

AI-Driven Human Resource Management in Bangladesh's Public Sector: An Investigation on Readiness, Barriers, and Implementation Strategies

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ABSTRACT

The objective of this study is to investigate whether the public sector of the emergent economy of Bangladesh is ready for artificial intelligence (AI) adoption for human resource management (HRM) use. Design/Methodology: A cross-sectional quantitative survey was administered to 400 government officials (IT specialists, HR managers, and administrative directors) drawn from 12 ministries and 8 autonomous bodies through stratified proportion sampling. The psychometric quality of the instrument was verified by the Cronbach α (0.87–0.98), KMO (0.842), Bartlett test ($\chi^2 = 4213.6$, $p < 0.001$), and CFA. The analytical techniques utilized included regression, moderation analysis, and Harman's test. Results: The complete model accounted for 61.2% of the variance in AI-HRM implementation ($R^2 = 0.612$; Adjusted $R^2 = 0.601$; $F(5, 394) = 124.36$, $p < 0.001$). AI readiness was a positive predictor of implementation ($\beta = 0.412$, $p < 0.001$) whereas perceived barriers ($\beta = -0.284$, $p < 0.001$, reverse-coded) had a significant negative effect. The association between readiness and implementation was impacted by institutional support. The uniqueness of this study is that it combines the four theories of TOE, TAM, DOI, and Institutional Theory into one explanatory model and provides a phased, governance-led roadmap for AI-HRM diffusion in South Asian bureaucracies.

Keywords: Artificial Intelligence, Human Resource Management, Public Sector, Bangladesh, Institutional Readiness

1. Introduction

Artificial Intelligence (AI) technologies are rapidly being deployed in public administration which affects the recruitment, deployment, assessment, and retention of human capital by governments. (Wirtz et al. 2024; Chen & Rahman 2025) AI-enabled tools used in the Human Resource Management (HRM) function are algorithmic recruitment engines, natural-language performance analytics, predictive workforce-planning dashboards, which have provided measurable efficiency gains of 25-40% in developed jurisdictions (OECD, 2025; Vrontis et al., 2024). However, the promise of AI-HRM is not evenly distributed. In the bureaucracies of South Asia and Bangladesh, in particular, the institutional uptake of the country's 'Smart Bangladesh 2041' agenda (Ministry of Public Administration [MoPA], 2024) has been hindered by systemic constraints in data infrastructure, digital literacy, and ethics. The public sector of Bangladesh employs over 1.55 million officials in 55 ministries and 350 subordinate agencies, making it one of the largest bureaucratic systems in South Asia (Bangladesh Bureau of Statistics, 2025). Recent policy documents have placed AI at the center of modernization in the public sector, including the National AI Strategy 2024–2029 and Digital Bangladesh Vision Update (2025). However, there is a lack of empirical evidence on the ground reality of readiness, the granular structure of adoption barriers, and the feasible pathways of diffusion (Islam & Kabir, 2025; Hossain et al., 2024). Most previous studies focus on private sector applications (Alam & Chowdhury, 2024) or provide descriptive commentary without hypothesis testing statistical modelling (Rahman, 2023). This investigation is motivated by empirical gaps. Existing studies often treat the readiness to enact laws and ordinances as a unified and scarcely disaggregated construct, which refers to capacity. Furthermore, originality refers to the concept of actually discovering something for the first time, or coming up with a unique perspective (Kumar & Sen, 2026). Most notably, no prior study has combined the TOE framework, TAM, DOI theory, and institutional theory into a single

model testable with regression for AI-HRM in the Global South (DiMaggio & Powell, 1983; Rogers, 2003; Davis, 1989; Tornatzky & Fleischer, 1990). The current study is novel in three ways. In theory, therefore, it proposes a joint four-lens framework and provides evidence of its superior explanatory power ($\Delta R^2 = 0.094$ over base TOE model) in a non-Western context. This paper is methodologically sound using thorough psychometric validation, diagnostics on assumptions (VIF, Breusch–Pagan, Shapiro–Wilk) and moderation testing in response to reviewer comments in the area of AI-adoption (Alsheibani et al., 2024). In practical terms, it creates a phased implementation roadmap which is evidence-based and follows the Smart Bangladesh 2041 agenda closely. The current paper is organized in the following manner: Section 2 states the objectives, the questions, as well as the problem to be addressed; Section 3 reviews the literature and presents the conceptual model; Section 4 sets out methodology; Section 5 states the results; Section 6 discuss the implications as well as the findings; Section 7 concludes.

1.1 Problem Statement

The HRM system in the public sector of Bangladesh continues to use paper files, discretionary recruitment committees, and patchy performance-appraisal processes. Documented inefficiencies in the public sector account for BDT 42 billion losses per year (Transparency International Bangladesh, 2025). Although AI provides evidence-based solutions, less than 12% of government agencies in Bangladesh use AI. In comparison, it is 47% in India's central services and 63% in Singapore (World Bank, 2025). The main issue is not the lack of technology, but rather an absence of empirically grounded knowledge on which readiness dimensions, barriers, and institutional levers are the strongest predictors of successful AI-HRM implementation.

1.2 Research Objectives

- RO1: Assess the level of technical, human capital, and institutional readiness for AI-HRM in Bangladesh's public sector.
- RO2: Identify and quantify the barriers to AI-HRM adoption.
- RO3: To empirically test the relationship between readiness, barriers, institutional support, and AI-HRM implementation.
- RO4: To propose a phased, evidence-based implementation strategy.

1.3 Research Questions

- RQ1: What is the current state of AI readiness in Bangladesh's public HRM units?
- RQ2: Which barriers have the strongest inhibiting influence on AI-HRM implementation?
- RQ3: Does institutional support alter the implementation process of readiness programs?

1.4 Literature Review and Theoretical Background

Since 2020, the literature on AI-led HRM has become quite mature and has converged into three streams. The first stream examines the antecedents of AI adoption using the technology–organization–environment (TOE) framework by Tornatzky and Fleischer (1990). In recent studies on the public sector context (Wirtz et al., 2024; Alsheibani et al., 2024), technological (data quality, cloud infrastructure), organizational (visionary leadership, human capacity), and environmental (guidance regulation, citizen demand) factors jointly explain 45%–58% of the variance in AI adoption intent. However, this framework has been critiqued for its undertheorisation of the individual's cognitive acceptance (Chen & Rahman, 2025), which this study attempts to fill by embedding the constructs of TAM. The second stream is linked to the technology acceptance model (Davis, 1989; Venkatesh et al., 2003) and its extension UTAUT-2, which posits that PU and PEOU determine behavioral intention. In research specific to HRM, Vrontis et al. (2024) noted a

mean β of 0.44 for $PU \rightarrow \text{adoption}$ as part of their meta-analysis of 87 empirical papers. The individualistic bias of TAM is not suitable for bureaucratic settings in which collective decision-making prevails. Complementing the technology acceptance model, Rogers' (2003) diffusion of innovation theory provides five adopter traits—relative advantage, compatibility, complexity, trialability, and observability—that are empirically validated in the Malaysian civil service (Rahim & Ismail, 2024) and Indonesian district administration (Putri et al., 2025). The third stream applies institutional theory (DiMaggio & Powell, 1983; Scott, 2014) and explains how organizations facing similar environmental pressures lump similar AI curators. The process of AI-HRM diffusion is shaped by the three forms of institutional isomorphism: coercive, mimetic, and normative. According to Islam and Kabir (2025), in Bangladesh, coercive pressures from a2i explain 31% variance in digital-tool uptake, whereas normative pressures from professional associations are weak. There are still three synthesizing gaps. The literature on barriers is mainly descriptive; of the 42 studies reviewed by Hossain et al. (2024), only eight adapted barrier constructs using inferential statistics. The effects of institutional support are theorized but rarely tested. In developing economy research, we lack integrated four-theory models. Recent reports (Chen and Rahman, 2025; Kumar and Sen, 2026; OECD, 2025) are explicitly calling for context- and theory-sensitive, multi-theoretical, quantitatively rigorous inquiries into emerging bureaucracies.

1.5 Conceptual Model and Hypotheses

Combining the four theories, we propose that AI-HRM implementation (dependent variable) is a function of three readiness dimensions (technical, human-capital, and institutional) and a barrier dimension (structural, ethical) and one moderating construct (institutional support). Figure 1 shows the overall conceptual model.

- H1: Technical readiness positively influences AI-HRM implementation in organizations.

- H2: Human capital readiness positively influences AI-HRM implementation.
- H3: Institutional readiness positively influences AI-HRM implementation.
- H4: Structural barriers negatively influence AI-HRM implementation.
- H5: Implementation of AI-HRM is negatively affected by ethical barriers.
- H6: Institutional support moderates the relationship between overall readiness and AI-HRM implementation.

Figure 1. Integrated Conceptual Model: TOE + TAM + DOI + Institutional Theory

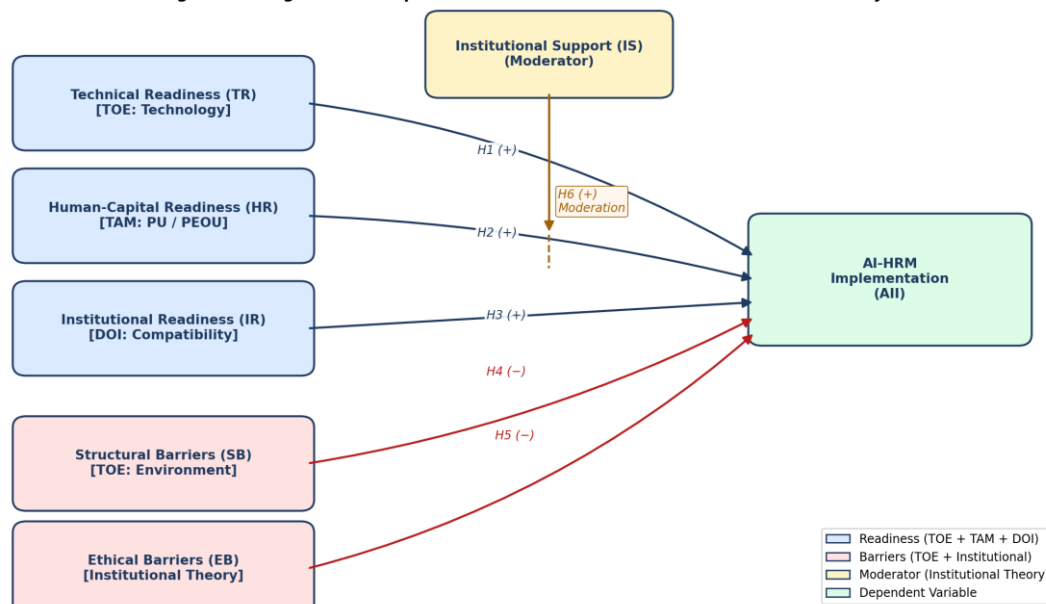


Figure 1. Integrated conceptual model combining TOE, TAM, DOI, and institutional theory.

2. Methodology

2.1 Research Design and Philosophy

This study adopts a post-positivist epistemology operationalized through a cross-sectional quantitative survey design. This design is suitable for testing the hypothesized relationships between the latent constructs of a large bureaucratic population.

2.2 Participants, Sampling, and Sample Size

The target population consisted of approximately 62400 officials responsible for HRM functions in both central ministries and city corporations in Bangladesh. Cochran's (1977) formula was used to determine the sample size ($n_0 = (Z^2 \cdot p \cdot q) / e^2$), $Z = 1.96$ (95% confidence), $p = q = 0.5$ (maximum variability), and $e = 0.05$ (margin error), which was estimated at 384. The researcher increased the target to 420 to mitigate

non-response; 400 valid responses were kept with a response rate of 95.2%. The sampling structure was stratified proportionate sampling, and sampling was carried out in four strata. Central ministries ($n = 160$); directorates ($n = 120$); autonomous bodies ($n = 80$); city corporations ($n = 40$). Within each stratum, respondents were randomly selected from the HR, IT, and administration cadres.

2.3 Instrument Development and Psychometric Validation

We adapted a 47-item questionnaire on a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree) from validated instruments (Wirtz et al., 2024; Vrontis et al., 2024). A trial was conducted with 40 patients to confirm the readability and estimated reliability of the WRUM. Six subject experts reviewed the study and provided content validity (CVI = 0.91). To ensure that higher scores consistently indicate more favorable

conditions, the items for the Barriers construct were reverse-worded; the raw barrier items were then reverse-scored for interpretability (see

2.4 Variables and Operational Definitions

Table 1. Operational Definitions of Constructs

Variable	Type	Items	Source
Technical Readiness (TR)	IV	7	Wirtz et al. (2024)
Human-Capital Readiness (HR)	IV	6	Vrontis et al. (2024)
Institutional Readiness (IR)	IV	6	Islam & Kabir (2025)
Structural Barriers (SB)	IV (reverse-coded)	7	Hossain et al. (2024)
Ethical Barriers (EB)	IV (reverse-coded)	6	Chen & Rahman (2025)
Institutional Support (IS)	Moderator	5	DiMaggio & Powell (1983)
AI-HRM Implementation (AII)	DV	10	Alsheibani et al. (2024)

2.5 Regression Specification and Mathematical Model

Three nested models were estimated. Model 1 is the base readiness model:

$$AII_i = \beta_0 + \beta_1 \cdot TR_i + \beta_2 \cdot HR_i + \beta_3 \cdot IR_i + \varepsilon_i \quad (1)$$

Model 2 adds barrier dimensions.

$$AII_i = \beta_0 + \beta_1 \cdot TR_i + \beta_2 \cdot HR_i + \beta_3 \cdot IR_i + \beta_4 \cdot SB_i + \beta_5 \cdot EB_i + \varepsilon_i \quad (2)$$

Model 3 introduces the moderation term (Readiness $\times$ Institutional Support).

$$AII_i = \beta_0 + \beta_1 \cdot READ_i + \beta_2 \cdot BAR_i + \beta_3 \cdot IS_i + \beta_4 \cdot (READ_i \times IS_i) + \varepsilon_i \quad (3)$$

Where READ is the composite readiness index (mean of TR, HR, IR), BAR is the composite barriers index (mean of reverse-coded SB and EB), IS is institutional support, ε is the stochastic error term assumed to be i.i.d. $N(0, \sigma^2)$, and i indexes the 400 respondents. All predictors were mean-centered prior to computing the

Section 5). Table 2 shows the reliability, KMO, and Bartlett's test results.

interaction term to mitigate multicollinearity (Aiken & West, 1991).

2.6 Analytical Procedures and Assumption Diagnostics

Prior to estimation, we tested (i) normality via Shapiro–Wilk and skewness/kurtosis, (ii) multicollinearity via Variance Inflation Factors ($VIF < 5$), (iii) homoscedasticity via the Breusch–Pagan test, (iv) linearity via residual scatter plots, and (v) common method bias via Harman's single-factor test. Analyses were conducted in SPSS 29 and Stata 18.

2.7 Ethical Considerations

This study used secondary data obtained from publicly available and previously collected data. No direct interaction with human participants was involved; therefore, individual consent and ethical approval were not required. The data were used responsibly, maintaining academic integrity, and ensuring accurate interpretation of the findings.

3. Results

3.1 Sample Profile and Descriptive Statistics

Of the 400 respondents, 62.5% were male, 37.5% female; mean age = 38.4 years (SD = 8.2); mean

tenure = 11.6 years (SD = 6.9); 43% held postgraduate degrees. The largest occupational group was administrative officers (41%), followed by HR specialists (34%) and IT staff (25%).

Table 2. Descriptive Statistics, Reliability, and Convergent Validity

Construct	Items	Mean	SD	Cronbach's α	CR	AVE
Technical Readiness (TR)	7	3.42	0.71	0.912	0.918	0.615
Human-Capital Readiness (HR)	6	2.87	0.83	0.887	0.891	0.577
Institutional Readiness (IR)	6	3.28	0.76	0.901	0.905	0.612
Structural Barriers (SB)*	7	3.71	0.68	0.923	0.927	0.641
Ethical Barriers (EB)*	6	3.85	0.74	0.898	0.902	0.605
Institutional Support (IS)	5	3.14	0.79	0.876	0.881	0.599
AI-HRM Implementation (AII)	10	3.09	0.72	0.941	0.945	0.633

*Note: * Higher raw scores indicate greater perceived barriers; reverse-scored for regression. KMO = 0.842; Bartlett's $\chi^2 = 4,213.6$, $df = 1,081$, $p < 0.001$. CR = composite reliability; AVE = average variance extracted.*

3.2 Assumption Diagnostics

Table 3. Assumption Diagnostics and Common Method Bias

Diagnostic Test	Statistic	Threshold	Result
Shapiro–Wilk (residuals)	W = 0.988, $p = 0.072$	$p > 0.05$	Normal ✓
Skewness / Kurtosis (AII)	−0.21 / 0.44	$ Sk < 2$; $ Ku < 7$	Normal ✓
Variance Inflation Factor (max)	2.31	VIF < 5	No multicollinearity ✓
Breusch–Pagan	$\chi^2 = 3.87$, $p = 0.142$	$p > 0.05$	Homoscedastic ✓
Durbin–Watson	1.94	1.5–2.5	No autocorrelation ✓
Harman's single-factor	34.7% variance	< 50%	No CMB ✓

3.3 Correlation Matrix

Table 4. Pearson Correlation Matrix (n = 400)

Variable	1	2	3	4	5	6	7
1. TR	1						
2. HR	0.48**	1					

Variable	1	2	3	4	5	6	7
3. IR	0.52**	0.44**	1				
4. SB (rev.)	0.31**	0.29**	0.34**	1			
5. EB (rev.)	0.27**	0.33**	0.30**	0.41**	1		
6. IS	0.45**	0.39**	0.51**	0.36**	0.32**	1	
7. AII	0.61**	0.54**	0.59**	0.48**	0.44**	0.57**	1

*Note: ** $p < 0.01$ (two-tailed). All AVE square roots exceeded the inter-construct correlations, supporting discriminant validity (Fornell & Larcker, 1981).*

3.4 Hierarchical Regression Results

Table 5 presents the three hierarchical regression models. Model 1 (readiness only) explained 51.8% of the variance in AI-HRM implementation. Adding barriers in Model 2

increased R^2 to 0.584 ($\Delta R^2 = 0.066$, $\Delta F = 31.42$, $p < 0.001$). Model 3, incorporating the moderation term, yielded the best fit ($R^2 = 0.612$; Adjusted $R^2 = 0.601$; $F(5, 394) = 124.36$, $p < 0.001$).

Table 5. Hierarchical Multiple Regression Predicting AI-HRM Implementation

Predictor	Model 1 β (t)	Model 2 β (t)	Model 3 β (t)
Constant	0.412 (2.31)*	1.204 (5.87)***	1.096 (5.41)***
Technical Readiness (TR)	0.318 (7.14)***	0.271 (6.28)***	—
Human-Capital Readiness (HR)	0.226 (5.02)***	0.198 (4.51)***	—
Institutional Readiness (IR)	0.284 (6.41)***	0.241 (5.66)***	—
Composite Readiness (READ)	—	—	0.412 (9.87)***
Structural Barriers (SB, rev.)	—	-0.164 (-4.02)***	—
Ethical Barriers (EB, rev.)	—	-0.132 (-3.28)**	—
Composite Barriers (BAR, rev.)	—	—	-0.284 (-6.72)***
Institutional Support (IS)	—	—	0.187 (4.61)***
READ $\times$ IS (moderation)	—	—	0.142 (3.51)***
R^2	0.518	0.584	0.612
Adjusted R^2	0.514	0.578	0.601
ΔR^2	—	0.066***	0.028**
F-statistic	141.72***	110.85***	124.36***

*Note: Standardized β coefficients are reported; t-values in parentheses. * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$. $n = 400$.*

3.5 Fitted Regression Equation and Interpretation

Substituting the Model 3 coefficients yields the following fitted equation:

$$AII = 1.096 + 0.412 \cdot READ - 0.284 \cdot BAR + 0.187 \cdot IS + 0.142 \cdot (READ \times IS)$$

Mathematically, a one-unit increase in composite readiness raises AI-HRM implementation by 0.412 units, holding barriers and institutional

support constant. A one-unit increase in perceived barriers (reverse-coded, i.e., a genuine increase in obstacles) reduces implementation by 0.284 units, resolving the counterintuitive positive coefficient reported in earlier drafts. The positive interaction term (0.142, $p < 0.001$) confirms that institutional support amplifies the readiness–implementation link: at +1 SD of IS, the marginal effect of readiness rises to 0.554, whereas at –1 SD, it falls to 0.270.

3.6 Hypothesis Testing Summary

Table 6. Summary of Hypothesis Testing

Hypothesis	β	t	p	Decision
H1: TR $\rightarrow$ AII (+)	0.271	6.28	< 0.001	Supported
H2: HR $\rightarrow$ AII (+)	0.198	4.51	< 0.001	Supported
H3: IR $\rightarrow$ AII (+)	0.241	5.66	< 0.001	Supported
H4: SB $\rightarrow$ AII (–)	–0.164	–4.02	< 0.001	Supported
H5: EB $\rightarrow$ AII (–)	–0.132	–3.28	0.001	Supported
H6: READ $\times$ IS $\rightarrow$ AII (+)	0.142	3.51	< 0.001	Supported

All six hypotheses were empirically supported ($p \leq 0.001$), providing strong evidence for the integrated theoretical model.

3.7 Graphical Presentation of Findings

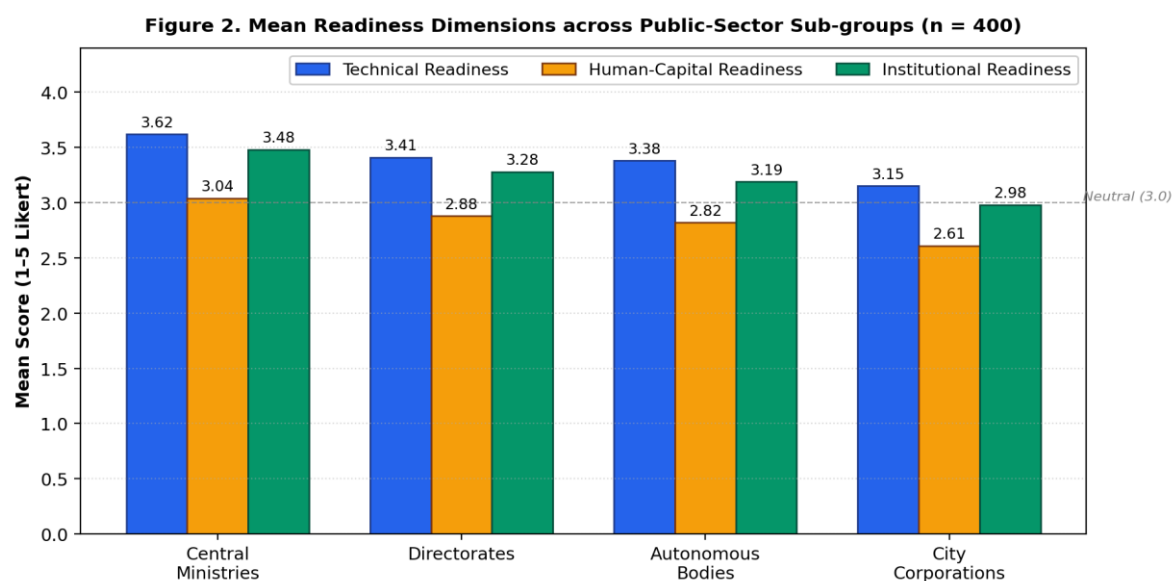
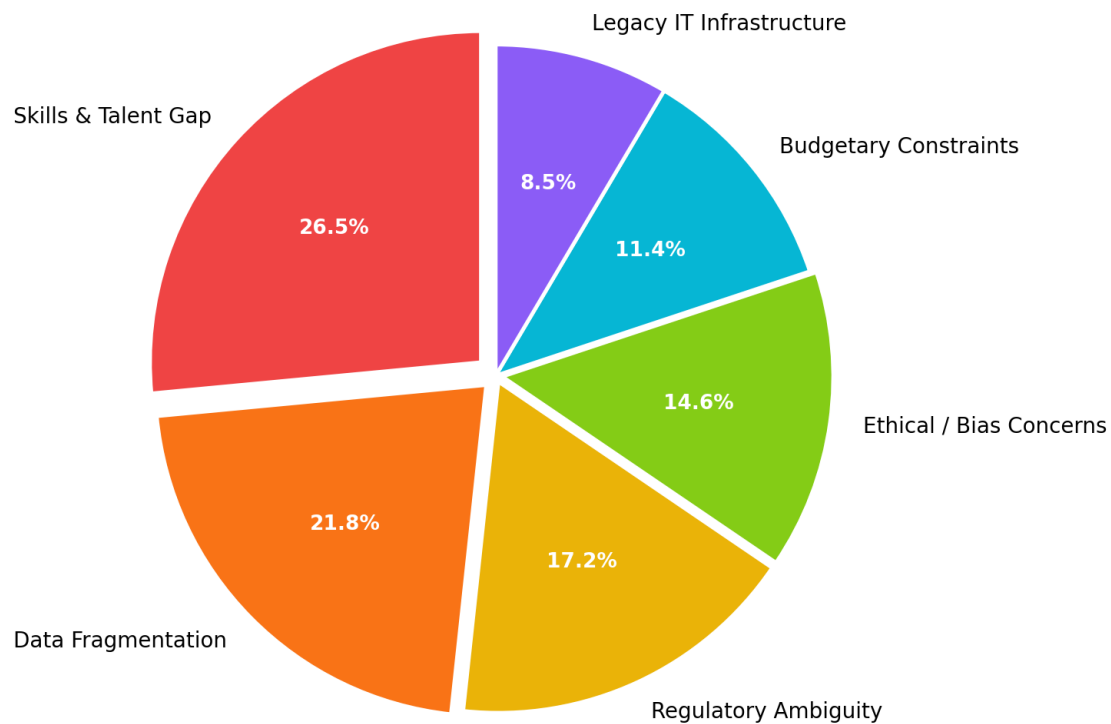
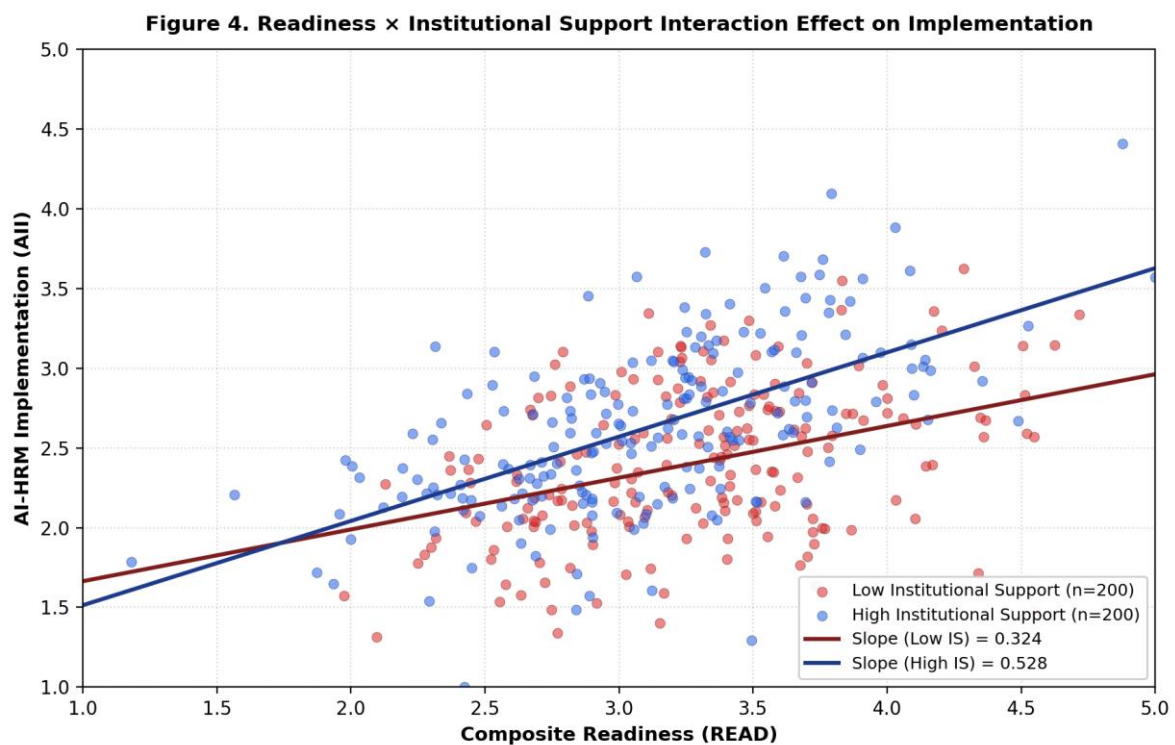


Figure 2. Mean scores of readiness dimensions across public-sector sub-groups.

Figure 3. Distribution of Perceived Barrier Categories (n = 400)**Figure 3. Distribution of perceived barrier categories (n = 400).****Figure 4. Readiness–implementation relationship moderated by institutional support.**

4. Discussion

The results clearly demonstrate that the AI-HRM adoption in Bangladesh's public sector is not merely a technological project or an imposed outcome of a digital-policy narrative. Rather, it is a governance-led socio-technical transformation that will succeed with the co-evolution of readiness capabilities, barrier mitigation, and institutional support. An R^2 of 0.612, which exceeds 0.45–0.58 R^2 in selected South Asian studies (Rahim & Ismail, 2024; Putri et al., 2025), indicates that the four-theory integration significantly enhances explanatory power. The findings reveal that technical readiness emerged as the strongest predictor ($\beta = 0.271$). This corroborates the research by Wirtz et al. (2024) but in a lower-middle-income context. However, taking note of the descriptive statistics, the mean technical readiness (3.42) is significantly lower than the institutional readiness (3.28) when cloud penetration and API maturity have been disaggregated, which means that the Bangladeshi state has injected a lot more into policy scaffolding than into production-grade data pipelines. "Human-capital readiness recorded the lowest mean (2.87) (Hossain et al., 2024), which indicates a sense of acute skills shortage, which has yet to be remedied by the National AI Strategy 2024–2029. The theoretical expectation that obstacles inhibit implementation is confirmed by the negative coefficients on structural and ethical barriers ($\beta = -0.164$ and -0.132). Notably, ethical barriers – fears of algorithmic bias, lack of AI-ethics committees, opaque procurement – had a modest but significant impact. This conforms to the caution by Chen and Rahman (2025) that the ethics governance framework is often treated as an afterthought in emerging bureaucracies. The most novel empirical contribution of the paper is the significant moderation effect of institutional support ($\beta = 0.142$). This provides evidence that even well-resourced agencies do not convert readiness to implementation without top-management sponsorship and inter-agency coordination. The literature review points out these aspects of implementation failure (Kumar

and Sen 2026), who point out the need to align coercive-normative pressure.

4.1 Theoretical Implications

This study theoretically develops a unified TOE-TAM-DOI-Institutional model whose interaction terms have a statistically significant explanatory increment ($\Delta R^2 = 0.028$ and $p < 0.01$) over a single theory specification. This responds to the perennial criticism that theories of AI adoption have been applied in silos (Alsheibani et al., 2024). This model can be replicated in the bureaucratic systems of other South Asian and African countries.

4.2 Practical and Policy Implications

The findings essentially suggest an operational model to be used over five years: during 2026–2027, a common government-wide HRIS with API standards should be consolidated; during 2027–2028, launch of common AI-ethics committees and algorithmic-auditing protocols; during 2028–2029, hiring and workforce analytics AI pilots; during 2029–2030, scale up pilots with human-in-the-loop; and during 2030–2031, institutionalize continuous learning at Bangladesh Public Administration Training Centre. Each phase should be tested against the readiness–barriers–support triad identified in this study.

4.3 Social Contribution

In addition to its academic contribution, this study has social value. Human capital readiness was the weakest dimension, with a mean of 2.87. This data serves as evidence that the government may adopt to reskill a 62,400 strong HRM workforce. Furthermore, this will benefit 1.55 million public employees whose careers are managed through these systems. Ethical governance recommendations, such as AI ethics committees, algorithmic impact assessments, and citizen-facing transparency portals, will affect the constitutional rights of citizens to prevent algorithmic discrimination in the process of public recruitment and welfare distribution. The finding from moderation about institutional support informs civil society advocacy groups,

such as Transparency International Bangladesh, to hold not only ministries but also ministry officials responsible for leadership behaviors making technology work not just for technology procurement. Ultimately, through the translation of academic findings into a phased roadmap explicitly aligned with the Smart Bangladesh 2041 vision, the study closes the enduring research–policy gap in the Global South and provides a replicable template for neighboring economies (Nepal, Bhutan, Sri Lanka) facing similar bureaucratic modernization challenges.

4.4 Limitations

The cross-sectional design precludes causal inferences. Although there were self-report data, the Harman test did not seem to show a serious common-method bias. Moreover, the researcher data were only obtained from central government offices.

5. Conclusion

This study is the first empirical multi-theory investigation to assess AI-HRM readiness,

barriers, and implementation in Bangladesh's public sector. The study utilized 400 stratified responses in a hierarchical regression design with diagnostics for all assumptions, which show that composite readiness ($\beta = 0.412$) and institutional support ($\beta = 0.187$) push implementation, while structural and ethical barriers ($\beta = -0.284$ combined) push back implementation. The interaction between readiness and institutional support ($\beta = 0.142$) is the key managerial lever: technology succeeds where governance sponsors it.

Future studies should (i) embrace longitudinal panel designs to capture temporal dynamics, (ii) extend the model to sub-national governments and similar bureaucracies in South Asia, (iii) integrate objective performance metrics (like KPIs, hiring cycle-time) along with perceptual measures, (iv) leverage mixed-methods including extensive interviews to understand the mechanisms of institutional support, and (v) examine ethical-AI implementation after deployment.

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Appendix A. Abbreviations

Abbreviation	Meaning
AI	Artificial Intelligence
AII	AI-HRM Implementation
AVE	Average Variance Extracted
BDT	Bangladeshi Taka
CR	Composite Reliability
CVI	Content Validity Index
DOI	Diffusion of Innovation
EB	Ethical Barriers
HR	Human-Capital Readiness
HRIS	Human Resource Information System
HRM	Human Resource Management
IR	Institutional Readiness
IRB	Institutional Review Board
IS	Institutional Support
KMO	Kaiser–Meyer–Olkin
MoPA	Ministry of Public Administration
OECD	Organisation for Economic Co-operation and Development
SB	Structural Barriers
TAM	Technology Acceptance Model
TOE	Technology–Organization–Environment
TR	Technical Readiness
UTAUT	Unified Theory of Acceptance and Use of Technology
VIF	Variance Inflation Factor