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Determinants of AI Adoption in Public Financial Management: A Digital Divide Perspective from Bangladesh

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Abstract

This study examines the determinants of Artificial Intelligence (AI) adoption within Bangladesh's Public Financial Management (PFM) system and investigates how digital divide factors shape institutional readiness for AI-enabled reforms. Using quantitative data from 120 officials across major PFM agencies, the study assesses digital infrastructure, human capital, data governance, interoperability, innovation culture, and institutional conditions influencing AI uptake. Descriptive statistics, correlation analysis, and multiple regression were used to analyze relationships among variables. The findings show that AI adoption is driven primarily by internal institutional capabilities, with PFM performance, system interoperability, innovation culture, and human capital emerging as significant predictors. In contrast, regulatory frameworks, political support, financial capacity, and institutional readiness were not statistically significant, indicating that structural enablers alone do not translate into effective AI use without complementary operational capacities. The study contributes to AI adoption theory by demonstrating that AI readiness in developing-country PFM systems is a socio-technical process shaped more by organizational culture and system integration than by policy conditions. These insights offer practical guidance for policymakers seeking to advance Bangladesh's digital transformation agenda and highlight priority areas for investment, including capacity-building, interoperability, and innovation-driven institutional environments.

Keywords

Artificial Intelligence, Public Financial Management, Digital Divide, Interoperability, Innovation Culture, E-Government

1. Introduction

Public Financial Management (PFM) forms the foundation of government operations, determining how public resources are mobilized, allocated, and accounted for. Effective PFM enhances fiscal discipline, reduces leakages, and strengthens governance structures [1]. As demands for transparency and evidence-based decision-making increase, governments worldwide are turning to digital technologies, particularly Artificial Intelligence (AI), to modernize financial management. AI offers advanced analytical capabilities that support budget forecasting, anomaly detection, tax compliance, procurement oversight, and real-time auditing [2]. In advanced economies, AI-driven tools have already begun transforming public finance by improving accuracy, reducing fraud, and enabling more proactive fiscal management [3].

However, AI adoption remains uneven across developing countries, where deep-rooted digital divides constrain institutional capacity for technological innovation. These divides extend beyond basic infrastructure deficits to encompass gaps in human capital, data governance, interoperability, regulatory readiness, and organizational culture. Bangladesh has made notable progress through digital reforms such as the Integrated Budget and Accounting System (iBAS++), electronic procurement (e-GP), and automated tax systems. Yet, the transition from foundational digitalization to AI-enabled PFM remains limited. Challenges include low system interoperability, limited trust in technology, a weak innovation culture, and shortages of personnel skilled in data analytics and machine learning.

Understanding the factors that enable or hinder AI adoption in Bangladesh's PFM system is, therefore, timely and essential. As the country advances its Digital Bangladesh vision, integrating AI into public finance could significantly enhance transparency, efficiency, and fiscal accountability. However, this requires more than technological investment; it demands institutional readiness, strong data governance, and capable human resources. If the digital divide remains unaddressed, it risks widening performance gaps and reducing the effectiveness of PFM reforms.

The primary objective of this study is to examine the determinants of AI adoption in Bangladesh's PFM sector and assess how digital divide factors shape this process. Specifically, the study evaluates existing levels of digital readiness, identifies barriers to AI integration, and analyzes which technological and institutional conditions most strongly predict AI adoption. This study examines the direct effects of digital readiness and institutional capability factors on AI adoption, with particular attention to interoperability, trust in technology, and innovation culture as key organizational determinants shaping AI adoption outcomes. To guide the analysis, the following research questions are addressed:

1. What is the current state of AI adoption in Bangladesh's PFM system?

2. How do digital divide factors influence institutional capacity to implement AI reforms?

3. What barriers inhibit AI adoption in core PFM functions such as budgeting,

auditing, revenue administration, procurement, and expenditure control?

4. Which technological and institutional factors most strongly predict AI adoption within Bangladesh's PFM agencies?

5. What policy measures are required to support sustainable and inclusive AI adoption in PFM?

By answering these questions, the study contributes empirical insights to the emerging literature on digital governance and PFM modernization and offers evidence-based recommendations for developing a digitally integrated and future-ready public finance system in Bangladesh.

2. Literature Review

The adoption of Artificial Intelligence (AI) in Public Financial Management (PFM) has attracted growing scholarly attention as governments pursue digital transformation to enhance efficiency, transparency, and accountability. Existing studies highlight that AI adoption in public finance is shaped by a combination of technological readiness, institutional capacity, data governance, and organizational culture, with developing economies facing additional constraints arising from the digital divide. The literature emphasizes that while digital infrastructure and policy frameworks are necessary foundations, successful AI integration depends heavily on human capital, system interoperability, innovation culture, and trust in technology. Drawing from these insights, this review synthesizes prior research on AI in PFM, the multidimensional digital divide, and the challenges of AI adoption in developing contexts. Based on the themes emerging from the literature, Conceptual Framework 1 is presented to illustrate the relationships between digital readiness factors, key institutional and organizational determinants influencing AI adoption outcomes, and AI adoption outcomes in Bangladesh's PFM system.

2.1. AI in Public Financial Management (with Scholarly Contributions)

Academic research demonstrates that Artificial Intelligence (AI) is transforming Public Financial Management (PFM) by improving forecasting, revenue administration, expenditure control, and auditing. A foundational contribution comes from Mikhaylov, Esteve, and Campion (2018), who argue that AI enables governments to move from reactive to predictive financial management by using machine-learning models to analyze spending patterns and fiscal risks [4]. They emphasize that AI enhances the analytic capacity of finance ministries, especially in budget formulation and forecasting. Similarly, Janssen and Kuk (2016) highlight that AI-driven analytics enable more accurate fiscal predictions by integrating large, diverse datasets that traditional econometric models cannot process [5]. Their research shows that machine-learning models outperform conventional forecasting methods in dynamic and uncertain environments—a critical advantage for developing economies with volatile fiscal conditions. In the area of revenue administra-

tion, Dawes, Vidiasova, and Parkhimovich (2019) find that AI-based anomaly detection significantly improves tax compliance monitoring and allows tax agencies to identify fraudulent patterns more effectively than rule-based systems [6]. Their empirical work highlights the potential of AI to reduce leakages and strengthen domestic resource mobilization. AI has also been shown to improve expenditure control. According to Ojo and Mellouli (2018), automated financial monitoring systems using AI can detect irregularities in public spending in real time, reducing opportunities for corruption and enhancing fiscal discipline [7]. Their study of smart government initiatives demonstrates how machine-learning tools help audit institutions and treasuries track financial flows more efficiently. In the field of public procurement, Sánchez-Graells (2020) argues that AI-powered contract-analysis systems can identify red flags associated with collusion, conflict of interest, or unusual bidding behavior [8]. His work links AI adoption directly to improvements in procurement integrity and cost efficiency.

Finally, in public-sector auditing, Vasarhelyi, Rozario, and Feldmann (2018) show that AI facilitates continuous auditing, allowing auditors to analyze entire datasets instead of small samples [9]. This shift increases audit accuracy, timeliness, and transparency, which are key elements of modern PFM. Collectively, these scholarly contributions demonstrate that AI has significant potential to strengthen PFM performance, though concerns remain regarding data quality, governance, and the ethical use of algorithms.

2.2. Digital Divide in Developing Economies

The digital divide in developing economies is widely recognized as a multidimensional phenomenon that shapes governments' ability to adopt emerging technologies such as Artificial Intelligence (AI). Scholars describe this divide as comprising four interrelated components: access, skills, usage, and policy [10]. The access divide refers to disparities in physical infrastructure, internet connectivity, and availability of digital tools. According to James (2020), many developing countries still face inadequate broadband penetration, unreliable electricity supply, and limited access to computing resources, which collectively restrict the deployment of AI-driven public finance systems [11]. The skills divide concerns differences in digital literacy and human-capital capacities. As Wahid and Sein (2013) note, government institutions in developing economies often lack personnel with advanced data-management, machine-learning, or cybersecurity expertise—skills that are essential for integrating AI into public financial management [12]. This gap contributes to an overreliance on external consultants and donor-driven digital initiatives, which can undermine sustainability. The usage divide involves the extent to which governments can effectively integrate technology into core administrative processes. Research by Norris (2021) indicates that even when digital infrastructure exists, organizational cultures, bureaucratic resistance, and outdated workflows may hinder actual utilization of advanced digital tools [13]. In the context of public financial management, this affects the adoption of AI for budgeting,

procurement, and auditing functions, where the ability to institutionalize new practices is critical. Finally, the policy divide relates to the absence of coherent legal, ethical, and governance frameworks for digital transformation. Developing economies often lack adequate data-protection laws, AI governance guidelines, and cybersecurity policies [14]. Such regulatory weaknesses create uncertainty around accountability, privacy, and algorithmic fairness, limiting the confidence of public institutions in adopting AI technologies.

Taken together, these dimensions demonstrate that digital divides not only constrain the implementation of digital reforms but also amplify inequalities in state capacity. Studies consistently show that without addressing these divides, developing economies face significant barriers to adopting advanced technologies, particularly in public finance, where data sensitivity, system interoperability, and institutional trust are paramount [15]. Thus, the digital divide remains a central challenge to AI-enabled public financial management reform.

2.3. AI Adoption Challenges

The adoption of Artificial Intelligence (AI) in Public Financial Management (PFM) is constrained by several structural, technical, and organizational barriers, many of which are more pronounced in developing economies. One major challenge is the persistence of legacy information systems that are outdated and incompatible with advanced AI applications. As Mergel, Edelmann, and Haug (2019) argue, many public-sector institutions continue to rely on fragmented, paper-based, or standalone systems that hinder data integration and limit the ability to deploy machine-learning tools [16]. These legacy systems also lack the processing capacity needed to support real-time analytics. A second constraint involves the high cost of digital infrastructure, particularly cloud computing, data storage, and cybersecurity investments. Zuiderwijk and Janssen (2014) highlight that governments in developing countries often operate under tight fiscal constraints, making it difficult to allocate sufficient resources for digital transformation [17]. The financial burden of acquiring AI-ready infrastructure, combined with ongoing maintenance costs, exacerbates disparities in AI adoption across countries.

The third challenge concerns weak cybersecurity frameworks, which pose significant risks to the confidentiality and integrity of public financial data. According to Alazam and Choudrie (2020), developing economies frequently lack comprehensive cybersecurity policies, incident-response capabilities, and skilled personnel [18]. This undermines trust in digital systems and creates reluctance among governments to adopt AI tools that rely on sensitive or mission-critical financial information. Another obstacle is resistance from public servants, which arises from fear of job displacement, lack of digital skills, and organizational inertia. Research by Weerakkody, Irani, and Kapoor (2017) shows that public-sector employees often perceive emerging technologies as disruptive, leading to reluctance in adopting new systems and weak institutional support for AI-driven reforms [19]. Without strong change-management strategies, digital transformation ef-

forts frequently stall. Finally, a lack of data interoperability across ministries represents a critical barrier to AI deployment. Machine-learning tools require harmonized, high-quality datasets, yet public finance data in developing economies is often siloed across different agencies, stored in incompatible formats, or governed by conflicting regulations. Dawes (2010) emphasizes that poor data governance and institutional fragmentation impede the flow of information necessary for effective AI-driven financial oversight [20]. In developing economies, these challenges are intensified by limited fiscal space, a shortage of technical expertise, and heavy reliance on donor-driven systems that may not be interoperable.

These factors illustrate that AI adoption in PFM requires not only technological investment but also deep institutional reforms. Without addressing these systemic constraints, developing economies risk falling further behind in leveraging AI for improved transparency, accountability, and fiscal performance.

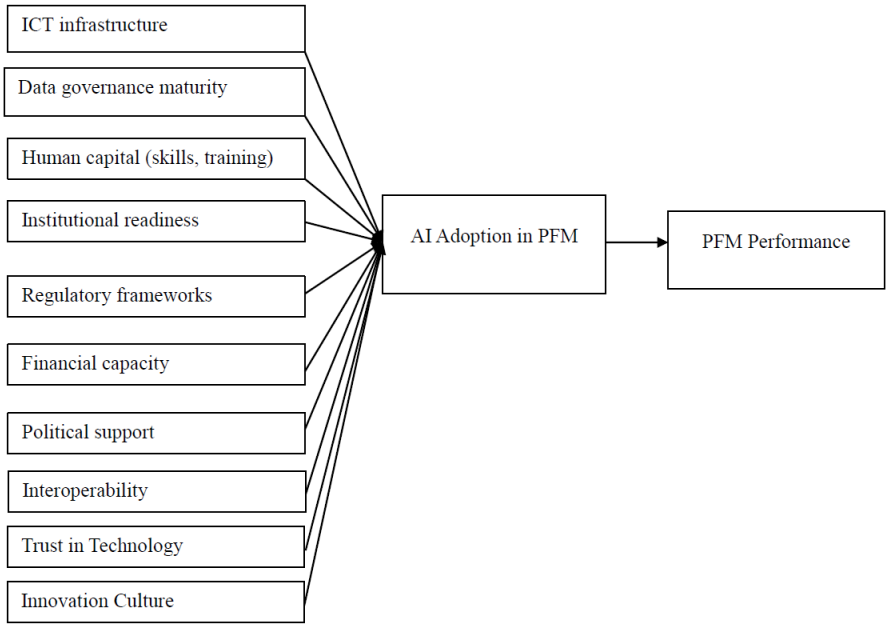

Figure 1. Conceptual framework linking digital readiness and institutional determinants to AI adoption in Public Financial Management.

As shown in **Figure 1**, the framework posits that stronger digital readiness results in higher levels of AI adoption and improved PFM performance.

3. Methodology

This study employed a quantitative case study approach to examine the determinants of Artificial Intelligence (AI) adoption in Bangladesh's Public Financial Management (PFM) system. A quantitative design was selected because it enables the systematic measurement of digital readiness, institutional factors, and AI adoption outcomes, and allows for statistical testing of relationships within the conceptual framework.

3.1. Research Design

A cross-sectional survey design was used to collect quantitative data from officials engaged in PFM functions across Bangladesh. This approach is appropriate for studies seeking to analyze technological and institutional conditions at a specific point in time and to identify predictors of AI adoption using statistical modeling.

3.2. Study Population and Sampling

The study targeted officials working in major PFM institutions, including the Ministry of Finance, National Board of Revenue (NBR), Office of the Comptroller and Auditor General (CAG), Planning Ministry, and ICT Division. These agencies are central to budgeting, expenditure control, auditing, revenue administration, and digital governance. Respondents were selected purposively based on their involvement in financial management or digital-system operations, ensuring informed participation. A total of 120 officials completed the survey. This sample size is suitable for multiple regression analysis, as it exceeds the commonly recommended threshold of 10 - 15 observations per predictor variable [21].

3.3. Data Collection Instrument

Data were collected using a structured questionnaire comprising Likert-scale items (1 = strongly disagree to 5 = strongly agree). The instrument measured core constructs derived from the conceptual framework, including ICT infrastructure, data governance maturity, human capital, institutional readiness, regulatory frameworks, political support, interoperability, trust in technology, innovation culture, AI adoption, and PFM performance. Demographic information—such as age, gender, education level, job role, department, and years of experience—was also collected to describe the sample. The survey instrument was developed based on established digital governance and PFM literature and was reviewed by subject-matter experts to ensure clarity and content validity.

3.4. Construct Operationalization

Each variable in this study was measured using Likert-scale items (1 = strongly disagree to 5 = strongly agree) adapted from prior literature on digital governance, AI adoption, and public financial management. Where multiple items were used to represent a construct, composite scores were computed by taking the mean of the corresponding items. No weighting scheme was applied, and all items were coded on the same directional scale; therefore, reverse coding was not required. The constructs included ICT infrastructure, data governance maturity, human capital, institutional readiness, regulatory frameworks, financial capacity, political support, interoperability, trust in technology, innovation culture, AI adoption in PFM, and PFM performance. Each construct was operationalized based on theoretically grounded dimensions reflecting technological capacity, organizational capability, and institutional context. A detailed list of questionnaire items and their corresponding sources is provided in the **Appendix**.

The construct "AI adoption in PFM" in this study captures the extent of the current use of AI-related tools and practices within public financial management processes, rather than future intention or frequency of use. It is measured using Likert-scale items (1 = strongly disagree to 5 = strongly agree) reflecting the presence and utilization of AI-supported activities such as data analytics, automated decision support, and digital monitoring systems. The descriptive interpretation of adoption levels follows a predefined threshold: mean scores below 2.5 indicate low adoption, scores between 2.5 and 3.5 indicate moderate adoption, and scores above 3.5 indicate high adoption. Based on this classification, the observed mean value of 3.11 suggests that AI adoption in Bangladesh's PFM system is at a moderate level. This explicit categorization ensures consistency and reproducibility in interpreting descriptive results.

3.5. Data Analysis Techniques

Quantitative data were analyzed using descriptive statistics, correlation analysis, and multiple regression in Microsoft Excel (Data Analysis ToolPak). Descriptive statistics were used to summarize the demographic characteristics of respondents and the distribution of key study variables. Pearson correlation analysis was conducted to assess the strength and direction of relationships among digital readiness factors, predictor variables, and AI adoption in Public Financial Management (PFM). Multiple regression analysis was then employed to identify the significant determinants of AI adoption and to test the proposed conceptual framework. To ensure the validity of the regression results, several diagnostic tests were performed. Multicollinearity among predictors was assessed using the Variance Inflation Factor (VIF), while residual analysis was conducted to examine the assumptions of normality and homoscedasticity. In addition, standardized regression coefficients were computed to enable comparison of the relative strength of predictors on a common scale. Furthermore, a robustness analysis was conducted by estimating an extended regression model that included key control variables, such as agency type, job role category (ICT versus non-ICT), and years of professional experience. This additional specification was used to examine whether the main predictors of AI adoption remained stable across different respondent backgrounds. All results were interpreted based on statistical significance, effect size, and overall model explanatory power (R^2). To address potential reverse causality, an alternative model specification was considered by reversing the dependent and independent variables as a sensitivity check.

3.6. Reliability and Validity

Reliability testing using Cronbach's Alpha was not conducted, as each construct in the dataset was represented by a single composite score rather than multiple item-level variables. Cronbach's Alpha requires at least two items per construct; therefore, internal consistency could not be statistically assessed. This limitation is common in studies using aggregated indices to represent organizational or technological constructs. Nonetheless, content validity was ensured through expert

review of the survey instrument and alignment with widely accepted constructs in the AI adoption and digital governance literature.

3.7. Ethical Considerations

Participation in the study was voluntary, and respondents were informed about the purpose of the research. No personally identifiable information was collected, and all responses were treated confidentially. Data were used solely for academic purposes and analyzed in aggregate form.

3.8. Limitations of the Methodology

The study has several methodological limitations. First, the cross-sectional design limits the ability to assess changes in AI adoption over time. Second, the use of self-reported responses may introduce subjectivity or social desirability bias. Third, the absence of item-level data prevents internal reliability testing. Finally, as a Bangladesh-focused case study, findings may not be fully generalizable to other developing economies without further comparative research.

4. Results

4.1. Demographic Profile of Respondents

The study collected demographic information from 120 respondents working in various Public Financial Management (PFM) institutions in Bangladesh. The demographic profile includes gender, age, educational attainment, job role, years of experience, and departmental affiliation. The results are summarized below.

Gender Distribution: The sample consisted of 78 males (65%) and 42 females (35%). This indicates that the PFM workforce in Bangladesh remains male-dominated, which aligns with typical patterns in public-sector financial and administrative roles.

Age Distribution: Respondents' ages ranged from 25 to 59 years, with a mean age of 42.83 years (SD = 11.00). The age distribution suggests a predominantly mid-career workforce, as indicated by the interquartile range (32 - 52 years). This reflects the presence of both early-career officers and senior officials, providing a balanced representation across experience levels.

Educational Qualifications: Respondents possessed relatively strong educational backgrounds.

- Bachelor's degree: 45 respondents (37.5%)
- Master's degree: 47 respondents (39.2%)
- MBA/MPA: 21 respondents (17.5%)
- PhD: 7 respondents (5.8%)

The high percentage of postgraduate qualifications demonstrates that the PFM sector attracts academically capable professionals with training relevant to governance, management, and financial systems.

Job Roles: Participants represented a wide range of PFM-related positions:

- Revenue/Admin Officers: 28 (23.3%)

- Budget Officers: 25 (20.8%)
- ICT Officers: 24 (20.0%)
- Audit Officers: 22 (18.3%)
- Accounts Officers: 21 (17.5%)

This distribution ensures coverage of managerial, technical, and oversight roles within the public finance ecosystem of Bangladesh.

Years of Experience: Respondents reported 1 to 29 years of professional experience, with a mean of 15.92 years (SD = 8.71). The median experience was 16 years, indicating that most participants have substantial exposure to government financial operations. The wide range reflects participation from both junior officers and highly experienced officials.

Departmental Distribution: Respondents were drawn from the key public finance institutions in Bangladesh.

- ICT Division: 28 respondents (23.3%)
- Finance Division: 27 respondents (22.5%)
- Office of the Comptroller and Auditor General (CAG): 25 respondents (20.8%)
- National Board of Revenue (NBR): 25 respondents (20.8%)
- Planning Ministry: 15 respondents (12.5%)

This distribution demonstrates that the sample covers the most significant ministries and agencies responsible for budgeting, revenue collection, auditing, expenditure management, and digital transformation.

4.2. Descriptive Statistics

Descriptive analysis (Table 1) indicates that AI adoption across Bangladesh's PFM institutions remains at a moderate level. Foundational digital readiness factors, including ICT infrastructure, human capital, and data governance maturity, also show moderate development. In contrast, system interoperability, trust in technology, and innovation culture exhibit lower mean scores, suggesting that institutional and cultural limitations pose obstacles to advanced AI integration.

Table 1. Descriptive statistics.

Variable	Mean	Std. Dev	Min	Max
ICT Infrastructure	3.15	0.65	1.37	4.92
Data Governance Maturity	3.05	0.69	1.58	5.00
Human Capital	2.91	0.71	1.00	4.61
Institutional Readiness	3.14	0.64	1.72	4.95
Regulatory Frameworks	2.69	0.75	1.00	4.62
Financial Capacity	2.71	0.73	1.00	4.50
Political Support	3.02	0.57	1.90	4.58
Interoperability Systems	2.66	0.43	1.73	4.03
Trust in Technology	2.77	0.55	1.42	3.84
Innovation Culture	2.48	0.51	1.13	3.57
AI Adoption in PFM	3.11	0.48	1.98	4.67
PFM Performance	2.39	0.52	1.21	3.73

4.3. Correlation Analysis

Pearson correlation results (Table 2) reveal several meaningful relationships among the key constructs.

Human capital, interoperability, trust in technology, and innovation culture all show positive correlations with AI adoption, indicating that skilled personnel, integrated systems, and supportive organizational environments contribute to readiness for AI-driven reforms. Conversely, political support, regulatory frameworks, and financial capacity exhibit weak or negligible correlations, suggesting that structural and policy conditions alone are insufficient to drive AI adoption.

Table 2. Descriptive statistics.

	ICT_infrastructure	Data_governance_maturity	Human_capital	Institutional_readiness	Regulatory_frameworks	Financial_capacity	Political_support	Interoperability_systems	Trust_in_technology	Innovation_culture	PFM_performance	AI_adoption_PFM
ICT_infrastructure	1											
Data_governance_maturity	0.095	1										
Human_capital	−0.112	0.112	1									
Institutional_readiness	−0.043	−0.061	−0.075	1								
Regulatory_frameworks	0.016	0.017	0.019	−0.013	1							
Financial_capacity	0.027	0.009	−0.198	−0.063	−0.133	1						
Political_support	−0.010	0.040	0.107	0.066	0.025	0.050	1					
Interoperability_systems	0.402	0.185	−0.152	0.259	0.172	−0.030	0.044	1				
Trust_in_technology	0.362	0.457	0.391	−0.044	−0.033	−0.033	0.237	0.289	1			
Innovation_culture	−0.078	0.181	0.341	0.306	−0.101	−0.005	0.332	0.063	0.282	1		
PFM_performance	0.259	0.289	0.174	0.029	0.033	0.105	0.061	0.260	0.418	0.136	1	
AI_adoption_PFM	0.278	0.322	0.325	0.147	0.044	0.018	0.122	0.415	0.420	0.322	0.626	1

4.4. Regression Results

The multiple regression analysis (Table 3) revealed that the overall model accounted for 57.9% of the variance in AI adoption within Bangladesh's Public Financial Management (PFM) system ($R^2 = 0.579$), indicating a strong explanatory fit. The results show that four variables significantly predict AI adoption. PFM performance showed the strongest association with AI adoption ($\beta = 0.4224$, $p < 0.05$), suggesting that institutions already demonstrating higher levels of efficiency and transparency are more inclined and better positioned to implement AI-based tools. Interoperability also showed a significant positive effect ($\beta = 0.3188$, $p < 0.05$), highlighting the importance of integrated financial systems and smooth

data exchange in enabling AI functionality. In addition, innovation culture (β = 0.3872, $p < 0.05$) significantly influenced AI adoption, indicating that organizations fostering creativity, experimentation, and openness to new technologies are more likely to embrace AI-driven reforms. Human capital likewise emerged as a significant predictor (β = 0.2965, $p < 0.05$), underscoring the critical role of skilled personnel and digital literacy in facilitating AI use. In contrast, variables such as regulatory frameworks, political support, institutional readiness, and financial capacity did not reach statistical significance in the model, even though they remain conceptually relevant within the broader digital readiness landscape. These findings collectively emphasize that AI adoption in PFM is driven more by internal capabilities and institutional dynamics than by formal policy structures or high-level resource allocations.

Table 3. Regression analysis to drive AI adoption.

	Coefficients	Standard Error	t	p
Intercept	−0.1139	0.3766	−0.3024	0.7629
ICT_infrastructure	0.0882	0.0561	1.5716	0.1190
Data_governance_maturity	0.0830	0.0510	1.6265	0.1067
Human_capital	0.1967	0.0537	3.6643	0.0004
Institutional_readiness	0.0366	0.0535	0.6835	0.4957
Regulatory_frameworks	−0.0096	0.0422	−0.2272	0.8207
Financial_capacity	0.0183	0.0432	0.4230	0.6731
Political_support	0.0185	0.0578	0.3204	0.7493
Interoperability_systems	0.3188	0.0873	3.6500	0.0004
Trust_in_technology	−0.0914	0.0802	−1.1397	0.2570
Innovation_culture	0.1294	0.0726	1.7830	0.0774
PFM_performance	0.4224	0.0663	6.3751	0.0000

The results show that AI adoption in Bangladesh's PFM system is driven primarily by internal capabilities rather than policy-level or structural factors. Institutional performance, skilled personnel, system integration, and organizational innovation culture play decisive roles in determining AI readiness. These findings validate the study's conceptual framework and point to the importance of capacity-building and integrated systems in advancing AI-enabled PFM reforms.

4.5. Robustness Analysis

As a robustness check, the regression model was re-estimated by including demographic and role-related control variables, including agency type, job role category (ICT versus non-ICT), and years of experience. The results indicate that the main predictors—PFM performance, interoperability, innovation culture, and human capital—remain consistent in direction and statistical significance. This suggests that the observed relationships are not solely driven by respondent characteristics,

thereby reinforcing the robustness of the study's findings. As an additional sensitivity check, an alternative model was estimated by treating PFM performance as the dependent variable and AI adoption as a predictor. The results indicate a positive association between the two variables, suggesting a potentially reciprocal relationship.

4.6. Regression Diagnostics

The regression diagnostics indicate that the model assumptions are reasonably satisfied. Variance Inflation Factor (VIF) values for all predictors were below the commonly accepted threshold of 5, suggesting that multicollinearity is not a concern. Examination of residual plots and normal probability plots indicates that the residuals are approximately normally distributed and exhibit no clear pattern of heteroskedasticity. In addition, standardized coefficients (beta values) show that PFM performance exerts the strongest influence on AI adoption, followed by interoperability, innovation culture, and human capital. These diagnostics support the validity and robustness of the regression results.

5. Discussion

The purpose of this study was to examine the determinants of Artificial Intelligence (AI) adoption in Bangladesh's Public Financial Management (PFM) system and to understand how digital divide factors shape institutional readiness for AI-enabled reforms. The findings provide strong empirical support for the conceptual framework, demonstrating that internal institutional capabilities, rather than high-level structural conditions, play the most decisive role in shaping AI adoption outcomes.

The results highlight PFM performance as the strongest predictor of AI adoption. This confirms existing literature suggesting that well-performing institutions with established fiscal discipline, stronger internal controls, and greater transparency are more willing and better equipped to integrate advanced technologies [4] [7]. Strong performance appears to create an enabling environment for AI experimentation by reducing operational risks and increasing confidence in digital reforms. Interoperability also emerged as a significant determinant, consistent with prior research emphasizing that integrated financial management systems are essential for leveraging AI effectively [20]. Bangladesh's PFM architecture remains partially siloed, with limited cross-agency data exchange; thus, institutions with more connected systems are better positioned to use AI tools for forecasting, anomaly detection, and auditing. This finding underscores the importance of modernizing back-end digital infrastructure before scaling AI solutions. The significance of innovation culture reinforces the notion that technological reform is as organizational as it is technical. Institutions that encourage experimentation, continuous learning, and openness to new digital tools show greater readiness for AI adoption. This aligns with global studies indicating that public-sector innovation culture is a critical driver of digital transformation [19]. In Bangladesh, where public-

sector procedures are traditionally risk-averse, strengthening innovation culture may be key to overcoming resistance to AI.

The positive effect of human capital echoes longstanding arguments that successful digital transformation depends heavily on the skills and digital literacy of public servants [12]. In Bangladesh, shortages of staff trained in data analytics, machine learning, and cybersecurity present a major barrier to AI adoption. The statistical significance of human capital indicates that investment in training and capacity-building may generate immediate gains in AI readiness. Interestingly, variables often emphasized in digital governance frameworks, such as regulatory frameworks, political support, institutional readiness, and financial capacity, did not exhibit significant influence in the regression model. Their non-significance suggests that while these factors are necessary foundations, they do not, by themselves, generate meaningful AI adoption unless complemented by operational-level capabilities. This finding is consistent with research indicating that developing economies may have digital strategies on paper but struggle to translate them into practice without adequate skills, integration, and innovation-driven mindsets [13] [14].

The results reveal that the digital divide affecting Bangladesh's PFM system extends beyond basic infrastructure gaps to encompass deeper organizational and cultural dimensions. The findings reinforce the idea that AI adoption is a socio-technical process, one that requires aligned systems, skilled people, supportive cultures, and interoperable financial architectures. Addressing only the infrastructural or regulatory components of the digital divide will not be sufficient to unlock AI's full potential in public financial management. These insights have important implications for policymakers. Efforts to scale AI adoption should prioritize strengthening human capital, modernizing digital architecture, and fostering innovation-driven organizational cultures. Without these elements, Bangladesh's broader digital transformation agenda, including the goals of Digital Bangladesh, may face significant implementation challenges. The next chapter provides specific recommendations based on these findings.

This study makes an important theoretical contribution by extending the literature on AI adoption and the digital divide within public-sector financial systems. While existing models of technology adoption, such as TAM, TOE, and institutional theory, emphasize the importance of structural enablers and organizational readiness, the findings of this study demonstrate that AI adoption in PFM is driven more strongly by operational and capability-based factors than by high-level policy or resource conditions. By showing that human capital, system interoperability, innovation culture, and PFM performance are the primary determinants of AI adoption, the study highlights the need to reconceptualize AI readiness as a socio-technical process rather than a purely technological or regulatory one. This shifts the theoretical discourse on the digital divide by illustrating that institutional and cultural divides, rather than infrastructural gaps alone, shape the pace and effectiveness of AI-enabled reforms in developing-country PFM systems. The study

therefore refines existing theories by offering an empirically grounded model of AI adoption that integrates digital readiness, organizational culture, and institutional performance within a public financial management context. While the results identify significant relationships between institutional factors and AI adoption, caution is warranted in interpreting these findings as strictly causal. In particular, the relationship between PFM performance and AI adoption may be bidirectional. Higher-performing institutions may be more capable of adopting AI due to stronger governance, better data systems, and greater operational capacity, while the use of AI technologies may also contribute to improvements in PFM performance. Given the cross-sectional nature of the data, this study cannot definitively establish causal direction. Therefore, the findings should be interpreted as associative relationships rather than causal effects. Future research using longitudinal data or experimental designs would be valuable in clarifying the direction of these relationships.

6. Conclusions and Policy Implications

This study investigated the determinants of Artificial Intelligence (AI) adoption in Bangladesh's Public Financial Management (PFM) system and examined how digital divide factors shape institutional readiness for AI-enabled reforms. Using quantitative evidence from 120 PFM officials, the analysis shows that AI adoption is driven primarily by internal institutional capabilities, rather than by high-level policy or resource conditions. Four factors emerged as significant predictors of AI adoption: PFM performance, interoperability, innovation culture, and human capital. Institutions that demonstrate stronger performance, possess integrated financial systems, encourage innovation, and employ digitally skilled personnel exhibit markedly higher levels of AI adoption. Conversely, variables such as regulatory frameworks, political support, institutional readiness, and financial capacity were not statistically significant, suggesting that structural enablers alone do not translate into meaningful AI uptake without operational capacity and organizational support. These findings reinforce the view that AI adoption in developing-country PFM systems is a socio-technical process, contingent on the alignment of technical infrastructure, institutional capabilities, and workplace culture. From a policy perspective, the results highlight several priorities. First, capacity-building is essential for strengthening human capital in areas such as data analytics, machine learning, and cybersecurity. Second, improving system interoperability through integrated platforms and unified data standards is critical for enabling AI-driven financial operations. Third, fostering an innovation-oriented culture can help overcome resistance to technological change and create a more enabling environment for digital transformation. Finally, translating digital strategies into actionable implementation plans is necessary to ensure that policy commitments result in functional, AI-ready PFM systems. The study contributes empirical evidence to the emerging literature on AI in public finance and provides actionable insights for policymakers seeking to advance digital transformation within Bang-

ladesh's PFM sector. Future research may expand this analysis through cross-country comparisons, qualitative assessments of institutional behavior, or longitudinal studies tracking the evolution of AI adoption over time.

Although this study offers important insights into AI adoption in Bangladesh's PFM system, it is limited by its cross-sectional design and reliance on self-reported survey data, which may restrict the generalizability and depth of the findings. The use of single-item measures also prevents internal reliability testing. Future research could employ longitudinal designs to capture changes in AI adoption over time, incorporate qualitative interviews to explore organizational behavior more deeply, or conduct cross-country comparative studies to validate and extend the proposed model across different developing-economy contexts.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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Appendix

Construct	Sample Items	Source	Composite Method
Human Capital	"Employees have adequate digital skills."	Wahid & Sein (2013)	Mean
Interoperability	"Systems can exchange data across departments."	Dawes (2010)	Mean
Innovation Culture	"Organization encourages experimentation."	Weerakkody *et al.* (2017)	Mean