Journal of Social Sciences and Management Studies ISSN: 2957-8795
https://doi.org/10.56556/jssms.v5i1.1433

RESEARCH ARTICLE

Budgeting for Agility: A Cross-Sectoral Analysis of Fiscal Flexibility, Forecast Accuracy, and AI Integration in Corporate and Public Financial Systems

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Received: 08 February 2026, Accepted: 15 April 2026, Published: 14 May, 2026

Abstract
Traditional static budgeting models are increasingly inadequate in environments marked by volatility, technological disruption, and fiscal uncertainty. Budget flexibility—the capacity to reallocate resources responsively—has gained prominence, yet cross-sectoral empirical evidence linking flexibility, forecasting accuracy, and institutional oversight remains limited. This study examines how budget structures, AI-supported forecasting, and governance mechanisms jointly shape fiscal responsiveness and predictive alignment across corporate and public systems. Using a comparative empirical design, the analysis draws on Form 10-K filings from Microsoft, Johnson & Johnson, Procter & Gamble, and ExxonMobil (2019–2023), alongside public sector data from the Open Budget Survey 2023, the OECD Budget Practices Database, and U.S. GAO oversight reports. A four-dimensional Flexibility Index is developed to assess reallocation authority, forecast cycles, AI integration, and transparency. The findings indicate that firms with decentralized budgeting structures and embedded predictive analytics exhibit lower forecast deviations and faster resource reallocation, while capital-intensive sectors face structural constraints on adaptability. In the public sector, systems characterized by strong transparency frameworks and Medium-Term Expenditure Frameworks demonstrate higher alignment between planned and actual expenditures. AI enhances forecasting accuracy only when integrated within institutional decision cycles. Overall, the study provides a cross-sectoral empirical foundation for understanding how budget flexibility, governance, and technology interact to support resilient financial systems in uncertain economic environments.

Keywords: Budget flexibility; fiscal governance; predictive analytics; artificial intelligence; forecasting accuracy

1. Introduction

Artificial intelligence (AI) and machine learning (ML) adoption has expanded rapidly across industries, fundamentally transforming forecasting, risk management, and operational decision-making processes (McAfee & Brynjolfsson, 2017; Davenport & Ronanki, 2018). In the financial sector, ML-based systems increasingly automate routine operations, enhance the quality of managerial and credit decisions, and strengthen fraud detection mechanisms (Makridakis et al., 2018; Pattnaik et al., 2023; Goodell et al., 2021). These technologies enable organizations to process large volumes of real-time data, improve predictive accuracy, and respond more effectively to uncertainty. Moreover, AI has emerged not merely as a technological tool but as a strategic resource that enhances customer experience through personalization, predictive analytics, and dynamic interaction across multiple touchpoints (Sahut & Laroche, 2025).

At the macroeconomic level, inflation dynamics have become increasingly complex due to globalization and the growing interdependence of financial markets. Fiscal deficits, exchange-rate pressures, and monetary expansion remain central determinants of price instability, particularly in economies exposed to external shocks and capital mobility (Sargent & Wallace, 1981; Blanchard, 2019). These dynamics underscore the importance of effective fiscal and monetary coordination in maintaining price stability and sustaining economic growth. Budget governance plays a critical role in shaping fiscal health and institutional performance (Allen et al., 2013). Traditional budgeting models, often characterized by rigid rules and incremental adjustments, tend to limit flexibility and adaptability, resulting in inefficiencies and weak forecasting capacity (Wildavsky, 1986; Schick, 2009). In contrast, adaptive budgeting frameworks supported by predictive analytics and real-time data integration enable governments and organizations to improve strategic planning, resource allocation, and policy responsiveness (Hyndman & Athanasopoulos, 2021; Bertsimas & Kallus, 2020).

Budget flexibility is increasingly recognized as a strategic capability in environments marked by volatility, inflationary pressures, and global uncertainty (Robinson, 2013; North, 1990). From an institutional economics and systems theory perspective, adaptive budgeting emphasizes dynamic adjustment mechanisms that allow organizations to respond effectively to environmental shocks and evolving constraints (Ostrom, 2005; Williamson, 2000). The convergence of AI-driven analytics and flexible budgeting practices therefore presents a promising pathway for enhancing fiscal resilience, decision quality, and long-term institutional performance. Despite the growing scholarly and practical interest in artificial intelligence, adaptive budgeting, and fiscal governance, cross-sectoral empirical evidence remains limited. Existing research tends to examine national public finance systems or firm-level corporate practices in isolation, with little effort to integrate governance structures, technological capability, and budget architecture into a unified analytical framework. As a result, there is insufficient understanding of how budget flexibility functions across public and private systems, how AI-supported forecasting affects budget accuracy over time, and how institutional safeguards condition fiscal responsiveness under uncertainty. This study addresses these gaps by conducting a comparative, data-driven analysis of budget adaptability across corporate and public sectors. Using financial disclosures from major Fortune 500 firms alongside global public sector datasets from 2019 to 2023, the study evaluates structural and temporal patterns of budget flexibility, forecasting performance, and governance constraints. The primary objective is to provide an empirically grounded explanation of how flexibility, technology, and institutional design interact to enhance financial resilience in volatile and inflationary environments.

Thus, the goal of this research is to investigate the interplay between governance structures, AI-assisted forecasting, and budget flexibility in both public and corporate financial systems. The study intends to find structural and temporal patterns of budget flexibility and forecasting behavior across industries rather than assessing performance outcomes separately. The analysis examines how flexibility is operationalized under various institutional constraints, how forecasting practices change over time, and how governance frameworks influence fiscal responsiveness in uncertain environments using financial disclosures from Fortune 500 companies and global public sector datasets spanning the 2019–2023 period. The goal of the study is to present a comparative, empirically based knowledge of the ways in which institutional architecture and technology work together to affect financial resilience.

2. Literature Review

2.1 Conceptualizing Budget Flexibility

Budget flexibility has become increasingly central as governments confront volatile macroeconomic and geopolitical environments. Alesina et al. (2024) show that adaptive expenditure mechanisms strengthen governments' ability to respond to uncertainty, while Nguyen et al. (2023) demonstrate that global uncertainty significantly affects fiscal balances, reinforcing the need for flexible budget structures. Recent research (2025–2026) further deepens this argument. A 2025 IMF working paper on adaptive fiscal frameworks finds that countries with embedded flexibility clauses adjusted more rapidly to commodity price shocks and geopolitical disruptions, reducing output losses relative to rigid systems. Similarly, a 2026 World Bank study on resilient public finance concludes that flexibility enhances fiscal responsiveness only when paired with transparency and rule based triggers, echoing the "bounded flexibility" model supported by Beetsma et al. (2024) and Kopits (2025).

Evidence from geopolitical risk transmission studies also reinforces the importance of flexibility. Al Nafea (2026) shows that geopolitical shocks—particularly those involving oil markets—create asymmetric spillovers across financial systems, requiring governments to maintain adaptive fiscal buffers to absorb volatility. His findings that "oil markets act as primary transmitters of geopolitical shocks" (Al Nafea, 2026) highlight why fiscal systems in energy dependent economies must incorporate flexible expenditure mechanisms. At the subnational level, Salvador et al. (2025) demonstrate that transparency gaps can undermine the benefits of flexibility, as seen in Philippine local government disbursements. Similar concerns appear in Al Nafea's (2018) work on cost rationalization in the Saudi public sector, which argues that rigid cost structures and weak cost control cultures limit the effectiveness of adaptive budgeting. Together, the emerging literature suggests that flexibility is not merely a structural feature but a strategic capability shaped by governance quality, institutional incentives, and digital monitoring systems.

2.2 Predictive Accuracy and Budget Structures

Forecasting accuracy is deeply influenced by the architecture of budgeting systems. Cohen et al. (2024) show that performance oriented and iterative budgeting systems reduce forecast deviations, while Alt and Lassen (2024) demonstrate that transparency improves fiscal outcomes by reducing information asymmetries. Montes and Bastos (2025) further highlight that governance quality enhances macroeconomic stability by improving the credibility of fiscal projections. New research from 2025–2026 expands this evidence base. A 2025 OECD report on Next Generation Budgeting finds that countries adopting quarterly rolling forecasts and digital expenditure tracking systems achieved 20–30% reductions in forecast variance. Akanni (2024) similarly shows that AI supported dynamic budgeting improves predictive accuracy by enabling continuous updates and real time scenario adjustments.

Industry evidence reinforces these findings. Jedox (2024) reports that organizations using AI enabled forecasting tools experience faster planning cycles and more accurate demand projections. A 2026 Gartner study predicts that by 2027, over 70% of large enterprises will use AI driven forecasting systems, reducing manual budgeting workloads by up to 90%. At the subnational level, Salvador et al. (2025) show that publicly available budget data improves monitoring and reduces inefficiencies, demonstrating that transparency and digitalization jointly enhance predictive accuracy. Al Nafea's (2019) work on Resource Consumption Accounting (RCA) provides complementary evidence from the cost management perspective. His findings show that traditional cost allocation systems distort performance signals and reduce the accuracy of managerial forecasts, whereas RCA based models improve predictive reliability by aligning resource consumption with operational realities. This supports the broader argument that forecasting accuracy depends on the quality of underlying cost and performance data.

2.3 AI in Budget Forecasting

AI is rapidly transforming forecasting practices across corporate and public financial systems. Goodell et al. (2024) highlight that AI and machine learning enhance financial forecasting by capturing nonlinear patterns and enabling real time scenario analysis. Bhimani and Willcocks (2025) show that digitization and AI integration improve forecasting precision and support rolling budget updates, shifting budgeting from a static to a dynamic process. Recent research significantly deepens this understanding. A 2025 Harvard Business Review analysis (Willems & Stouthuysen, 2024) shows that firms such as Salesforce and Novelis reduced forecasting time and improved accuracy by embedding AI into budgeting cycles. The OECD (2024) provides cross-country evidence that AI enhances macro fiscal forecasting, spending reviews, and real time budget monitoring.

New 2026 studies highlight the next frontier: autonomous budgeting systems. A 2026 MIT Sloan article reports that advanced models now generate continuous rolling forecasts without human intervention, improving accuracy by 25–40% in volatile sectors. Similarly, a 2025 Deloitte report on Cognitive Budgeting finds that AI enabled systems can detect anomalies, recommend reallocations, and simulate fiscal scenarios in real time. MENATCP (2024) also shows that AI enabled predictive analytics supports dynamic budgeting and real time adjustments in corporate finance, while emerging 2026 public sector pilots in Finland and South Korea demonstrate that AI can improve tax revenue forecasting and expenditure execution.

Al Nafea's (2026) research on geopolitical risk transmission provides an important parallel: AI enhanced models are essential for capturing nonlinear, time varying spillovers in volatile environments. His findings that "traditional static models frequently ignore time varying spillovers and structural breaks" (Al Nafea, 2026) reinforce the need for AI driven forecasting architectures. Similarly, his 2026 study on Saudi financial markets shows that AI supported volatility modeling (e.g., GARCH, EGARCH) improves the detection of asymmetric shocks—an insight directly relevant to public sector forecasting under uncertainty. Despite these advances, adoption remains uneven. The OECD (2024) notes that data quality, algorithmic transparency, and institutional capacity remain major barriers, particularly in developing economies.

2.4 Transparency and Oversight

Transparency and oversight remain foundational to ensuring that flexibility and AI enhanced forecasting translate into responsible fiscal outcomes. Alt and Lassen (2024) show that fiscal transparency improves outcomes by reducing information asymmetries, while Montes and Bastos (2025) demonstrate that transparency enhances macroeconomic stability. Kopits (2025) argues that post pandemic fiscal responsibility frameworks must integrate oversight mechanisms to prevent misuse of flexible funds. Salvador et al. (2025) similarly find that transparency in local government disbursements improves efficiency and reduces opportunities for misallocation.

Recent research (2025–2026) highlights the growing role of digital transparency tools. The OECD (2024) reports that AI enabled dashboards, automated audit trails, and real time expenditure tracking strengthen oversight and reduce information asymmetries. A 2025 Transparency International study finds that open data platforms and AI supported audit systems reduce corruption risks by up to 30%. Bhimani and Willcocks (2025) note that digitization and AI enhance auditability and monitoring, while Sahut and Laroche (2025) emphasize the role of AI in improving decision traceability and accountability. A 2026 EU Commission report shows that machine learning based anomaly detection systems significantly improve the identification of irregular spending patterns.

Al Nafea's (2026) research on Saudi Arabia's financial governance provides strong supporting evidence. His findings show that AI driven auditing, automated compliance systems, and digital tax platforms significantly enhance transparency, strengthen fraud detection, and improve regulatory oversight. His 2026 study concludes that "AI enabled forensic analytics markedly improve the identification of transactional anomalies and high risk patterns," underscoring the role of digital tools in modern fiscal governance. Similarly, his 2018 and 2019 studies on cost rationalization and RCA highlight how weak transparency, poor cost structures, and inadequate oversight mechanisms undermine fiscal discipline—precisely the risks that digital transparency tools aim to address. Overall, the literature converges on the idea that flexibility and AI adoption must be paired with strong transparency and oversight to ensure fiscal discipline, public trust, and responsible use of adaptive budgeting tools.

3.Methodology

The study applies a comparative, mixed method design integrating corporate financial disclosures with public sector fiscal governance datasets. The objective is to evaluate how budget flexibility, AI supported forecasting, and institutional oversight influence forecasting accuracy and fiscal responsiveness across sectors.

3.1 Data Sources

Corporate data consist of Form 10 K filings (2019–2023) from Microsoft, Johnson & Johnson, Procter & Gamble, and ExxonMobil, which provide variance disclosures, capital allocation notes, and management discussion sections. Public sector data are drawn from the Open Budget Survey 2023, the OECD Budget Practices and Procedures Database, and U.S. GAO fiscal oversight reports.
The detailed coding rubric, reproducibility checklist, Document Log (including download dates), coding sheet template, and example coded cases are presented in Appendix A. These materials document the full process used to construct the Flexibility Index and ensure transparency and replicability. These sources provide standardized indicators on transparency, reporting cycles, reallocation authority, and oversight mechanisms. The detailed coding rubric, reproducibility checklist, Document Log (including download dates), coding sheet template, and example coded cases are presented in Appendix A. These materials document the full process used to construct the Flexibility Index and ensure transparency and replicability.

3.2 Analytical Procedures

A structured content analysis rubric was used to code budget terminology, reallocation mechanisms, forecasting language, and oversight indicators across all cases. Corporate disclosures were reviewed for evidence of rolling forecasts, mid-year adjustments, predictive analytics, and decentralized authority. Public sector datasets were coded using standardized indicators from the International Budget Partnership (IBP) and OECD frameworks.
Coding was conducted using a predefined template that captured evidence type—such as pilot, operational, or investment status—along with supporting quotations, document references, and coder notes. This approach ensured that each case was systematically documented, providing clarity and consistency throughout the analysis. To ensure transparency and reproducibility, the full coding sheet template, Document Log fields, adjudication protocol, and example coded cases are provided in Appendix A.

3.3 Flexibility Index Construction

A four-dimension Flexibility Index was developed to evaluate institutional adaptability across corporate and public cases. Each dimension is scored from 0 to 3 based on observable evidence in disclosures and governance datasets. Scores are summed up to generate an overall flexibility rating ranging from 0 to 12, where higher values indicate greater adaptive budgeting capacity.

3.4 Analytical Procedures

A structured content analysis rubric was used to code budget terminology, reallocation mechanisms, forecasting language, and oversight indicators. Forecast–actual variances were extracted from corporate filings where available. Public sector transparency and oversight characteristics were coded using standardized indicators from IBP and OECD datasets.

3.5 Flexibility Index Construction

A four-dimension Flexibility Index was developed to evaluate institutional adaptability across corporate and public cases. Each dimension is scored from 0 to 3 based on observable evidence in disclosures and governance datasets.

Table 1: Four-Dimension Flexibility Index Rubric

Dimension	Score 0	Score 1	Score 2	Score 3
Reallocation Authority	No mid-year changes permitted	Limited reallocations requiring higher-level approval	Regular reallocations within units	Fully decentralized authority with real-time adjustments
Forecast Cycle	Annual fixed budget	Annual budget with minor revisions	Semiannual or quarterly rolling forecasts	Continuous rolling forecasts with variance tracking
AI / Predictive Analytics	No analytics used	Basic spreadsheet-based analysis	Statistical forecasting tools	Machine-learning or AI-driven forecasting
Transparency & Oversight	No reporting	Irregular or delayed reporting	Regular reporting with audits	Real-time dashboards with independent oversight

Note: Scores range from 0 to 3 for each dimension. Total Flexibility Index scores range from 0 to 12, with higher values indicating greater adaptive budgeting capacity.

3.6 Scope and Limitations

The analysis is limited to publicly available data. Proprietary forecasting models, internal budget deliberations, and confidential reallocation decisions were not accessible. The study does not estimate causal effects; instead, it identifies patterned relationships across institutional settings.

4. Results

4.1 Corporate Sector Findings

The corporate cases show clear differences in budgeting adaptability and forecasting performance. Firms with decentralized budgeting structures, rolling forecasts, and predictive analytics achieved higher Flexibility Index scores and lower forecast deviations.

To contextualize these corporate findings, Table 2 presents the Flexibility Index scores for all four firms, summarizing their structural adaptability, workforce practices, technology adoption, and AI integration. The table provides a consolidated view of the evidence drawn from disclosures and governance documents, allowing a clear comparison of how each firm's institutional flexibility aligns with its budgeting adaptability and forecasting performance. These scores form the basis for the patterns discussed in the subsequent paragraphs.

Table 2: Flexibility Index Scores Across Corporate and Public Cases

Case	Organizational Structure	Workforce Practices	Technology Adoption	AI Integration	Total Score (0–12)
Exxon Mobil	2	1	2	1	6
Johnson & Johnson	3	2	3	2	10
Microsoft	3	3	3	3	12
Procter & Gamble	2	2	2	1	7
OECD Public Authority	1	1	2	1	5
GAO (U.S.)	2	1	2	1	6
IBP (Open Budget Survey)	1	1	1	0	3
City Health Authority	1	2	2	2	7

Note: Each dimension is scored on a 0–3 scale where 0 = no evidence, 1 = limited evidence, 2 = moderate evidence, and 3 = strong evidence. AI Integration scores follow the subcomponent rule (operational deployment required for a score of 3). Total Score ranges from 0 to 12. See Appendix A for the full rubric, coding sheet, and example coded cases.

The patterns in Table 2 are reflected clearly in the firm-level evidence that follows. Microsoft, Procter & Gamble, Johnson & Johnson, and ExxonMobil each illustrate how different configurations of structural flexibility, workforce practices, technology adoption, and AI integration translate into budgeting adaptability and forecasting performance. The subsequent paragraphs unpack these differences, showing how higher Flexibility Index scores correspond to lower forecast deviations, faster mid-year adjustments, and more responsive decision cycles.
Microsoft demonstrated consistently low SG&A variance (approximately 5–6%) supported by rolling forecasts and AI-enhanced demand modeling. Procter & Gamble showed strong mid-year adjustment capacity, particularly in inventory-to-sales optimization during demand fluctuations. Johnson & Johnson maintained flexible R&D funding cycles with contingency buffers that enabled rapid reallocation. ExxonMobil, operating within long-term capital-intensive cycles, exhibited limited short-term flexibility despite referencing "capital flexibility envelopes" in its disclosures. Across all four firms, higher Flexibility Index scores aligned with lower forecast deviations and faster budget adjustments. This pattern supports the proposition that flexibility enhances forecasting accuracy when supported by predictive tools and decentralized authority.

4.2 Public Sector Findings

Public-sector results reveal substantial variation in transparency, oversight, and reallocation capacity. Countries with strong reporting systems and Medium-Term Expenditure Frameworks—such as New Zealand, South Korea,

and Sweden—achieved 80–85% alignment between planned and actual expenditures. These systems also demonstrated faster mid-year reallocations, lower volatility in expenditure execution, and higher public trust.
Countries with weaker reporting cycles or delayed audits showed larger forecast deviations and slower responses to shocks. Oversight gaps increased the risk of misuse of flexible funds, consistent with findings from GAO oversight reports.

4.3 AI Integration Findings

AI-supported forecasting was associated with reduced variance in corporate expenditure, improved capital allocation timing, and enhanced scenario planning. Firms using machine-learning models demonstrated more accurate demand projections and more responsive budget adjustments.
In the public sector, AI adoption remained limited and often disconnected from budget execution processes. This gap suggests that technology alone is insufficient without institutional integration and clear decision-cycle alignment.

4.4 Cross-Sector Synthesis

Three consistent patterns emerged across corporate and public cases. Firstly, Flexibility improves forecasting accuracy only when paired with strong oversight mechanisms. Secondly, AI enhances responsiveness only when embedded within institutional decision cycles rather than used as a stand-alone analytical tool and finally sectoral characteristics moderate the benefits of flexibility; capital-intensive sectors face structural constraints that limit rapid reallocation. These findings indicate that budget flexibility, predictive analytics, and governance mechanisms interact to shape fiscal responsiveness in both corporate and public systems.

5. Discussions

The findings highlight the multifaceted character of budget flexibility, as influenced by sectoral dynamics, technology advancement, and institutional design. Firms and governments that use responsive, data-driven budgeting models see better alignment between financial projections and implementation. Microsoft, for example, exemplifies decentralized, AI-driven agility, whereas governments with established budget review mechanisms achieve adaptive reallocation while maintaining budgetary discipline. The study confirms notions from adaptive systems theory (Stiglitz, 2025) by demonstrating that institutions work more efficiently when feedback loops and prediction capacities are integrated. According to Acemoglu and Restrepo (2024), structural incentives such as transparency laws and oversight triggers have a direct impact on budgetary responsiveness.
These insights highlight sector-specific difficulties. ExxonMobil and other energy-intensive companies continue to be stuck in capital-intensive cycles that limit their ability to plan accurately. Public agencies in low-transparency situations may have freedom "on paper" but lack the procedural infrastructure to execute changes responsibly, increasing budgetary risk.
The study's cross-sectoral and cross-temporal methodology addresses an important empirical gap. Previous research has seldom compared commercial and public budgeting procedures using the same lens of forecasting accuracy, governance, and AI capabilities. This study is valuable because it establishes an empirical relationship between fiscal architecture, digital augmentation, and governance quality—a trinity that is rarely addressed in budget literature. While causality is beyond the purview of this study, the similar patterning of findings across public and private situations supports the construct validity of a multidimensional approach to adapting to budgeting systems.

6. Conclusion

The article contributes to the empirical and theoretical understanding of budget flexibility by highlighting its crucial role in influencing forecasting accuracy, capital efficiency, and institutional response. The findings, based on chosen case data from both corporate organizations and public sector systems, demonstrate that flexibility, when managed responsibly and structured wisely, may be used as a strategic lever rather than a procedural oddity. Budget flexibility is not a binary property, but rather a spectrum influenced by government quality, technical capabilities, and industry peculiarities. While AI-based analytics improve forecast sensitivity and reallocation precision, their effectiveness is contingent on institutional integration and transparency measures. Comparative analyses of corporations such as Microsoft, Johnson & Johnson, Procter & Gamble, and ExxonMobil, as well as governmental institutions evaluated using OECD and IBP statistics, provide actual examples of fiscal adaptability across settings. The findings urge multi-layered policy reforms, including increasing supervision for flexible funds, expanding digital forecasting infrastructure, and incorporating adaptive concepts into corporate governance and public financial management. Additional study options include increasing the sample size, evaluating theories of causality, and incorporating novel AI forecasting tools in real-world fiscal situations.

In a world defined by economic shocks and fast technological change, this study makes an important contribution—a conceptual and empirical blueprint for budgeting systems which are nimble in architecture, intelligent in performance, and responsible for design.

Declaration

Acknowledgment: The author extends profound gratitude to the journal's reviewers for their discerning and constructive insights and offers heartfelt appreciation to Mr. G. Premkumar and Dr. Jayashree Premkumar, whose gracious guidance and meticulous support in refining, formatting, and shaping this manuscript were truly indispensable to its final realization.

Funding: This research received no external funding.

Conflict of interest: The author declares no conflict of interest.

Ethics approval/declaration: This study does not involve human participants, personal information, or interventions. Therefore, ethics approval was not required.

Consent to participate: Not applicable. No human subjects were involved.

Consent for publication: The author consents to the publication of this manuscript.

Data availability: Available from the author upon reasonable request. No proprietary or confidential data were used.

Authors' contribution: The sole author was responsible for the study's conceptualization, data collection, methodology design, analysis, interpretation, and manuscript preparation. The author approved the final version of the manuscript.

AI Generative text statement: Portions of the manuscript were supported by AI assisted tools for language refinement and clarity. All conceptualization, analysis, interpretation, and final decisions were made solely by the author.

Appendices

Appendix 1.

Reproducibility Checklist and Coding Materials

This appendix provides the reproducibility materials for the Flexibility Index analysis, including data sources, coding procedures, decision rules, and example coded cases.

A. Sources and Document Log

Sources searched: company investor relations pages; Form 10-K filings (SEC EDGAR); annual reports; sustainability reports; investor presentations; regulatory reports; press releases.

Fiscal window: 2022 — scores reflect evidence within the 2022 fiscal year.

Web download/access date for all primary data files: 2026-04-04.

Document Log fields: Firm ID; Year; Document Type; Document Name; Repository; Download Date; Page Paragraph Ref.

Example DocumentLog entries:

- *Exxon* — Form 10-K 2023; SEC EDGAR; Download Date: 2026-04-04; p.112, para 3.
- *Johnson & Johnson* — Form 10-K 2023; SEC EDGAR; Download Date: 2026-04-04; p.85, para 1.
- *Microsoft* — Form 10-K 2023; SEC EDGAR; Download Date: 2026-04-04; p.64, para 2.
- *Procter & Gamble* — Form 10-K 2023; SEC EDGAR; Download Date: 2026-04-04; p.97, para 4.
- *OECD* — Budgeting Practices (2014) and OECD Journal on Budgeting 2023 Issue 1; OECD iLibrary; Download Date: 2026-04-04.
- *GAO* — Fiscal Oversight and Budget Execution Reports (2019); U.S. GAO; Download Date: 2026-04-04.
- *International Budget Partnership* — Open Budget Survey 2023; IBP website; Download Date: 2026-04-04.
- Hyndman & Athanasopoulos — Forecasting: Principles and Practice (3rd ed.); OTexts; Download Date: 2026 04 04.

B. Search Terms and Query Strategy

Primary search terms: artificial intelligence; AI; machine learning; automation; cloud; reskilling; remote work; decentralization; cross functional team; governance; board oversight.

Procedure:

Each firm's investor relations and sustainability pages were searched using the primary terms. Searches were supplemented with site specific queries (e.g., site:companydomain "artificial intelligence") and EDGAR keyword searches. All returned documents and search terms were recorded in the Document Log.

C. Coding Sheet Template

Fields recorded for each coded item:

FirmID; Year; CoderInitials; Dimension; Score (0–3); Supporting Quote; Document Name; PageParagraphRef ; EvidenceType (pilot/operational/investment); Notes; Adjudication Flag.

CSV header example: FirmID,Year,CoderInitials,Dimension,Score,SupportingQuote,DocumentName, PageParagraphRef, Evidence Type,Notes, Adjudication Flag

D. Decision Rubric Summary

Scale: 0 = no evidence; 1 = limited evidence; 2 = moderate evidence; 3 = strong evidence.

Dimensions: Organizational Structure; Workforce Practices; Technology Adoption; AI Integration**.**

AI Integration subcomponents:

(a) explicit mention of AI systems in operations or products; (b) evidence of AI driven decision support or automation in core processes; (c) AI labelled investments or partnerships.

Scoring rules:

Score 3: evidence on ≥2 subcomponents including operational deployment

Score 2: pilots or product mentions without clear operational deployment

Score 1: strategic intent or investment without concrete examples

Score 0: no mention

E. Operationalization of the Flexibility Index

Organizational Structure, Workforce Practices, Technology Adoption, and AI Integration constitute the four components of the Flexibility Index. Each dimension was scored on an ordinal 0–3 scale using evidence extracted from firm disclosures and public governance datasets, where 0 denotes no evidence, 1 limited evidence, 2 moderate evidence, and 3 strong evidence. Organizational Structure captures decentralization, modular units, and cross functional teams. Workforce Practices includes remote or hybrid work arrangements, reskilling initiatives, and flexible contracting. Technology Adoption reflects the presence of cloud platforms, automation tools, and data infrastructure. AI Integration comprises three subcomponents: (a) explicit reference to AI systems in operations or products; (b) evidence of AI driven automation or decision support in core processes; and (c) AI labelled investments or partnerships.

F. Scoring Rules and Application Across Cases

A consistent decision rubric was applied across all cases. A score of 3 for AI Integration required evidence of at least two subcomponents, including operational deployment. A score of 2 indicated pilots or product mentions without clear operational deployment. A score of 1 reflected strategic intent or investment without concrete examples, and a score of 0 indicated no inclusion. When multiple documents provided inconsistent signals, coders recorded the highest level of concrete operational evidence observed within the fiscal window. Longitudinal scores represent the firm's position at the end of the fiscal year. Supplementary materials include the full rubric, sample coded cases, and supporting quotations.

G. Coding Protocol and Adjudication

Two independent coders reviewed each firm. Coders recorded the exact supporting quotation and document reference for every nonzero score. Ambiguity handling:

Items flagged with Adjudication Flag = Yes were reviewed by a third coder, who recorded the final decision and rationale.

Conflict rule: When documents conflicted, the highest level of concrete operational evidence within the fiscal window was use. Example adjudication note:

Coder A scored 2 (pilot evidence), coder B scored 3 (operational deployment claim). Third coder adjudicated to 3 based on explicit operational deployment evidence.

H. Interrater Reliability:Cohen's kappa was computed on a random 20% sample of coded firms.

Reported values:

Organizational Structure: $\kappa = 0.80$

Workforce Practices: $\kappa = 0.75$

Technology Adoption: $\kappa = 0.76$

AI Integration: $\kappa = 0.81$

Overall: $\kappa = 0.78$

Values indicate substantial agreement. If $\kappa < 0.60$ during pilot coding, coders were retrained and the rubric refined.

I. Data Availability Files and Access Statement

Files included in supplementary materials:

Additional materials are available from the corresponding author upon reasonable request**.**

J. Limitations and Notes for Reproducers

FlexibilityIndex_Rubric.xlsx
CodingSheet_AllFirms.csv
DocumentLog.csv
InterraterReliability_Report.pdf

CodedQuotes_ByFirm.pdf

1. Public disclosure bias may undercount internal practices not publicly reported.
2. Scores reflect evidence within the 2022 fiscal window; later developments are not captured.
3. A high score indicates documented evidence of flexibility practices, not their effectiveness.

K. Example Coded Cases

Example 1 — Corporate Case (Firm X)

Score: 3 (AI Integration)

Supporting quote: "Since Q2 2022 we have deployed AI based demand forecasting…"

Rationale: explicit operational deployment + product/operations evidence.

Example 2 — Public Case (City Health Authority)

Score: 2 (AI Integration)

Supporting quote: "The Authority has initiated pilot projects using machine learning…"

Rationale: pilot stage evidence without full deployment.

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How to cite this article:

Alnafea, F. (2026). Budgeting for Agility: A Cross-Sectoral Analysis of Fiscal Flexibility, Forecast Accuracy, and AI Integration in Corporate and Public Financial Systems: Nil. Journal of Social Sciences and Management Studies, 5(1).