10.1787/880f3195-en.

Park, Nowook (2017). *Current Issues of PFM Reforms in Korea*. Korean Institute of Public Finance (KIPF). Presentation at UNESCAP, Bangkok (May, 2017). https://www.unescap.org/sites/default/files/Panel%201-2.%20KIPF_Dr.%20Nowook%20Park.pdf

Pessoa, M. & Uña, G. (2017). Implementing a Public Services Cost System in São Paulo. *IMF PFM Blog.*

Premchand, A. (1995). Cost Measurement, Accounting Standards, and Other Issues. In *Effective Government Accounting*. IMF.

Public Expenditure and Financial Accountability (PEFA) Secretariat. (2018). *PEFA Handbook*.

Public Services and Procurement Canada. (2022). Practitioner's Guide for Procurement Pricing.

Radics, A. & Fernández, R. (2019). Budget management: how to improve the link between budget allocation and performance results in Uruguay. https://blogs.iadb.org/gestion-fiscal/en/budget-management-uruguay.

Rahim, F., Wendling, C. & Pedastsaar, E. (2022). How to Prepare Expenditure Baselines. *How to Notes 2022/002.* IMF.

Ranta, M., Ylinen, M. & Järvenpää, M. (2022). ML in Management Accounting Research: Literature Review and Pathways for the Future. *European Accounting Review,* 32(2), pp. 1-30.

Red Interamericana de Compras Gubernamentales. (2022). Informe de implementación de Algoritmos de sistemas de alertas tempranas de irregularidades y banderas rojas en la compra pública.

Ribeiro, R. et al. (2024). Management Public Accounting: An Analysis of Cost Information in Light of Public Managers' Perception. Brazilian Business Review, 21(1).

Rivenbark, W. C. (2005). A Historical Overview of Cost Accounting in Local Government. *State and Local Government Review*, 37(3), pp. 217-227.

Rivenbark, W. C. (2017). The Intrinsic Value of Cost Accounting for Benchmarking Service Efficiency. In Mohr, Z. T. (Ed.), *Cost Accounting in Government: Theory and Applications.* Routledge.

Rivero del Paso, L., Bonari, D. & Iles, C. (2022). Consolidation of the Cost Accounting System – CUSTOS. *Technical Report*. IMF.

Rivero del Paso, L., Pattanayak, S., Uña, G. & Tourpe, H. (2023). Digital Solutions Guidelines for Public Financial Management. *Technical Notes and Manuals 2023/007*. IMF.

Robinson, M. (2007). Performance Budgeting Models and Mechanisms. *Performance Budgeting: Linking Funding and Results*, pp. 1-18. https://doi.org/10.1057/9781137001528_1.

Robinson, M. & Last, D. (2009). A Basic Model of Performance-Based Budgeting. *Technical Notes and Manuals 09/01*. IMF.

Rogošić, A. (2021). Public sector cost accounting and information usefulness in decision-making. *Public Sector Economics*, 45(2), pp. 209-227. https://doi.org/10.3326/pse.45.2.2.

Salazar, C. & McKinney, J. (2024). Cardinal, an open-source library to calculate public procurement red flags. https://www.open-contracting.org/2024/06/12/cardinal-an-open-source-library-to-calculate-public-procurement-red-flags/

Sarker, I. H. (2021). Data Science and Analytics: An Overview from Data-Driven Smart Computing, Decision-Making and Applications Perspective. *SN Computer Science*, 2(5). https://doi.org/10.1007/s42979-021-00765-8.

Secretaria do Tesouro Nacional. (2024). *Relatório Foco em Custos – RFC 2023*. Ministério da Fazenda, Brasil. https://www.tesourotransparente.gov.br/

Simson, R. & Welham, B. (2014). Incredible Budgets – Budget credibility in theory and practice. ODI.

Tanzi, V. (1998). Corruption Around the World: Causes, Consequences, Scope, and Cures. *IMF Staff Papers.*

Thomas, P. G. (2006). Integrating Budgeting and Performance Measurement. In *Performance Measurement, Reporting, Obstacles and Accountability: Recent Trends and Future Directions.* ANU Press.

Trenovski, B. & Nikolov, M. (2015). Cost-benefit analysis of Performance Based Budgeting Implementation. *CEA Journal of Economics,* 10(2). https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2723791.

United Nations Children's Fund (UNICEF). (2021). *AdaMM: Administrative Data Maturity Model Ver 1.0*.

United States Government Accountability Office (U.S. GAO). (2020). *Cost Estimating and Assessment Guide*.

U.S. GAO. (2023). F-35 Joint Strike Fighter: More Actions Needed to Explain Cost Growth and Support Engine Modernization Decision.

World Bank. (2010). Fraud and Corruption Awareness Handbook.

World Bank (2017). Improving Public Sector Performance through Innovation and Inter-Agency Coordination: Malaysia's Experience with PEMANDU. Washington, DC: World Bank. https://documents1.worldbank.org/curated/en/318041492513503891/pdf/114270-WP-PUBLIC-13-4-2017-13-0-58-WorldBankReportPemanduFAFULLWeb.pdf.

PUBLICATIONS

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