# Understanding Government's AI Readiness in Public Financial Management: A Case Study of AI for Financial Advisors

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**Abstract**

Claimed to offer promising benefits in terms of efficiency and transformation, the implementation of AI in government organizations faces many challenges and requires certain readiness. It is thus important to explore what factors influence the government's readiness for AI, particularly for specific AI technologies in specific domains. This research examines factors influencing government readiness to implement predictive AI for public financial management (PFM). We conducted a case study in the Indonesian central government that develops AI for financial advisors (AIFA) to monitor and evaluate regional governments' budgeting and spending. We explore technical, societal, ethical, and governance readiness and reveal AI-specific and PFM-specific factors in the context. Some of those factors are the use of AI to obtain AI-ready data, alignment of accuracy and functionality, commitment to data-driven decision-making, and user acceptance. We find that this AI tool receives great user acceptance as it answers users' needs and provides financial transparency to the public. Nevertheless, the examined government organization precedes technical and societal readiness efforts before ethical and governance readiness, leaving auditing and regulatory frameworks of AI in place.

**Keywords**

Artificial Intelligence (AI), AI readiness, Government organization, Public financial management, AIFA.

## 1. Introduction

Implementing AI in public organizations offers promising benefits, such as improving the effectiveness and efficiency of public service delivery, resulting in more accurate work, reducing human error, and transforming internal processes (Valle-Cruz et al., 2019; Mellouli et al., 2024). Lately, AI capabilities in automating repetitive tasks, processing large datasets for informed decision-making, personalizing services, and providing virtual assistants have been progressively used in public administration (Mikalef et al., 2023). AI has transformational potential across various fields, including finance (Smith & Ayele, 2025). AI can be used in public financial management (PFM), which refers to the applications of AI techniques in macroeconomic and macro-fiscal forecasting, spending decisions, budget planning and monitoring, and financial management and reporting functions in government (Allen et al., 2013; OECD, 2024).

Implementing AI in government organizations, at the same time, is challenging. Some challenges associated with integrating AI into public financial management systems include data privacy concerns, the need for skilled personnel, and the importance of developing regulatory frameworks that ensure ethical use and transparency (Bouchetara et al., 2024). Moreover, AI exists within sociotechnical systems, where technology and human actors interact to achieve specific goals. The lessons learned from integrating AI systems also emphasize the critical need for developing strong governance structures, ethical frameworks, and regulatory supervision (Bouchetara et al., 2024).

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As AI is a collection of applications and technologies, different types of AI applications relate to unique resources or variations in the underlying machine learning algorithm, design, data sources, or deployment scenario. Hence, the capability requirements for implementing predictive AI are different from, for instance, generative AI or image recognition systems (van Noordt & Tangi, 2023). In fact, predictive AI is one of the most used AI technologies in government organizations (Misuraca and van Noordt, 2020) due to its potential to significantly reduce operational costs and improve business decisions. Although research presents AI readiness assessment models and frameworks, most studies do not specify the AI application types they examined. Subsequently, existing research often remains at a high level of abstraction. The specific elements, such as prediction accuracy and impact on data-driven decision-making, that characterize predictive AI remain unexplored.

In addition, looking deeply into the use of predictive AI in specific domains, in this case, public financial management, allows us to perceive unique insights into the applications of AI techniques using financial data, such as making predictions of budget expenditure to help with strategic decisions. Proper management and oversight with AI can significantly improve efficiency, risk management, and the overall performance of public financial management, thereby yielding benefits (Bouchetara et al., 2024). However, limited research has examined the readiness of the government to use AI in managing public finance.

To address the gaps in the literature that predominantly originate from unspecified types of AI applications and the unspecified domain, this paper provides insights into influencing factors of the government's readiness, specifically for implementing predictive AI in public financial management. The scientific relevance of this research is to explore and explain factors and strategies influencing AI readiness in government organizations, particularly for public financial management. The practical relevance concerns providing insight for public sector practitioners who have started using AI and need to improve their organization's readiness to make the implementation of predictive AI more successful.

## 2. Research Background

### 2.1. Potential and Challenges of Predictive AI

AI offers significant opportunities in public financial management. AI can enhance risk management in the public sector with more precise predictive models for forecasting business failures and assessing fiscal risks (Bouchetara et al., 2024). AI facilitates various analytical and decision-making processes through scenario analysis, resource allocation, and policy impact analysis (OECD, 2024). It increases operational efficiency by automating business processes and handling repetitive tasks efficiently and with minimal error, such as data entry and form processing (Smith & Ayele, 2025).

Despite its potential, AI adoption in public financial management also presents various challenges. Key challenges include the potential for bias and discrimination, which can arise from algorithms that are either poorly designed or trained on biased data. Implementing AI in public financial management necessitates higher transparency, accountability, and explainability compared to the private sector (van Noordt & Tangi, 2023) or other domains. This is due to the need for public scrutiny, accountability for the use of public resources, and the potential impact on citizens (OECD, 2024). Automating fiscal decisions can shift accountability from human judgment to system-based processes, raising challenges in defining accountability. The use of AI in public financial management raises important ethical concerns related to data protection and fairness, especially potential impacts on vulnerable or marginalized groups (Bouchetara et al., 2024). Another challenge of AI in public financial management is integrating into existing financial management systems, which are often fragmented and outdated, lacking the necessary infrastructure and compatibility for advanced AI functionalities (OECD, 2024).

### 2.2. Theoretical Framework of Government's AI Readiness

For public organizations to commence AI use, they are expected to attain certain states of psychological, behavioral, and structural preparedness (Lokuge et al., 2019) and possess relevant resources, capabilities, and commitment to AI adoption (Jöhnk et al., 2021). Previous research on AI capabilities takes the resource-based view as the theoretical baseline (Mikalef & Gupta, 2021; Neumann et al., 2022; Mikalef et al., 2023; van Noordt & Tangi, 2023). That earlier research informed what resources determine successful AI adoption. However, government organizations should prepare beyond sufficient resources to be ready for AI. Many studies also use the Technology-Organizations-Environment (TOE) framework to list the factors influencing AI readiness (Pumplun et al., 2019; Jöhnk et al., 2021; Mikalef et al., 2022; Maragno et al., 2023). Yet, this framework often captures high-level factors and is limited in exploring the unique requirements of AI.

In the socio-technical systems approach, distinct but interrelated social and technical subsystems are integrated, and all stakeholders can contribute to developing technical functionality and the evolution of the social side (Fischer & Herrmann, 2011). This theory is considered relevant to studying AI systems in the organizational context because AI systems are not just technical tools but also have a social impact on the people who use them and are affected by them. It requires technology and human conformity in an intervention strategy for organizational development (Oswald, 2018; Straub et al., 2023) and the interplay between technology and the social context of public administrations (van Noordt & Tangi, 2023; Young et al., 2022). Moreover, most AI applications in the public sector consider ethical aspects and principles of responsible design. The concept of AI governance is closely associated with responsible and ethical principles embedded throughout the design, deployment, and evaluation process (Oswald, 2018; Gupta & Parmar, 2024; Bouchetara et al., 2024). Considering the nature of AI as a socio-technical system and being ethically sensitive, this paper incorporates those existing concepts into an integrated framework to study the government's AI readiness. The framework comprises elements of technical, societal, ethical, and governance readiness.

## 3. Research Methodology

This research adopts an exploratory case study approach to examine readiness factors for implementing predictive AI in public financial management. It aims to understand how and why these factors influence AI implementation, based on insights from diverse stakeholders. Given the limited discussion of predictive AI in the financial sector and the often abstract nature of existing AI research, a case study is appropriate. As Yin (2003) and Benbasat et al. (1987) argue, case studies are well-suited for investigating contemporary, context-dependent phenomena and addressing "how" and "why" questions involving personal experiences and behavior.

To select a specific case for this research, we set the case selection criteria as follows:

1. The case concerns the implementation of predictive AI in Indonesian government organizations responsible for public financial management. The Indonesian case is convenient because the first author speaks the language and has the network to reach the organization.
2. The case involves at least two years of experience with AI implementation, and the AI system is still in use. This criterion allows us to capture the organization's AI readiness dynamics. The use of AI referred to in this research is the use of the organizational deployment of AI systems. It does not include individual civil servants' use of AI, such as a personal ChatGPT account.

3. The case enables access to relevant interviewees, observations, supporting documents, and potentially other information sources for analysis.

We selected one institution that fulfilled those criteria. Focusing on a single case study allows deeper exploration of the real practice by interviewing multiple stakeholders. Without intending to generalize the findings, this specific case study is valuable to learn from for some reasons. First, the studied organization is the central public financial management of the country, which has always been leading in digital transformation, and the AI use case was awarded as the best AI innovation in 2024 by the Indonesian Ministry of State Apparatus Utilization and Bureaucratic Reform.

The primary data for this research was gathered from interviews and relevant document analysis. Table 1 describes the roles of the selected interviewees and their experience in the organization. The informants are selected purposively from each role and varied backgrounds to share relevant insights.

**Table 1:** Overview of interviewees, where (T), (S), (E), and (G) stand for technical, societal, ethical, and governance expertise, respectively.

| ID | Interviewee Job Role | Organization employment |
|---|---|---|
| I1 | Data analytics and AI developer (T) | 14 years |
| I2 | Data analytics and AI developer (T) | 10 years |
| I3 | Data analyst in the business domain (T) | 14 years |
| I4 | Algorithm Auditor / Head of data science community (E/G) | 8 years |
| I5 | Senior Data Analyst in the Central Transformation Office /Data Management Officer (G) | 18 years |
| I6 | Data analytics and AI developer (T) | 18 years |
| I7 | Regional government as AI user (S) | 17 years |

Interview questions were based on readiness factors identified in the literature, allowing us to refine and extend existing models for predictive AI. One-hour online interviews were conducted between October 2024 and February 2025, with follow-up questions addressed via email. All interviews were recorded, transcribed, and thematically coded using Atlas.ti software. We applied deductive coding to the transcripts, in which we developed labels for the interview data based on theory and concepts from the “Research background section” before starting the coding process. We also applied inductive coding to identify unlabeled sub-factors based on interviewees’ views.

## 4. Case Description

In this paper, we conducted a case study in the Ministry of Finance, Republic of Indonesia. This organization serves in the capacity of the chief financial officer of the central government, with one of its major functions including the formulation and implementation of fiscal policy and budget management. With more than 78,000 employees, the organization has 800 offices in all regions of Indonesia. The Ministry of Finance has shown efforts to apply AI innovations by forming the Central Transformation Office with a dedicated data analytics unit. This unit drives innovations in data-driven technologies, including supervising and controlling AI innovations from whole departments in the Ministry. Approximately forty data analytics projects and at least ten predictive AI initiatives were officially recorded, with some currently under development, and others already in use. However, with no inventory built in the organization, detailed information about all algorithms used in their public services is hardly accessible.

Among the AI innovations, we specifically analyzed the use of AI for Financial Advisors (AIFA). The Directorate General of Fiscal Balance runs this AI tool and has initial objectives to classify the unstandardized nomenclature of regional government accounts from SIKD (regional financial database) to provide regional financial data in a real-time manner, more accurately and reliably, to support data-driven policy formulation. It also aims to strengthen the role of the Ministry of Finance in improving the quality of regional financial management. Financial advice for regional governments expected from this AI tool includes data anomaly detection as an early warning system, performance evaluation of budget execution, forecasting regional income and expenditure, and analysis of spending priorities to increase the impact of regional revenue and expenditure budgets.

In AIFA, several AI techniques are used for different purposes. It uses a rules-based system for anomaly detection and data validation; natural language processing for standardization of regional governments' budgets and financial data and budget tagging; machine learning for forecasting budget realization and optimization; and computer vision for remote sensing. Every month, the Ministry of Finance will transfer regional funds allocation to regional governments based on their historical spending in previous months. As a prerequisite, regional governments should provide their financial data to AIFA every month by authorizing data integration from different accounting information systems to AIFA. If the data is detected as anomalies or invalid, the regional governments will be punished, delaying the transfer of regional funds.

## 5. Empirical Results from the Case Study

### 5.1. The Influencing Factors of Governments' AI Readiness

Through seven interviews with public administrators involved in developing, using, monitoring, and governing AI for financial advisors (AIFA), prominent factors influencing their readiness for AI are derived (Figure 1). The findings revealed some factors specific to predictive AI, such as aligning accuracy and functionality in choosing AI prediction models, and the need for standards and guidelines for good AI prediction models. Also, some factors are specific to PFM, such as commitment to data-driven financial decision-making and using AI to process unstructured financial data to provide analytics.

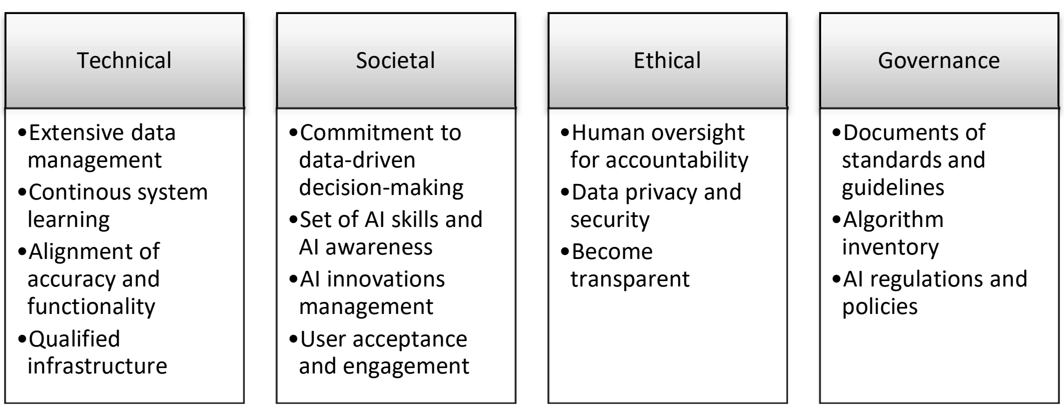


**Figure 1**: Classification of readiness factors found in the case study

### 5.2. Insights into the Government's AI Readiness in Public Financial Management

This sub-section presents a narrative description of the factors mentioned in Figure 1, supplemented by quotations from interviews, identified by their respective identity numbers in brackets..

1. *Technical: Having AI-ready data by utilizing AI techniques*

AIFA was initially designed to analyze regional financial data, gathered from several information systems with different account standards (unstandardized) and vast data variations. Tracking and consolidating that kind of financial data from 546 local governments in one application is difficult. Thus, AI techniques are applied to process the input data and result in AI-ready data for the database warehouse. In this process, data anomalies are detected using the box-plots model, and the text data is classified and standardized with a transformer algorithm. These AI techniques validate the data and warn data owners if the discrepancy exceeds 10%. When AI-ready data is present in the database warehouse, machine learning-based models are applied to process the data and do budget tracking and optimization in the form of a dashboard.

2. *Technical: Applying continuous system learning*

As indicated in (Maragno et al., 2023), ensuring a continuous learning process is one of the AI system requirements. AI models are rapidly developing, so they require continuous learning to choose and update the best model for certain tasks. Same with AIFA, the first version was created in 2019. At that time, data anomaly detection was performed using Benford's law model, and text classification using a rule-based SQL query. Later, the classification technique became inefficient for more detailed thematic analysis. Then, the second version of AIFA was built in 2020 with improvements: data anomaly detection using a box-plots model, text classification using natural language processing, and implementing budget tagging, tracking, and analysis. The budget auto-tagging applies a natural language processing technique for thematic analysis, such as education, health, or stunting. The analysis gives predictions and financial advice for policymakers. Technically, the developers evaluate the existing models two times a year. A change in the model should consider two core factors: significant impact and efficient process. Although the model continues to learn, this procedure runs incidentally due to the lack of a defined governance framework.

3. *Technical: Ensuring accuracy aligns with the functionality*

The system's accuracy in predictive AI is essential because it shows how precise the predictions are. However, no single source has precisely mentioned the standard accuracy of a good AI model. Tuning the system's accuracy requires group deliberation about performance beyond statistical forecast accuracy (Montes, 2023). A high accuracy rate should align with the functionality of the AI system, which means it should meet user expectations. In our case, the AI models used in AIFA give an accuracy rate of 95-96%; however, different stakeholders highlight the system's accuracy distinctly. For AIFA developers, setting accuracy has a trade-off with implementation simplicity and data quality. For AIFA users, the main concern is on how the system can support their work. The user found out that the accuracy constraint in AIFA is caused by the lack of data integration between diverse data sources and standards. Thus, although the system has a high accuracy rate, manual work is still needed for data validation. From the auditor's perspective, the system's functionality should go beyond the accuracy rate. The function of AIFA for decision-making should be optimized further. The budget spending impact analysis using AIFA is not yet available. From the governance perspective, the interviewee claimed, "It is difficult to rigidly determine an AI system's minimum accuracy because the consideration is case by case and is influenced by the different complexities of the predictions and imbalanced data conditions. Although higher accuracy is better, no best practices mention accuracy standards" [I5].

4. *Technical: Provide qualified infrastructure*

AI infrastructure involves hardware and software to create and deploy AI applications. Typically, AI infrastructure comprises four components: data storage, computing resources, machine learning (ML) frameworks, and MLOps platforms. AI applications frequently require extensive storage and graphics processing units (GPUs) for the computing power, rather than the more traditional central processing units (CPUs). The implementation of AIFA in this organization is enabled by adequate infrastructure, as perceived by the informants. However, this organization still faces limited computing power as one of the challenges to developing more AI solutions, particularly for ones that handle images and videos. The problem in procuring advanced computing power is not necessarily limited to budget, but is also related to the availability of machines in the market. As indicated by interviewees, cloud-based infrastructure can be an option in their organization for AI innovations that process huge amounts of public data.

5. *Societal: Commitment to data-driven decision-making*

In our case, the studied government is particularly devoted to creating a data-driven culture. Initiated by the top leaders, they build commitment and demand for evidence-based policies. As indicated during the interviews, "Since early 2021, the Minister instructed all employees to explore data utilization massively. The Ministry of Finance is like a hub for numerous types of financial data, from macroeconomics up to small transaction details. Processing the data will make more impactful and data-driven decisions" [I4]. AIFA is one of the tools that offers potential benefits to support data-driven financial policies. AIFA makes it easier for the central government to monitor and evaluate budget planning and the realization of the regional governments. AIFA also facilitates more transparent government financial data to the public, as processing the data is now simpler and yields a clearer understanding. However, we need to interview more regional governments to conclude whether AIFA has been useful in data-driven decision-making. Moreover, data literacy of the public administrators and change management of the organizations are essential to build and maintain a data-driven culture.

6. *Societal: Developing AI skills and AI awareness*

The studied organization prioritizes efforts in building AI skills and AI awareness within the organization through several initiatives. In 2020, a data analytics Community of Practice (CoP) was initiated to gather data science and AI experts in the organization to mutually share their knowledge. Started from a competition inside the organization to trigger data science innovations, it continued to grow. The community now has 50-60 members and has been institutionalized for bigger impacts. A pulling factor to join the community is that the members can serve as training instructors for other employees and get additional monetary benefits. The community members can also be involved in other AI projects outside the organization to improve their skills. The community regularly holds competitions, hackathons, and sandbox experiments that invite innovation from AI enthusiasts inside and outside organizations. Besides skills, AI awareness of all employees is also developed to avoid misperceptions about AI. Several levels of training are available in the organization to shape extensive AI awareness and skills. It ranges from the basic level covering data literacy, to the high level of AI skills specialists.

7. *Societal: Manage AI innovations*

The progressive use of AI and data analytics inside the studied organization has affected its organizational structure. The Central Transformation Office (CTO) was initiated in 2020 to accelerate digital transformation in the Ministry of Finance. As part of it, the Data Management Office (DMO) was designed specifically to manage data analytics and AI implementation in the organization. However, the organization applies decentralized AI innovations, which means innovations can come from any team integrated into the business domain, not necessarily from the CTO/DMO. It is found that almost all the Directorate Generals in the Ministry have implemented predictive AI for their specific purposes. The innovations also come from the community of practice, AI competitions involving internal and public participants, and sandbox policies. Then, the DMO is responsible for supervising the AI applications, deciding which ones are good to be implemented, and monitoring the implementation.

8. *Societal: Ensure user acceptance and engagement*

In our case, the acceptance of using AIFA is high. The first reason is that AIFA is mandatory for regional governments to use due to the central government's authority to require it. Second, this application clearly helps users work more efficiently. With data validation and budget tagging, for example, it helps regional governments easily monitor their budget. The system also increases user engagement in feeding the data. Previously, the regional governments only sent their data without guaranteeing quality. With the gatekeeper in the form of anomaly detection in the system and publishing the data on the organization's website open to the public, it raises, by design, user involvement to provide good-quality data. Over time, the system has barely found anomaly data compared to the initial state. As mentioned by interviewees, "The most important thing in developing AI-based solutions is that the tool answers the user's needs and makes the work easier, not merely follow the trend of technology. By that, user acceptance and engagement with the AI tool will be high" [I1, I2].

9. *Ethical: Human oversight to support accountability*

In our case, one potential bias in the AIFA system is errors from the algorithm in classifying text data. With an accuracy rate of 95-96%, it leaves a 4-5% discrepancy, which matters in financial data and can make significant differences. To overcome this bias, human oversight is applied to evaluate the prediction result of NLP. Another potential bias is data discrepancy that might affect policy-making. AIFA utilizes financial data from several databases with unstandardized accounts and huge data variations. It results in a data discrepancy every time. This bias is handled by setting a maximum of 10% data discrepancy monthly in the system. For higher discrepancies, the system will warn the data owners to correct their data. At the end of the year, the data owners should provide consolidated data. Although inefficient, human oversight and manual work are indispensable in this matter.

10. *Ethical: Ensuring data privacy and security, even with cloud-based infrastructure*

It has often been a dilemma for public administrators whether or not to utilize cloud-based infrastructure. The decisions are made between data confidentiality, security, and regulation. Cloud services offer a bigger capacity to run AI models, cheaper cost, and sometimes more reliable data security. The studied organization utilized cloud-based infrastructure to run several AI solutions with strict non-disclosure agreements (NDA) with the service provider. However, the cloud is used only for public data, while an on-premise server is used for confidential and very confidential data.

11. *Ethical: Attain transparency*

Transparency in the AIFA system covers processes and results. Process transparency is intended for the users and is achieved by communicating how the system works and its weaknesses. Transparency in results is intended for the public and is achieved by publishing real-time and valid data from AIFA about regional revenue and expenditure on an open-access website.

12. *Governance: The need for documented AI standards and guidance*

Our studied organization faces challenges in AI governance documentation. There is no reference yet to the requirements of good AI models, for instance. The existing procedure is to negotiate it between the data management office (DMO) and the business owners. The absence of this requirement gives flexibility in different conditions of use cases. "In some cases, an accuracy of 70% is already good, considering the quality of the data and the complexity of the cases, but for other cases, it requires more than 85% accuracy. That is why the minimum standard of good AI models can not be set in documents; they should be evaluated case by case" [I5]. However, a minimum accuracy should be determined for clearer governance. Many aspects are important to be administered in a governance framework, such as how to audit the data and the used algorithms, and how regular models should be validated.

13. *Governance: The need for an algorithm inventory*

Although many AI innovations have already been developed, and some of them have been implemented in the organization, not all innovations are officially recorded. Some AI innovations are out of the data management office's (DMO) supervision because they are only intended for internal purposes, and no legal standing is required. Thus, an inventory platform to register all existing AI innovations in the government organizations is important. This platform can help with supervision work, provide public information, and build transparency in the use of algorithms in the public sector.

*14. Governance: Designing AI regulations and policies*

Besides guidelines, laws and regulations are required for AI governance. Since Indonesia has no national AI law yet, the studied organization designs its own regulation with international references. They started with data governance and policy about data quality. Some sectoral-level regulations, such as those in customs, were designed to permit AI to be used for decision-making exclusively in the sector. In the use of AIFA, some technical rules are designed as legal standing and reference for regional governments, auditors, and other relevant parties about the options made in the system, such as the choice of models and the upper and lower limits of data anomaly.

## 6. Discussion

Our study uses an integrated approach to investigating government readiness to implement AI by looking at socio-technical systems theory and considering AI characteristics that are ethically sensitive and institutionally reliant. AI systems in the organizational context are not just technical tools but also have social impacts on the people who use them and are affected by them. Therefore, our study explores government readiness from multiple stakeholders' perspectives. Through a case study on predictive AI in public financial management, our study explains overlooked factors to complement the current AI readiness models, which are often at a high level of abstraction.

From previous research on AI capabilities with the resource-based view (Mikalef & Gupta, 2021; Neumann et al., 2022; Mikalef et al., 2023; van Noordt & Tangi, 2023), we know that having sufficient resources is not enough to determine successful AI implementation. In studies using the Technology-Organizations-Environment (TOE) framework to list the factors influencing AI readiness (Pumplun et al., 2019; Jöhnk et al., 2021; Mikalef et al., 2022; Maragno et al., 2023), we find that the unique requirements in specified AI technologies are still unexplored. By applying an integrated framework to study the government's AI readiness, which comprises technical, societal, ethical, and governance readiness, this paper revealed several factors specific to predictive AI, such as aligning accuracy and functionality in choosing AI prediction models, and the need for standards and guidelines for good AI prediction models. Also, some factors are specific to public financial management, such as a commitment to data-driven financial decision-making and using AI to process unstructured financial data to provide analytics.

From our case study, we observe the technical nature of AI innovations, including the need for contextual alignment with existing business processes, the complexity and quality standards contextual on a case-by-case basis, and the requirement for regular maintenance to update data and models. Given those characteristics, the self-development of AI innovations in government organizations can offer several advantages over external procurement. Self-development allows for the creation of AI solutions tailored to the unique needs and contexts of the organization (Smith & Ayele, 2025). Unlike externally developed systems, in-house teams have a deeper understanding of the organization's specific tasks, data, and operational processes. This can lead to AI innovations that are more aligned with operational needs and, thus, more effective (Selten & Klievink, 2024). In addition, the confidentiality of data owned by the organization for the AI system will be better preserved. However, the organizations' limited AI skills and infrastructure are common obstacles to self-development. Our studied organization overcomes this limitation by organizing multiple levels of training and competitions and institutionalizing a community of practice that gathers all data science and AI experts in the organization to share knowledge mutually.

The algorithm audit recommendation in our studied organization questioned the effect of the prediction given by AIFA in making an impactful budget structure for regional governments. This finding aligns with a report from the OECD (2024) that resumed a cautious and incremental approach to AI implementation, often taken by finance ministries, typically focusing on "task automation" and "predictive" applications before moving towards more complex "prescriptive" AI that suggests courses of action. Furthermore, the report also stated that the implementation of AI in public financial management calls for government-wide AI standards and guidance covering key areas for safe implementation, including data exchange, privacy protection, bias avoidance, and cybersecurity risks (OECD, 2024), which is also indicated in our case.

## 7. Conclusion

This study provides in-depth insights into factors influencing the government's readiness to implement predictive AI in public financial management. We conducted a case study on an Indonesian government organization that has been implementing an AI-based tool called AI for Financial Advisors (AIFA) for two years. We interviewed seven stakeholders from different roles to cover the integrated technical, societal, ethical, and governance readiness. The results of this research give an empirical contribution to existing literature that predominantly originates from the general domain and applications of AI, and is taken solely from the product management standpoint.

The scientific contribution of this study is reflected in overlooked factors found in the government's AI readiness dynamics. This exploration went beyond the resource-based view and TOE-based research. Our findings revealed some factors specific to predictive AI, for instance, the importance of aligning accuracy and functionality to have users' acceptance, and institutionalizing commitment to data-driven decision-making. High accuracy is crucial in predicting AI, but it does not always imply high usefulness. Hence, tuning the system's accuracy requires group deliberation about performance beyond statistical forecast accuracy. Additionally, the organization should have a data-driven culture in place to ensure that the AI tool's predictions work. Our findings also pointed out factors unique to public financial management (PFM), such as using AI algorithms to process multisource unstructured financial data. With features for anomaly detection and auto-tagging, this AI tool can process and provide analytics to typical financial data that is rigid and changes in real-time. Besides, we also recognized some factors to be ethically and governance-ready in AI. Documented standard requirements and guidance for proper AI models, regulations to legalize the use of AI in the decision-making process, and making a data analytics and AI inventory are found in the studied organization as ongoing efforts.

As a societal contribution, this case study has shown how implementing predictive AI to manage public finance offers great potential to support data-driven decision-making. With AI for Financial Advisors (AIFA), the central government can provide financial advice to regional governments, such as data anomaly detection as an early warning system, and performance evaluation of regional budget execution. It also facilitates financial transparency to the public with a simple dashboard.

The limitation of this study concerns its single-case approach. Although it offers a deeper investigation, the findings may not necessarily reflect the situation of other government organizations. Besides, as an ongoing research, the number of informants involved is limited. More interviews with AI users and leadership roles will be conducted to create a better understanding of the practical implementation and governance of such AI systems in public financial management. For future research, survey-based research can complement the generalizability of the findings in this case study with broader organizational contexts. Future research can also focus on user experience and engagement in using an AI system for decision-making. Furthermore, the application of other AI technologies for public finance, such as generative AI, is another area of potential research.

### Declaration on Generative AI

The author(s) have not employed any Generative AI tools.


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