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Leveraging AI, Big Data, and Cloud Computing for Enhanced Tax Compliance, Fraud Detection, and Fiscal Impact Analysis in Government Financial Management

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Abstract: ***The continuous increase of international trade plays an increasingly greater role in boosting global economic growth, productivity, trade and investment. Emerging and developing economies, especially, have successfully participated in this process, thus making significant social progress and economic growth. With the extensive development of information technologies and electronic data interchange, traditional paper-based exchange modes have been unable to support modernization of the international trade. All countries know that the greatest economic benefits can only be reaped by proper restructuring of the international trading system based on on-line commerce. The subsequent implement of e-businesses requires the whole trading system be reformulated. This can only be achieved through the establishment of a single-window mechanism, thus guaranteeing more efficient customs clearances with better control in compliance with international standards and gradual adaptation to changing consequences of trade driven by globalization in good faith. With the increasing growth of international trade, the volumes of trade transactions thus generated are also increasing at an explosive rate. Efficient customs clearance plays an important role in the modernization of the international trading system, so that it is important to take full advantage of the latest information technologies to digitize the existing paper-based processes. In modernized procedures, electronic data, in digital forms, could be successfully exchanged among the trading partners thereby replacing the paper-based documents. With the advancements of information and network technologies, electronic data interchange is emerging as the means to conduct trading businesses on-line. As trading precedes verifying practices and thus dealing with considerable uncertainties stemming from it, however, electronic data interchange cannot completely replace traditional trading processing practices. Without being formally specified, internationally accepted trading standards cannot be directly utilized in electronic data interchange. Failure in any of the steps thus taken inappropriately can dramatically increase the chances of cross-border crimes, harm to safety and unfriendly competitions, as a number of recent incidents have shown, thereby causing considerable damages in loss of lives and properties. The resulting complexity of existing laws and regulations about international trading becomes a major obstacle to cross-border trades conducted in good faith. Despite the global necessity, nevertheless, little success has been achieved on understanding, harmonizing and standardizing such trading laws and regulations. E-Government is being used to describe strategies and policies of governments to use and implement information and communication technology. Common characteristics of e-Government are, but not limited to, government on-line services and administrative works via Internet, using internal networks to manage administrative information and exchanging it with organizations, and the application of information and communication technology to collect public opinions. It is well known that cloud computing has emerged as a new computing paradigm. During the past few years, cloud computing has been widely used in many domains such as business, science applications, and ecommerce/businesses. Due to its usefulness, cloud computing is also believed to be a major enabler of e-Government. Nevertheless, few attempts have been made in this regard. This paper presents important research towards analyzing the core and primary elements of cloud computing, utilizing them to examine how cloud computing can be applied to benefit the e-Government. Six top sectors have been analyzed to examine the core and primary elements, and the results are in favor of the proposed framework MASC. It also exposes many interesting patterns related to e-Governance and highlights the true actors that are playing a vital role in the development, sustenance, and growth of e-Governance systems using cloud.***

Keywords: AI, Big Data, Cloud Computing, Tax Compliance, Fraud Detection, Fiscal Impact Analysis, Government Financial Management, Data Analytics, Predictive Modeling, Digital Transformation, Risk Assessment, Automation, Real-time Monitoring, Public Sector Finance, Machine Learning

1. Introduction

Governments around the world are recognizing a profound transformational impact from Big Data and Artificial Intelligence (AI), taking center stage in reshaping finances and service delivery, with the potential to revolutionize Public Finance Management (PFM) systems . Decentralized ledger technology and associated innovations open new avenues for tackling age-old challenges in handling public finances, allocating resources efficiently, and enhancing transparency and accountability. Cloud computing, combined with AI tools and Big Data analytics, enables authorities to plan and train knowledgeable personnel to track public finances in real-time . Nevertheless, public leaders may need support to ensure appropriate stakeholder engagement, balancing innovative solutions with privacy, and dealing with possible disruptions from established practices.

Government PFM and associated service systems structure processes, tools, and controls to manage and report financial, resource utilization, and service delivery information. Offered services include procuring and valuing assets, scheduling resource tax obligations, and integrating revenue forecasts into budgetary plans. Public transparency in reporting external PFM-related information fosters citizen participation in decision-making, establishing community-level accountability through scepticism. Highly prominent and manually-intensive, these systems are often regarded as

inadequate due to overriding transaction costs, in turn affecting accountability, service delivery, and fiscal enigmas. Demand for public services is soaring from rapidly growing urbanization rates, socioeconomic inequalities, and climate vulnerability, ascending to information asymmetries, the ineptness of authorities, corruption, and increased citizen scepticism.

Countering these phenomena are organic and political factors that support establishing data-driven, Agile, Smart governments (ASGs), remarking that existing information systems in government structures are causing or amplifying public sector shortcomings. Technology is changing at an exponential rate, whereas government and society change at a logarithmic rate. Young people regarded as Digital Natives visualize the World Wide Web as differently from Adults. What is at stake is the incapacity of the political class to manage the rapid technology change pace, given the fundamental shift in the power toward technology companies, undermining human rights. ASGs are ecological subjects, observing environmental norms and implications, cognizant of limited natural resources, preserving the planet for future generations.

Eqn:1. Logistic Regression Risk Probability

$$P_i = \frac{1}{1 + e^{-(\beta_0 + \sum_{j=1}^{n} \beta_j x_{ij})}}$$

- P_i: Probability that taxpayer i is non-compliant
- β_j: Coefficients learned from labeled training data
- x_{ij}: Input features (same as above)
- Used to classify taxpayers above a certain threshold as "high risk"

2. Overview of Government Financial Management

Great uncertainty surrounds the foundational frameworks supporting government financial management (GFM), which refers to the acquisition and expenditure of funds by governments . Based on institutional theory, GFM is viewed as a multi-layered system consisting of rational-agents, organizations, social norms, and rules. Each layer is critical to shaping GFM reform processes, outcomes, and failures. Studies suggest that these layers are usefully sub-divided into internal (organizations, norms) and external (fundamental forces, politics, legislation) factors, which together reflect attention to the Anglosphere . Principal and agent theorizing and simplistic models of state formation have relegated many internal factors to the status of noise with limited theoretical traction. GFM is a complex process involving engineering transparency into long-standing hierarchies. Consequently, GFM debates draw heavily on the complex systems and actor-network scholarship, which utilize semi-empirical approaches to conceptualise system behaviour, with only occasional attention to direct complexity measures. Here, the political economy of GFM is explored as a highly complex dynamical system whose intrinsic behaviour is probed using a numerical model. Motivating factors behind the expressed concern over the sustainability of GFM arrangements may therefore include concerns about bad behaviour in accounts of soil erosion and food webs, which exhibit "critical" local sensitivity to parameter-value perturbations. Wall-street disappointment over early GFM systems and movements to combat excess price volatility across various assets also loom large for actors analysing GFM, poorly-adaptive agents, norms, energies, and excitations.

Dynamical systems analysis is a rigorous but obscure sub-field of discrete mathematics which permits a nuanced view of GFM systems, agents, and behaviour through local bifurcations and basins of attraction. These methods reveal bounds on quantified behaviour change and offer better system understandings for more effective manipulation. Designed behaviours are also outlined. Given the mutuality of GFM framing and instrumentality, such research could improve agent design and GFM reform more generally. Just as easily, however, findings regarding entropic growth and de-stabilisation could be used to suppress expression of GFM systems and are thus expected to be instinctively resisted by users of GFM. To aid the adoption of complex reflections on GFM, methods are employed to rigorously examine a simple reinforcement-learning actor model of fiduciary GFM behaviour.

3. The Role of AI in Tax Compliance

A key consideration in tax compliance assessments is the need for data quality. Data quality is often defined to include a range of dimensions that highlight the extent to which data is accurate, complete, consistent, timely, and relevant. In the tax compliance context, concerns regarding data quality can arise from the source of the data, its transmission between operational systems, the data feeding the analysis itself, and processing of the data within the analysis. A data quality assessment framework has been developed to clarify the sources of data quality concerns, propose specific information quality dimensions relevant to data quality, and compile manifested examples that data analysts may face in their day-to-day practice. This framework uses Bentley's typology of data claims to develop questions that data specialists may ask when working on their tasks. This typology details four types of data claims—accuracy, completeness, consistency, and timeliness—that can compromise downstream analysis results.

Figure 1: Financial Management cycle

However, few data quality tools link the data quality dimensions with domain-specific data quality problems. Domain agnostic data tools often miss domain-specific

problems that require domain knowledge to diagnose and rectify. Nevertheless, the concerns are stated at a high abstraction level, which requires users to recall their domain knowledge to understand the situations. In addition, none of the existing frameworks have actively engaged with user studies, which can properly and comprehensively bridge the gap between the frameworks and the analysts' actual needs [4]. This involves engaging in training to ensure that their work on conceptual models, ready-to-use templates, or domain-specific knowledge bases are actually useful in tax compliance assessments across different contexts.

3.1 AI Algorithms for Compliance Monitoring

Governments are entrusted with a fiduciary responsibility to use public funds in accordance with laws and regulations. Compliance with legal and regulatory requirements can create significant overhead costs for companies. To ensure compliance with laws and regulations, many organizations have established compliance monitoring systems. However, with complex regulations and huge data volumes, it is not possible to conduct continuous manual compliance checks. Existing automated methods for compliance checking focus heavily on structured legal texts, while leaving compliance monitoring without a readily available procedure. With these problems in mind, a Data-Driven Compliance Monitoring (DDCM) framework has been proposed, which can automatically read and track compliance cases that are relevant to the Local Government Unit (LGU) using natural language processing (NLP) technology, which is part of big data technology. The proposed DDCM method consists of three primary parts: reading and extracting compliance mentions, ranking compliance mentions, and constructing compliance monitoring evidences. By using DDCM, compliance with legal regulations can be tracked and automated governance can be implemented. The dispersion of governance structures, via many financial management systems in different agencies or departments, leads to information islands and incomplete data for financial supervision departments. To evaluate local financial situations, financial supervision departments must conduct audits. Efficiency and accuracy of audits are improved with the internet-based Financial Audit Approach (FAA). FAA involves three terms: Model (M) is an audit model based on AI Big Data and Cloud computing; Approach (A) is an auditing approach based on IA Big Data; and Service (S) is a service platform based on AI technology for financial supervision departments.

3.2 Predictive Analytics in Taxation

Predictive analytics is a powerful technology that leverages data, statistical algorithms, and machine learning techniques to identify the likelihood of future outcomes based on historical data. Most of the predictive analytics methods are now implemented with modern technologies of data warehousing, big data, data mining, machine learning, and cloud computing. Predicting tax revenues is a challenging and important task for tax authorities because a tax revenue shortfall can hinder the attainment of any nation's goals, priorities, and policies. On the contrary, a tax revenue surplus can lead to inefficiency in utilizing public funds. Thus, it would be critical for tax authorities to implement a well-functioning system that can predict at an acceptable accuracy tax revenues and help tax revenue planners in their crucial job. A number of approaches to predict tax revenues have been tested, with inductive machine learning techniques of neural-based models in high regard for their accuracy advantages over other alternative techniques, especially with big data. A new approach to the prediction of tax revenues, namely an adaptive wage-tax-revenue-forecasting neural-based model with a dual calendar system, was developed. The implemented model consists of two major components: a dual calendar system and a multilayer feedforward neural network with backpropagation learning and momentum enhancement. The first component, aimed to represent the tax calendar in which tax revenues are shifted across the fiscal year and the civil year, was a combined Warner-First-order difference system. The second component, aimed at estimating future revenues based on past revenues up to five years, was implemented as a neural-based model according to the definition of multilayer feedforward neural networks.

4. Big Data in Fraud Detection

Financial fraud is an important issue with far reaching consequences for the finance industry, government, corporate sectors, and ordinary consumers. In recent years, dependence on new technologies including cloud computing, mobile computing and storage has rapidly increased and organizations with a significant amount of financial data have begun to embrace these technologies. However, with this increase in dependence on new technologies comes the risk of an increase in financial fraud. As the prevalence of financial fraud increases, organizations must be able to efficiently and reliably analyze all transactions and detect fraud to prevent losses. Financial fraud can be defined as the intentional use of illegal methods or practices for the purpose of obtaining financial gain. There are many different kinds of financial frauds and different approaches to detect them including network traffic analysis, relational database, data stream analysis, spatial and web data. It is possible to detect fraud in various domains, however, there is still a great deal of research to be done in finding the best way to detect each type of fraud efficiently and reliably. Financial statement fraud is the intentional misstatement or omission of information in the financial statements to mislead users to their advantage. Examples of this fraud include overstating inventory values, exaggerating sales and reducing liability amounts. New technologies such as the internet and mobile computing have led to an increase in this type of fraud in recent years. As the level at which companies use modern technologies increases, so too does the sophistication of fraud and ultimately the requirement for detection.

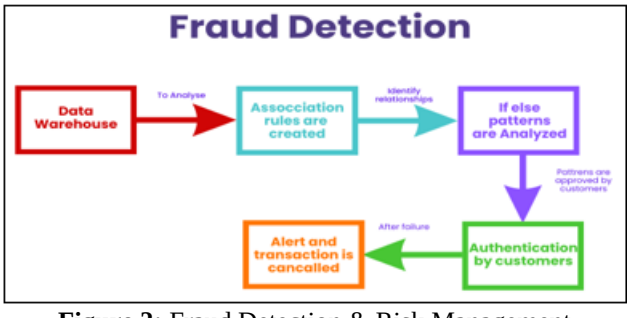

Figure 2: Fraud Detection & Risk Management

4.1 Data Sources for Fraud Detection

Data sources primarily used in financial fraud detection include transaction data, customer profile data, database records, telecommunication data, social network data, and their combinations. In most fraud detection practices, payment and transaction data are directly used to detect fraud. These data can either trigger alerts that need to be further examined in detail or be labeled as fraudulent. Despite being the key to fraud detection systems, such data can result in unnecessary alerts due to different reasons for transactions that can typically be attributed to network and data structure noise or voltage fluctuations. In some cases, race, language, and social class also play a key role in filtering incoming data. Local currency differences are another cause of divergence. A few detection applications focus on the customer profile and records explicitly and use its similarities or disparities as the basis of fraud detection. This profile and record data is among the known static properties of fraudsters and fraud actions and is metafeed information that should always help answer why the fraud happened. Telecommunication data and social network data are also used in detection applications to overcome the anonymity problems that rise along with the increasing independence of the internet. Combining different types of data sources is more common in recent years. For example, in these detection approaches, social network data is used in conjunction with payment and transaction data or combinations of sensor data with telecommunication data in order to make fraud detection goals more non-traditional and challenging. Analytics used by practitioners vary, and unused analytic methods abound. While the existing unions among the data analytics are very limited at best, solutions for them are many. Currently, there is no unified methodology pool available for a fairly large domain of objective domains and data types, and even a good coverage of a particular objective domain with better analytics would not be able to massively produce more implementations as its functionalities are limited in a single domain.

4.2. Machine Learning Techniques for Anomaly Detection

Recent years have seen a concerted effort in developing machine learning techniques to robustly detect anomalous transactions in financial markets. Because of the burgeoning number and complexity of transactions in the financial market, the limitations of conventional techniques have been increasingly highlighted. Interest in leveraging statistical and machine learning techniques for detecting market anomalies has also been rising as it covers algorithms to deal with various complexities of the data and transactions, and a wealth of evaluation measures are also available for assessing the performance of the algorithms.

A proposed framework illustrates an advanced methodology for anomaly detection within the financial markets. The proposed workflow starts with detecting anomalies in the tabular financial data through the existing detection methods. The detection methods range from basic techniques like rule-based methods and z-scores to more advanced methods like unsupervised clustering and deep-learning based ones. Once detected, the anomalies are then all introduced into the LLM-based multi-agent framework to validate and interpret the detected anomalies. This proposed multi-agent AI framework for financial market anomaly detection, validation, and interpretation is a step toward automating the whole process of getting an intuition about anomalies from raw financial market data. It is expected that the proposed methodology and tool will improve the efficiency of financial market analysis while ensuring its accuracy and reliability.

5. Cloud Computing in Financial Management

Governments at all levels have begun to use Big Data technology to modernize their operations, business models, and financial capabilities. As part of this reform, for the first time, the data and financial data assets of government finance entered one place, and a multi-dimensional, full-range, and intelligent big data platform for analyzing government financial data was constructed [10]. With the rapid development of the Internet of things, cloud computing, big data, and artificial intelligence, the intensive use of all kinds of financial big data has become a key direction of the intelligent transformation of financial management reform and a vital front to prevent and control financial risks. Therefore, it is particularly important to build an intelligent financial risk prediction and assessment system based on big data technology. At the onset of financial management reform or ITS application, although intelligent financial management data gathering systems or data sharing systems are constructed with the application of cloud technology, the processing of financial data mainly relies on traditional office software. The human-computer interaction of data analysis is mainly based on descriptive analysis based on the graphics drawn by office software. With the rapid growth of financial data in quartiles, comprehensive and complete availability of data cannot be guaranteed, resulting in the phenomenon of "data islands." Moreover, due to the complicated structure and model of financial data, efforts to analyze data in an intelligent manner are inadequate. Measuring account system, budget performance, reliance on transaction authority, and allocation mechanisms are complex financial management reform projects. However, conflicts of interest can occur due to asymmetric information, which progress control and assessment difficult. With multiple participants, project risks are difficult to detect from the outset. During the implementation, budget indicators are distorted to present a positive result. This study provides a combined prediction analysis model to evaluate risks of the construction, operation, and assessment phases of financial management projects. The estimation of cascading failure probabilities and the maximum number of failures is transformed into a linear programming model based on the moment matching method. A review of exploratory regression for identifying efficient assets in different maturity bands was conducted. The phylogenetic tree was applied to explore the interrelations between the factors driving interest rates, after which a wavelet-based dynamic network was constructed to estimate the impact intensity and time-lag correlations of various market shocks.

5.1 Infrastructure as a Service (IaaS) for Scalability

Cloud computing infrastructure services mark an evolution in computing where the burden of managing local hardware, software, and network capacity is shifted from the user to a service provider. While this infrastructure has long been

available, it has historically been very expensive, proprietary, inflexible, and required substantial application porting activity [11]. IaaS provides a low-cost and flexible alternative, enabling users to pay only for what they consume and allowing applications to scale up and out to meet changing business needs. Not surprisingly, IaaS is the fastest growing segment of the cloud market. The introduction of a heterogeneous, dynamically adjustable pool of computer resources that are separately billed to customers offers both an opportunity and a challenge. The opportunity comes from knowing what data is being processed, where it is being processed, and what the aggregate workload will be across the system. This information provides the basis for increased overall throughput and efficiency, aiding in capacity planning. Cloud service providers seek to have full visibility across their data centers, which comprise thousands of individual computing components, consisting of processors, network switches, and storage devices, each of which may be assayed via thousands of data points. They explore data analytics to determine the conditions of all of the components, remotely requesting and obtaining this data, and using it to do predictive analytics .

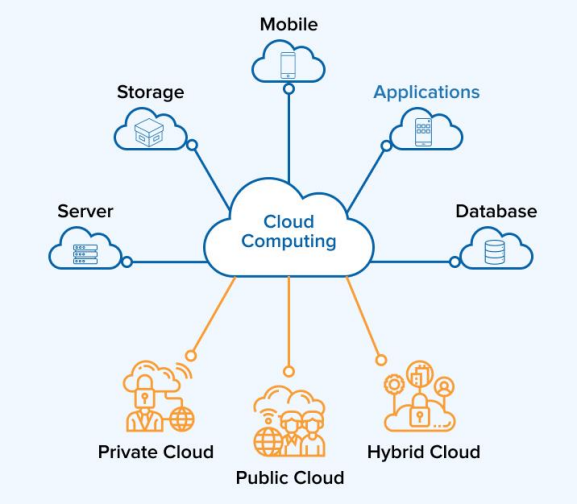

Figure 3: Cloud Computing

Cloud providers have an interest in the upcoming fields of big data and deep learning, to which they have already dedicated considerable resources. Deep learning requires big data, and the cloud ecosystem is an optimal platform for both storage and availability. On-demand remote training of neural networks across a cluster of individual model-server-client interactions gives rise to the need for cloud-based solutions to the challenges arising from this new paradigm. Despite the rapid convergence of enormous data storage and complex computation, the problems of remote usage of big data in multiple formats remain unsolved. The viable adjustment of a processing task to the data situation at a site sensitive to a computer load change is a challenge that has so far only received limited attention concerning cloud-based and distributed systems.

5.2 Software as a Service (SaaS) for Financial Applications

Software as a Service (SaaS) is a means for providing capabilities, typically for business applications in public time-sharing facilities. A SaaS application is designed to be used via a browser, while relying on server-side engines. The term SaaS encompasses everything from complete applications with integrated workflow and data feed, to lightweight web-based front ends to traditional software. A wide range of factors affect the cloud media of a SaaS application that range from security, redundancy, scalability, and functionality [13]. It is more cost effective to examine the functionality of the SaaS-in-cloud, and how its financial benefits are distributed to potential providers and customers. Such comparisons are critical in financial industry due diligence, enabling customers to forecast long-term returns on their investment. SaaS, meanwhile, is an essential concept for software providers, prompting questions such as how to carefully evaluate feature sets, and justify pricing tiers or advanced functionality.

SaaS applications are designed for collaborative use, with communities forming around a best-of-breed financial application. Corporate-to-financial service provider interfaces are reliant on new application programming interfaces, with data protection, cloud-side-only functionality and regulatory compliance challenging to implement when companies overlap their financial information flows across community SaaS applications. These applications are sometimes universally recognized and include issues such as subscription fees, ensuring continued satisfactory service levels, avoiding lock-in, and failure or takeover of the supplier. Outsourcing options broaden and become more complex, as tool, platform, and infrastructure ownership shifts, challenging financial capabilities for corporate size, ecosystem loyalty, regulatory compliance, and vendor reliability.

Some organizations might decide on a broader infrastructural environment that allows more versatile capabilities, preferring more control on data services. Such Software-as-Provider (SaaP) applications are typically equally challenging at a financial application level. Compliance with numerous regulations containing mandatory localisation and privacy specifications ensuring piping capabilities of sensitive information is by no means trivial, as issues about network traffic integrity, cross-platform fixity, information sanitization and inherent risks of centralization are present. Compared to cloud media challenges prevalent across SaaP applications, challenges imposed by locally-installed apps are generally organizational first rather than financial.

6. Integration of AI and Big Data

Big Data, derived from the convergence of transformational technologies, is seen as a phenomenon that should be grasped and understood. Data is the raw material from which intelligence and knowledge are created. History demonstrates that governments have used data to make informed choices, policy choices, address economic and societal challenges, and provide services [1]. However, the manner of data appears to be changing. As sources of data proliferate and the capability to analyze data advances, a revolution in data appears plausible. It opens the possibility of a paradigmatic shift in attempts to harness data. It remains to be seen who will make the greater assessment of the possibilities and challenges that these developments provide for governments.

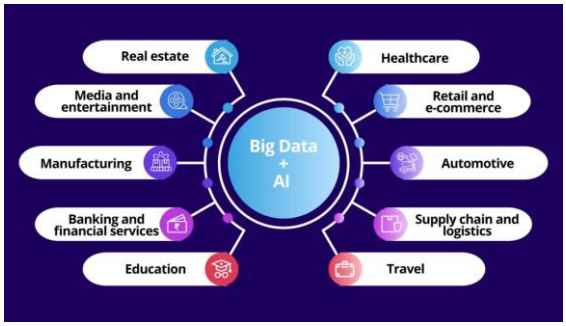

Figure 4: Big Data and AI Revolutionize Major Industries

The concept of Big Data has evolved under multiple meanings over recent years. Big Data within the same stream for the public sector as Web 2.0 and social networking services with a paradigmatic change of a government 2.0 model. Seemingly Big Data are also ubiquitous in a variety of types of structured and semi-structured data along with sensor devices. The ability to generate and store data has exploded with the invention of advanced methods such as the internet, social networking services, satellite images, smart meters, RFID, etc. Governments around the world have embarked on an open data initiative and government 2.0 model. Open data fever has affected many public policy areas. For example, from citizens to government 2.0, it is required that these open data become part of national strategic policies to improve the dispositional view of data/information seekers. Also included is the perception of data as public resource/information infrastructure.

Eqn 2: Statistical Z-Score Method

$$z_i = \frac{x_i - \mu}{\sigma}$$

- x_i: Individual data point
- μ: Mean of the dataset
- σ: Standard deviation
- If $|z_i| > k$ (e.g., $k = 3$), then x_i is considered an anomaly.

6.1 Data Integration Techniques

The data integration process in reverse, starting from a hard drive in the rightmost call of the integration system, is mostly made up of modules or needed technologies. The Database Development and Maintenance Module is an important module that is in charge of managing, moving, and developing all the non-trading data on the server Smart e-Government. The database will be the storage and management of Big Data. There are also multiple databases on this platform [14]. The governments have the central database for governmental purposes and the back-end database for Smart e-Government. These databases are different from each other as the G2G institutions as well as the Smart e-Government institutions both have their own database and data. As the output of the data integration process is by applying this module, then it produces these different databases automatically and actively.

After a data warehouse is built with technology that suits the needs of an institution, data blending must be employed in all integrated data systems development. One very important function of this module is to grant data blending as a batch tapestry through data shovel or window. Each batch tapestry data ensemble is going to apply its own data extraction, transformation, and/or loading procedure. The data extracted from the databases and produce CSV files as the work products. The Excel files contain report tables in the last row pertaining to each agency is going to be produced with the balanced number of rows as well following with its numbers. The central agency's report is delivered to all back-end agencies through this module and will be also developed as visual analytic images. This module is also responsible for controlling whether a batch tapestry is still active or completing, as per the needs of an institution. A visual analytic is an integrated system of that can visualize data involving as parts of images and follow some rules to manage the interactions between them to produce a new image.

6.2. Real-time Analytics for Decision Making

Recent developments in the field of computer and data sciences can support government financial management through the integration of artificial intelligence (AI), big data (BD), and cloud computing (CC) applications. The public sector also produces vast amounts of data that could provide valuable insights into consolidating information, acquiring predictive analytics, and data trends of possible frauds, among others. However, most of the innovation cases fall within the private sector than in governmental institutions. The adoption of AI, BD, and CC in government financial management could enhance accountability and transparency in public services. These technologies already exist in the MOSSQUAD platform and its modules addressed to public administrations in public finance management, procurement and grants. While other firms have accessed financial data from EU countries through CC, they have mainly provided data observation through BI analysis techniques. Although policy experts usually use BI tools, they are not able to create predictive analytics, but only to generate observations on specific statistics. Having the possibility to leverage all AI techniques that allow predictive modelling would enhance both detection and prevention of frauds. A simplified usage with either conference rooms or an interactive dashboard would render it usable for non IT skilled policymakers. This use could be via a private organizational cloud and what-if simulations of financial scenarios that needed to follow consolidated procedures. While it might seem exaggerated to request this BDA, having a cap to forecast spikes in expenses would help policy decisions taken in time and on budget.

The MOSSQUAD platform could use BD and cloud based techniques to merge and process data on procurement activities at tender, contract and implementation level. This could enhance data visualisation and reporting, combining either multi-dimensional aspects or raw characteristics of public spending in the EU. In summary, although the public policies field has been largely untouched by the BDA revolution, there are already existing conventions to conduct analyses that could help policy experts and managers to make better decisions on the financial management of public bodies. To better understand how to bridge this gap and how

to exploit the value of the existing financial data, it might help to understand hypothesis taken for granted. For example, before 2003, there was only the possibility to visualize data due to a lack of standardised data taxonomies across Member States; with the open access to financial data, a reactive attitude based on possible static indicators and visual outputs was taken (but with limited foresight analyses). Then, a dialogue about accountability and public money visibility within the EU raised issues on widespread open data but also on heterogeneity troubles (emerging different countries' characteristics or public administration peculiarities). These insights led to joint comparisons across countries but at the expense of local decision making weakness.

7. Fiscal Impact Analysis

AI and big data become essential in generating better foresight analyses for developing fiscal impact policies on the outcomes of a planned tax regime or budget attempts. Analysing the fiscal impact of a new public policy is chiefly a software-intensive study, since it relies on micro-simulation methods that need estimating the behavioural responses of agents under the new policy and prognosticating the individual outcome. For publicly held data tables, the building and use of this kind of data currency on upcoming events is not regularly open, as it is disadvantaged in regard of accountability, utilising elaborated national accounts adjustments and that much more analytical skill is required. However, micromodels for assessing treatment effects of public policy are well known, particularly in environmental economics, and will be used in what follows to expose how €398.61m could have been saved in 2015 alone as a result of cutting out land taxes. A data discovery system that allows public sector agencies to share their data in anonymised ways that would have provided essential relief for governments pressed about the forthcoming accounting period. As for huge amounts of verifiable data, the approach will accessfully be based on open public data sets readily available to governable agencies. By employing cloud computing it allows to further analyse these databases, matching rumoured data regarding public regulation measures with the disclosed and or holdings, and to visibly expose how a planned enactment of action could yield measurable benefits in terms of unblocking economic profit, continuing extensiveness, and public utility.

Normally public policy is not enforced on static quantities alone. Primarily a legislation lays down a new regulation, which is expected to hold change the way individuals behave or at least how much they report and/or pay. The possible outcomes are cherry-picked where public decisions are put to hold measure on selected counts, often in non-equivalent equivalences. It is the possible assignments of the decision outcomes that in a theory-orientated approach constitute the deterministic knowledge domain for a net analysis. Technically the known variables of a regression model would be transformed into shrunk distributions centered on their previously estimated parameters, underlying assumptions having to be examined beforehand. This state of art is limited however. Such understanding of the interplay of both policies and behaviour never arise generative models of agents resolving time-evolving calculations on the conditions of their applicable exchanges. Furthermore no analytic formulation close to the right handle of nonlinear dependences of strict countable domains has been proposed. It appears that a quadrant would suffice if one only proceeded to examine representative samples.

7.1 Modeling Economic Scenarios

Link prediction is a fundamental issue in many real-world applications whose data can naturally be represented as a network or graph. Growing interest in link prediction has resulted in significant progress in developing predictive modeling approaches aimed at forecasting future links of evolving networks. However, most of the existing techniques focus either on extracting static topological features or on capturing time-varying temporal evolution patterns, which restricts their perspective. They are either feature-based or end-to-end but neglect the use of pairwise proximity. In contrast to these limitations, a novel link prediction framework, which consists of a graph encoder and a temporal encoder that utilize a novel self-supervised proximity-based (SSP) ability, is proposed.

The proposed approach seeks to predict the future link status based on modeling historical time-varying interactions of nodes, with temporal information incorporated as a dynamic hidden state. The graph encoder captures the static and structural information, such as k-hop neighbors, which strengthens a node's representation by aggregating neighbor nodes. To exploit the time-evolving behaviors of temporal link lists, a temporal encoder that integrates the advantages of self-attention and recurrent networks is devised. It consists of two branches: a dynamic hidden state generator using a recurrent layer with tests, and a temporal attention network that designs the attention mechanism to extract effective interactions from candidate past interactions. In addition, a novel SS-based training framework is designed to construct a supervised prediction task from the proximity of a node pair. It produces positive and negative instances, along with other fictive node pairs, to conduct self-supervised link prediction tasks. Employed as a high-fidelity evaluation metric along with a rank-based evaluation method, the multimodal link prediction framework demonstrates its superiority from multiple aspects, even on large-scale networks.

7.2 Evaluating Policy Impacts

One of the key adjustments necessary to better harness these extensive data sources in the public policy management domain is the establishment of methods and tools that automate the fusion of a variety of data sources and types in real time, along with the discovery and preservation of knowledge within them. Traditionally, data management in this domain requires significant human resources and effort to be devoted to activities such as data retrieval, linking and preparation, which can often be a couple of years' worth of effort prior to any actual policy analysis taking place. Additionally, the automated management of the newly created knowledge raises significant additional challenges that need to be addressed in order to ensure its proper utilization and future accessibility. Various initiatives and projects have been undertaken to assess and understand the added value of these complex datasets to the public decision-making process.

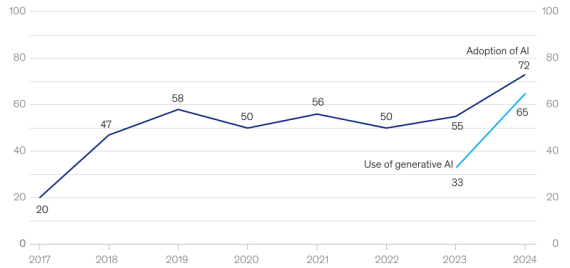

Figure: Gen AI in Accounting: Epic Transformation, or Overheated Hype

The tremendous volume of available data surrounding policymaking offers public authorities unprecedented opportunities to create the necessary evidence base for understanding the behavior of different populations, policies, and program designs and to forecast the consequences of alternative actions on target groups of the population. Such an understanding would significantly enhance the quality and legitimacy of the public policies developed and subsequently better serve the public interest and welfare. By statically and dynamically modelling such a complex system, policy authorities may automatically identify the set of policies that maximize well-defined objectives while minimizing costs. In this regard, the cloud computing paradigm can facilitate all stages of the policy cycle by creating an ecosystem of data and knowledge where all relevant data are accessible, exploited, archived, and shared by many actors interacting via these services.

8. Case Studies of Successful Implementations

Studies of how technology is used in the public sector of various shapes and forms have been published in the recent past. Examples of such published works include algorithmic government and its associated anti-patterns; and big data in public sector management and associated challenges. All of these studies examine technology in the context of recent incidents, and all of them have recognized a research gap regarding the effect of how technology is used in the public sector in Africa.

A case study of how big data, AI and cloud computing (BAIC) are used in public financial management (PFM) of the public sector in Kenya is discussed in this study. Kenya is a leader in the use of technology in the public sector in Africa. Evidence of the effect of BAIC on PFM was collected using a variety of techniques and analysed thematically. It emerged that BAIC is being usefully employed in planning, budgeting, accounting, procurement and treasury functions in the execution of PFM in the public sector. It also emerged that the employment of BAIC enhances strategic approach, change management, stakeholder engagement & collaboration, and enforcement of laws or regulations in the execution of PFM in the public sector.

Eqn 3: Cost Savings from AI Integration

$$\Delta C_{\text{saved}} = C_{\text{manual}} - (C_{\text{AI}} + C_{\text{training}})$$

Where:

- C_{manual}: Cost of manual/legacy operations
- C_{AI}: Cost of implementing AI systems
- C_{training}: Human resource training/upskilling cost

The uniqueness of the study is that it is among the few, if not, the first empirical studies of how BAIC is used in PFM in the public sector in general, and in Africa specifically. Its findings strengthen emerging evidence of the current state of knowledge of how technology is employed in the public sector, especially in low income countries (LICs). Public financial management (PFM) is a broad term that encompasses planning, budgeting, accounting, and budgeting functions and is viewed as a process that spans numerous years; each stage typically follows the preceding stage to enhance stakeholder participation, accountability, transparency, and regulatory compliance.

8.1 Case Study 1: AI in Tax Compliance

In order to develop case studies, various techniques including expert interviews and document analysis were deployed and applied to the respective use cases. Accordingly, key characteristics, processes, and outcomes were systematically collected. The aforementioned six categories were used as an analysis framework to organize the collected information. This ensured a systematic and consistent overview of the gathered perspectives.

This section will illustrate the evaluation method on two selected use cases: AI for tax compliance and Big Data and cloud computing in risk, evaluation and analysis of the Defence Intelligence Organisation.

For the tax compliance case, "AI for tax compliance" is chosen as a specific topic. AI is involved in expecting and assessing tax returns as well as the tax compliance risk of a tax return or regard check request of the tax refund treatment of a party. It automates a human-led process and assesses income tax risk and VAT compliance risk with Integrity, E-Check, Fraud, and Money Laundering scores to sort records and determine which records need final verification with the final review product.

In further detail, ‘The automated process’ product is developed for use by a tax office with rules and algorithms built into the IT landscape. This technically uses various methods and implementations. The product involves the process of preparing the needed input, executing the algorithm, quality check, decision making, and output. AI techniques are used in the verification decision making and assurance/statistical sample output. Most techniques are explained but not all: it could be more transparent.

Two training modalities were used. The minimum expertise requirements for users of the approach and/or product were well observed. A dedicated end-user training curriculum is attended by all stakeholders both technical process and

functional domain experts intensively. There is a good communication and development culture between expert teams, process experts, and business.

8.2. Case Study 2: Big Data in Fraud Detection

A collaborative project performed by and for the public sector in Southern Norway employed advanced risk prediction models to systematically identify fraudulent activity within financial transactions. All 39 municipalities in Agder County participated with no prior solutions implemented. The fully implemented risk detection models contributed to a 12% increase in the fraud detected rate and a 57% increase in expected costs of fraud founded. The results present a logical selection hyperparameter search for commonly used machine learning algorithms. Supervised detection models have custom feature creation involved in structuring fee and payment-text transactions, which typically carry good information for fraud detection. Novel feature significance analysis and modelling performance impact together with the validation check.

Utilizing big data and advanced analytics, they developed risk-based algorithms to assist in identifying potentially fraudulent financial transactions. The performance of the model was evaluated with a focus on how the systematic approach in using machine learning techniques could yield a fair predictive model. Fraudsters' tactics utilized legitimate payment methods such as buy-sell requests for services, fake invoices for payments, donation requests for charities, and refund requests for invalid shipping costs [18]. Fraudulent texts typically contain rare words and it is concluded that classification performance is expected to be better when filtering out high and low frequency terms as compared to training without filtering. There was a minor improvement in performance from including stop words and numbers because they are generally common in scams.

Detection of payment fraud was investigated by classifying transactions in a variety of patterns, which included manually created unsupervised payment fraud classification rules that could constitute a potential first step. The results showed that there were high-profile results amongst four of the eight conditions, while the other four conditions fell into the context of misuse. The former possibility led to ambiguous implications for fraud detection since inadvertently misclassifying a payment as fraudulent could result in serious impacts to municipalities' relationships with service providers if many payments were continuously misclassified. Tuning parameters of the moulding techniques on ascii characters reduced potentially serious loss risks. Optimal selection of one parameter compared to others gave rise to better accuracy in reclassification of manual tokens, possibly yielding strong relationships between one or several detected parameters and detected characteristics.

9. Challenges in Implementation

The movement of Artificial Intelligence (AI) into government and industry has been accompanied by unprecedented societal and technology challenges, new technological capabilities, and developments in finance, computers, and the economy. The risk of being out-of-date is enormous. The use of AI has also grown rapidly in government financial management (GFM), which has led to a proactive feedback loop whereby initiatives in AI technology have led immediately to implementations in GFM and further enhancements in technology. Almost hourly new specific task-oriented capabilities emerge with the constant deluge of news articles and discussion of their impact in various domains . Public financial management–like all of government management–encompasses various activities using datasets that are both structured, such as records from accounting systems, and unstructured, such as email and audio-visual formats. An impending shift in demand is occurring from queries based on keywords to those based conversationally, or in natural language processing (NLP) terms, in context-aware embedding.

Beyond just retrieval and search engines, more recently the large language models which also parse structure have led to the coining of widely deployed tools known as generative AI. As a new frontier for public GFM with already ongoing implementations being piloted or researched worldwide. Starting from a primer of generative AI and its capabilities, this Artificial Intelligence and Machine Learning (AI/ML) primer describes capabilities that will shift demand in the near future, namely, large language models, tools for coding and analysis, autonomous digital twins, recommender systems, and black-box algorithms. The AI/ML landscape and corporate partner engagement are discussed. Potential ethical issues and considerations, such as their propensity to generalize behavior leading to unfairness and bias, hallucinations, and their environmental carbon footprint due to GHG emissions. Résumé on prioritization and responsible and effective deployment over wider and more immediate public sector impact.

Robust automations are imperative for efficiency and innovation in finance; hence their proactive cognizance is vital to avoid being out-of-date. As with the world, government finance is entering a new generation of AI which will revolutionize operations and oversight. It is, however, a paradigm shift which necessitates new sophisticated capabilities, a close watch on evolving use cases, and a strong understanding of baseline ethical considerations. Many large-scale operations result in both perilous leverage of data sensitivity and adversarial attacks to or from implementation. Hence, governance concerns such as opacity, trust, and liability will likewise evolve, insisting on transparent and understandable solutions. Moreover, immense training and data resources are required for AI tools to thrive. Hence, equity and affordable access considerations are likely to emerge at new levels.

9.1 Data Privacy Concerns

The urging need of big data has brought to the forefront a variety of concerns about privacy and confidentiality, data monopoly, discrimination, the violation of rights, the lack of transparency, and other ethical issues. This concern is primarily at two levels: The first set of concerns includes access, use and control of patient data in private hands. Recent public–private partnerships for implementing AI have resulted in poor protection of privacy and misuse of patient information. There have been calls for greater systemic

oversight of big data health research. Appropriately designed safeguards must be put in place to maintain privacy and patient agency. In addition to ensuring that public organizations retain control of sourced data, the competencies of private custodians of data and the checks on their use or interpretation of source data are very important. Private custodians of data can get conflicted as they run a business to sell the data collected. As their priorities on data may change, they should be structurally encouraged, as well as mandated, to ensure data protection and not use it for their own gain.

Another set of concerns relates to the external risk of privacy breaches through AI-driven methods. The information derived from population-level or aggregate statistics that don't point to identifiable individuals may be accurately guessed if the covariates are known to the adversary. The ability of generic deidentification or anonymization methods to protect the data from reidentification is under scrutiny, as new algorithms have been developed that successfully reidentify previously anonymized patient health data. AI algorithms use such reidentification routines to decode otherwise hidden information in health or cognition models trained on achievable data. The violation of patient privacy in view of the development of advanced and associated methods puts public organizations at risk and thus brings in the urgency of understanding the impacts of AI. Understanding the external privacy risks will help governments seek for needed oversight.

9.2 Integration with Legacy Systems

After selecting suitable data collection and analytics solutions, the next significant undertaking in setting up the framework is to integrate these chosen solutions with existing legacy systems that governments have been using to deliver services over time. Despite the inefficiencies or other issues that those systems may present, it is essential to preserve their operation or reuse the relevant components if such a thing is technically feasible. Otherwise, backtracking both politically and securely may be too hard to afford. In addition, government institutions are usually impossible to reroute the delivery mechanism or reconsider the complete databases or other storages, which, along with the hierarchically organized applications, typically take huge effort to relocate. Therefore, next to deploying greenfield solutions, substantial attention should be paid to supporting and enhancing the existing systems [21]. Theoretical knowledge or previously researched solutions come as good advisors, but appropriate know-hows and fine-tuned tools should also be in the asset portfolio.

Integrating legacy systems is a serious effort that usually spans over long times and concerns a wide range of issues. Some of these issues include human-centered concerns. Operator-related tasks consist of resource and workload measurements, log parsing operations, error tracking and analysis, recovery procedures, and so on. All such tasks should be carried out by former operators trained to work with the new solution instead of the legacy one, which is supported by modern, more intuitive interfaces. The predictability of the outcome may also become an issue. An unclear understanding of output terms and calculation methods may also slow the integration period, given that upon failing the adjustment of the knowledge workforce to the new solution, operation falls back to the legacy systems.

It is probable that this much effort gone into integrating a solution with the previous systems does not pay back for the operator institution with reduced quality or completely lost pieces of minor importance but attached to the governmental services. Assigning an outside team for the integration process may save the institution from distractions and other inconveniences due to premature development and engineer overload. Even if complicated, using the outside integration team may be part of a much wider reorganization plan to upgrade the whole state administration on a politically favorable level.

10. Future Trends in Financial Management

AI and Big Data: The Next Frontier for More Direct Use by Citizens Cascading the above-mentioned machine learning algorithms into a robust data pipeline can ultimately lead to a comprehensive financial uplift for the public service delivered to the citizens within the framework of governance. This brings forward the next frontier in all the related frameworks of the discussed machine learning algorithms, which is giving back the mantle of AI learning to the citizens they concern. To give checks and balances to such projects aimed at massive financial uplift of the public sector, it should at first be ensured that the machine learning doesn't replicate the bias in regards to equality of choices in the governance already established through traditional means. Therefore, this approval phase needs broad discussions on technical, methodological, ethical, regulatory and supervisory concerns, participatory decision-making inclusion, and public awareness campaigns.

The Agility of Cloud for Business Agility The world is transforming into a world of non-stop business interaction where on-demand access to resources instead of ownership of assets is being sought out globally. An alternative work environment is being created where the initial need for services, storage, data, and applications needs to be on-demand. These considerations have collided and combined various new technology paradigms along with traditional ones into a hyperconnected environment. Along with their services, Cloud-based solutions are being commoditized, and Cloud-based enterprise resource planning companies are getting money-oriented and over cash-flow-based investment schemes. A matrix of the above-mentioned new paradigms is to be constructed and the multi-faced, multi-nature capacities of Big Data, Cloud, and AI are to be introduced, implemented, and operated.

Smart-Cities and Future Smart-Governance Smart cities will be the output of a far and broad intelligence gap between the current most advanced services nowadays, primarily in unique cities, and the rest of the globe whose services are old, not-up-to-date, and even under-served. Supported primarily by City Data Exchange laboratories once steered by the Unit of Smart Cities formulated by the United Nations in collaboration with a consultancy firm, cities and consolidated service-consigners will start interconnecting and inter-working on AI sandbox and knowledge production. Lessons learnt are to encompass newly throughout regulatory

frameworks on mainly discriminatory algorithmic outputs on both governance and earnings.

10.1 Emerging Technologies

Emerging technologies like artificial intelligence (AI), big data, and cloud computing, among others, can be exploited by government in reforming financial management and accomplishing objectives. Meanwhile, challenges of adopting AI, big data, and cloud computing in finance management along with future use of technologies in supportive the achievement of government financial management objectives are queried. This chapter provides suggestions for government financial agencies on such technologies' utilization. New technologies like AI, big data, and cloud computing can be adapted by government for reforms in fiscal policy, budget policy, expenditure policy of treasury management and public procurement, robust collection of taxes and debts, and for audit financial control. The aim of AI is not aiming to replace human capability but to augment it. AI can allow government finance departments to focus on complicated works while letting routine work on AI "robots." AI not only handles manual and cognitive tasks, but also integrates algorithmic and human insight to handle judgment-based tasks. AI is viewed as the brain, whereas big data is seen as the lens. Government agencies can assess questions or predictions using data as input. Data science models built on a big data platform can regularly learn and make successful predictions. Multiple sources of data can be integrated seamlessly through cloud computing, data can be accumulated, and regular analysis can be achieved efficiently and effectively. Cloud computing provides theoretically infinite computing and storage resources for data acquisition and storage. While high tech can improve finance management mode, since it is new for government agency, an immediate shift to high tech is not practical. Analyzing financial data with feedforward neural network modeling, monitoring budgets with a data warehouse, and module-based financial management system construction are orally satisfied and hence need more validation. Also, data need to be compatible with AI, big data, and cloud computing application, which is hard where separated systems are adopted. The government financial system is traditionally proprietary software, where concerns of data leakage and record retention exist. Understanding and acceptance of data-oriented modeling needs (training) and consideration of social concerns on employment, mistrust, accountability, control, etc. need. A finding term is that as technologies grow up, moderate level of modulation and explanation is needed so that better tests or audit or control can be conducted with higher trust.

Figure 5: Trends Shaping the Future of Investment

10.2. Policy Recommendations for Adoption

To ensure a successful transition towards the utilization of innovative technologies, multinational government agencies must strategically navigate the adoption process. As seen with numerous previous technological turns, agencies will encounter various challenges over time. Those that master the complex adoption landscape will be more versatile in adapting to new disruptive technologies in the future, providing better services to their populations and countries. The policy recommendations laid out here provide a comprehensive framework to understand the elements influencing the adoption of novel technologies in government agencies.

Digital technology adoption implies significant changes in organizational work processes. Therefore, the agency using innovative technology will need to adapt to the technology by changing work processes, tasks, and internal roles. Any leader in the decision-making chain will need to consciously reflect on how the innovative technology affects the agency's nature of work, the expectations of stakeholders (both internal and external), the agency's mission and goals, and how its tasks should be reevaluated in a world transformed by innovative technology. A comprehensive understanding of the transformative potential of the disruptive technology and the possible challenges of such change for the agency will be fundamental to prioritize and better grasp the nature of the change, thereby also enabling more tailored engagement and outreach plans.

Understanding the function(s) of the new technology will enable better insights into what technologies best serve an agency's mission, how to realistically adopt and utilize them, and how this adoption will affect various stakeholders. Several aspects of the technology will need to be assessed to provide a good picture of the technology. In particular, an agency leader will need to evaluate how much flexibility is granted by the technology and how this technology's functions link to public management. The adopted technology's level of complexity will be critical, as more complex tools usually require more extensive and prolonged training. Therefore, the extent to which technology will have to be adapted or modified should also be assessed. Different stakeholders will often have varying concerns regarding new technologies. Consequently, efforts to build internal public understanding and stakeholder management plans will differ from case to case.

11. Conclusion

AI, big data and cloud computing services have the potential to change and improve the public sector through the introduction and successful embedding of a new computing paradigm. However, to realize the potential for improvement, action by a focused group of agencies is required, backing up their ambition and resources with political engagement and will. To facilitate those futures, there will need to be a broad program of work targeting the identified needs and developing the cognizance and momentum required to initiate and sustain the changes. Here, it must be acknowledged that the levers of change do not reside solely in government

agencies, but also rely on participation from industry and academia. There is a pressing need for more cloud development and hosting facilities within the UK and European Union and for those facilities to be co-built and operated by agencies and industry players.

There is currently a wealth of cloud services suppliers, both local and sector specific, which are providing AI, Big Data, and cloud computing services that are coupled together into coherent ecosystems. However, those clouds do not currently target the particular features, control, and governance of public sector agencies that would be necessary to realize the improvements discussed above. The cloud service providers need to understand the specifics of the public sector better. The public sector needs to specify, work with, and invest in projects and programs that will deliver the necessary development and interfacing such that bespoke public sector clouds can successfully interoperate with the myriad data and computation services available on publicly available clouds. This crossing of the divide between the public and the private sectors is complex, difficult, and requires deliberate consideration and developing new frameworks for engagement, contract structure, and levels of trust.

Academia must also play a transformative role: deploying their modeling methodologies to understand in depth both separately and together the AI, Big Data, and cloud opportunities for public sector agencies, demonstrating the need for major change and the particular design and governance changes required to enable that change. Currently, the testing and modeling of cloud, AI, and Big Data services are generally being carried out independently and without access to the version of the cloud, Big Data services, and platforms that the public sector would need. True emulation is needed that brings together the commercial and educational opportunities that they provide and understanding of how their bespoke versions might be scientifically constructed. Transformation of the public sector is needed and desired, and this transformation challenges current boundaries between sectors and disciplines. Reforming and improving European governance through the adoption of AI, Big Data, and cloud computing would be a sign of significant modernity, maturity, and intention.

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