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Artificial Intelligence Readiness in Bangladesh's Public Administration: Linking Digital Leadership, Employee AI Capability, and Service Innovation

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ABSTRACT

AI will emerge as a significant force behind administrative change, although public organisations vary in their preparedness to do so. This paper investigates the impact of digital leadership and employee AI ability on artificial intelligence preparedness and innovation in services in the Bangladesh public administration. A four-reflective construct survey model was created, including digital leadership, employee AI capability, AI readiness, and service innovation. It was analysed with a synthetic dataset of 835 cases that are intended to test the methodology and prove PLS-SEM. The data were evaluated using descriptive statistics, common method bias tests, evaluation of the measurement model, structural model, mediation, and predictive assessment. The findings revealed that the positive impacts of digital leadership and employee AI capability on AI preparedness were significant. Service innovation was also positively impacted by AI readiness significantly. Digital leadership and employee AI capability had a direct impact on service innovation. Both relationships were partially mediated by AI readiness. The model explained 45.4% of the variance in AI readiness and 41.0% of the variance in service innovation. All the predictive relevance values were positive and the PLS model yielded lower prediction errors than linear benchmark. The results reveal a readiness pathway that is coherent where leadership, employee capability, and institutional preparedness contribute to innovation in the delivery of public services.

INTRODUCTION

AI is transforming the information process, resource allocation, communication with users and service design used by organisations. This transition is also being made by public administration. Government organizations are progressively becoming more dependent on digital platforms, electronic records, web-based service portals, automated workflow, and data-driven decision systems (Rahman & Parvin, 2024a). AI can then build on such innovations by aiding in document processing, forecasting, communication with citizens, detecting fraud, prioritisation of cases, policy analysis, and coordination of administration. Nevertheless, the presence of AI tools does not necessarily lead to successful adoption (Saini, 2025). They need to be prepared by first becoming usable by the public organisations.

The preparation of AI is particularly relevant with the creation of the administrative systems. Public agencies are known to work under strict procedures, splintered databases, disproportional infrastructure, minimal technical staffing, and decisions cultures (Gazi *et al.*, 2024). These aspects may decelerate the technological change. They are also capable of posing risks when AI is deployed uncontrollably, without proper staff training or institutional backing. Preparedness is not just about hardware and software. It also entails leadership dedication, worker expertise, dependable information, moral protection, financial assets, mechanisms of coordination, and ability to redefine established working habitual practices (Mazumder & Hossain, 2024).

The broader public-sector modernisation has seen the expansion of digital public services and administrative information systems in Bangladesh. These advancements establish a platform on which AI can be adopted in the future (Islam *et al.*, 2025). However, institutional preparedness will most likely differ among ministries, departments, directorates, regulatory bodies, district offices, and local government institutions. There are those organisations that can have effective digital leadership and trained employees, on the other hand, others can be challenged by lack of skills, poor data connection, or lack of implementation support (Del Barone *et al.*, 2026). To introduce AI on scale, it is important to understand such organisational differences.

This paper concentrates on three related drivers. Digital leadership is the capacity of top-level leaders to articulate a vision of technology, encourage experiments and resource allocations, as well as lead responsible change (R. & Archana, 2025). The capability of AI among the employees indicates the level of knowledge, confidence, flexibility, analytical judgment and ethical awareness that is needed to operate AI-aided systems. AI readiness represents those organisational circumstances that enable AI initiatives to become an administrative practice (Lentejas *et al.*, 2023). Service innovation signifies advancements in the practices, avenues of delivering the public services, attentiveness, dependability, openness and a citizen centric approach.

The paper constructs and measures a model where digital leadership and employee AI capability has a direct

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and indirect impact on service innovation by way of AI readiness (Shatila, 2025). The partial least squares structural equation modelling is applied since the model comprises of a number of latent constructs, a number of indicators, direct effects as well as mediation paths. This research also assesses predictive relevance as opposed to statistical significance.

The analysis obtained is reported on a synthetic dataset that is prepared to test questionnaires, demonstrate analytics, and validate the models (Sikder, 2023). It is not a reflection of what real-life government workers have witnessed. Such a difference is vital. The findings thus reveal the behaviour of the proposed theoretical model with a structured survey design. They present a clear analytical template of an upcoming field study in the field of public administration in Bangladesh (David, 2024).

The paper makes three contributions. Firstly, it consolidates leadership, employee capability, organisational readiness, and the innovation of services within a single framework. Second, it establishes AI preparedness as an intermediary organisational process and not an outcome of technology-adoption (Bhat, 2025). Third, it shows a comprehensive PLS-SEM evaluation, which incorporates the quality of measurements, the explanatory power, mediation, effect sizes, and out-of-sample prediction.

The key issue is whether we can create innovative services using leadership and employee capability and without institutional support. The model considers readiness as support (Sultana *et al.*, 2026). It translates strategic direction and personal competence into action and describes how AI-related capacity can enhance innovation in the public service realm.

LITERATURE REVIEW

Artificial Intelligence in Public Administration

Artificial intelligence is a term used to describe computational systems, which execute tasks that involve pattern recognition, prediction, classification, language processing, optimisation, or adaptive decision support. These functions can be used in public administration in both the internal administration and external service provision (Rahman & Parvin, 2024b). External applications encompass digital assistants, automated appraisal of application, service recommendation, classification of complaints and citizen information systems.

There is a difference between the public-sector environment and the one of the private sector. Government judgments impact on rights, accessibility, fairness and trust among people (Trajkovski, 2024). Administrative organisations should, therefore, take into account the notion of legality, transparency, accountability, explainability, privacy and equal treatment. Speed or cost reduction are not the only possible ways to assess AI adoption. It should also be in line with institutional obligations and societal values (Cernat & Bercu, 2024). These necessities render organisational preparedness as a focal point of accountable adoption.

Digital Leadership

Digital Leadership is the ability of organisational leaders to steer technology-based change. It encompasses the strategic vision, resources dedication, communication, coordination, experimentation, learning, and ethical direction. Leaders in public organisations also decipher policy priorities and translate them into operational decisions (Yevtushenko, 2025). Their approval determines the finances allocated to digital projects, training of employees, and the collaboration of departments in implementation.

There are various ways in which leadership can influence AI preparedness. An effective digital vision minimises confusion on organisational priorities (Wujarso *et al.*, 2025). Infrastructure, data preparation and technical assistance are supported by the allocation of resources. Experimentation is legitimised by visible managerial support and minimises resistance. Ethical leadership also assists an organisation to develop privacy, security, accountability rules and responsible use rules (Amirova *et al.*, 2025). Digital leadership, then, must reinforce the institutional aspects required in adopting AI.

H1: Digital leadership positively and significantly influences AI readiness.

Digital leadership can have a direct effect on service innovation as well. Leaders will have an opportunity to motivate employees to reinvent processes, launch digital service delivery systems, utilize administrative data, and respond faster to citizen needs (Magsi *et al.*, 2026). They are able to eliminate procedural distance and establish cross-functional problem-solving space. Even in advance of the extensive deployment of sophisticated AI systems, then service innovation can be driven by leadership behaviour (Kurhayadi, 2025).

H4: There is a positive and significant impact of digital leadership on service innovation.

Digital Leadership

Employee AI capability is the potential of employees to be aware of, judge, learn, and use AI-based technologies responsibly (Porrás *et al.*, 2025). It is an amalgamation of simple conceptual knowledge, technical confidence, analytical judgement, flexibility, and exposure to ethical risks. Not every employee working in the government should become a programmer. They must, however, have the necessary ability to identify appropriate uses, query computer outputs, safeguard confidential information, and incorporate new systems into daily practice (Mergel *et al.*, 2023).

It matters to organisations that employees are capable, since organisational technologies are adopted via human action. Experienced workers are also able to recognize their processes which can be automated (Ojiako *et al.*, 2024). They are also able to convey requirements to technical teams and notice errors or inappropriate suggestions. Lowly confident employees might steer clear of new systems or use them in a mechanized manner without sufficient evaluation (Raavi *et al.*, 2025). Increased

AI potential should consequently heighten organisational preparedness.

H2: AI readiness is positively and significantly impacted by employee AI capability.

The AI capability of employees can also be of direct contribution to service innovation. Skilled workers are in a better position to come up with new service concepts, analyze citizen data, increase the accuracy of workflow, and adjust the digital tools to the requirements of the local administration (Misuraca *et al.*, 2024). Their expertise can enable incremental innovation in cases where the organisation has not undertaken a massive change in AI.

H5: AI capability of the employees positively and significantly impacts service innovation.

Artificial Intelligence Readiness

The level of AI preparedness refers to the number of resources and arrangements that an organisation has to implement AI. It encompasses digital infrastructure, data availability, data quality, technical support, financial resources, governance, legal protection, security processes, interdepartmental coordination, process compatibility (Thakur, 2025). Ready is not one technology. It is a state within an organisation that renders implementation possible and sustainable.

An organisation that is ready can link AI tools with the current information systems. It has the ability to give credible data and introduce responsibility in the use of the system (Hossain *et al.*, 2025). It is also able to handle implementation risks and assist employees through transition. The latter enables public agencies to transcend individual digital experiments to sustained service enhancement (Li & Gu, 2025). The preparedness to AI must thus enhance service innovation.

H3: AI readiness has a positive and significant effect on service innovation.

Service Innovation in Public Administration

Service innovation is the innovation or betterment of the processes involved in the delivery of services to the populace, channel of delivery, the decision process and the interaction among the citizens (Saini, 2025). It can involve quicker application processing, easier processes, better accuracy, better transparency, personalised information and responsive communication. Innovation may be in the form of technology, organisation or process. In reality, such forms usually coexist with each other.

The innovation of the public services is based on the individual and organisational conditions (Gazi *et al.*, 2024). The employees might have valuable skills, yet their ideas cannot advance unless there are infrastructures, data, authority, and coordination. Leaders can talk a powerful digital vision, yet the organisation might not have an operational implementation capability (Mazumder & Hossain, 2024). The inputs can be linked together by AI preparedness through the provision of a favorable operating climate.

Mediating Role of AI Readiness

The proposed model considers AI readiness as an intermediary (Islam *et al.*, 2025). Digital leadership is supposed to enhance preparedness using the methods of strategic direction, support of resources, and governance. Service innovation is then sustained through preparedness which helps in implementation (Del Barone *et al.*, 2026). This chain indicates that some of the effect of leadership is achieved via institutional preparedness.

H6: AI readiness positively mediates the relationship between digital leadership and service innovation.

The same applies to the AI capability of the employees (R. & Archana, 2025). Proficient workers bring expertise, flexibility, and responsible decision-making. These attributes enhance the pragmatic capacity of the organisation to be ready to adopt AI. When preparedness is achieved, the ability of the employees can be made more productive in enhancing services by the organization (Lentejas *et al.*, 2023).

H7: AI readiness positively mediates the relationship between employee AI capability and service innovation.

MATERIALS AND METHODS

Research Design

The research design was quantitative, cross-sectional and explanatory. The analytical goal was to study the correlations between digital leadership, employee AI capability, AI ready, as well as service innovation (Shatila, 2025). Specifically, the model was defined as a reflective model of PLS-SEM that has two exogenous constructs, a mediating construct, and a final endogenous construct. A total of 835 synthetic survey responses were used in the analysis. The cases were created such that they could generate plausible response distributions and theoretically plausible relationships between the constructs (Sikder, 2023). The data was ready to undergo questionnaire pretesting, creation of statistical workflow, and demonstrating the model. It was not gathered among the employees of the public administration of Bangladesh. In turn, the empirical findings can be viewed as being based on simulation-based evidence regarding the proposed model instead of population estimates.

Instrument Development

The questionnaire had two sections. The demographic and professional attributes were assessed in the first part. They were gender, age, academic qualification, employment level, length of service, type of organisation, place of work, AI training, digital government training, frequency of using AI-tools, and prior use of AI-tools.

The four latent constructs were measured in the second part. Eight items were contained in digital leadership. There were eight items in employee AI capability. Ten items were included in AI preparedness. There were ten items of service innovation (David, 2024). The Likert scale was made with 5 points with 1 being strongly disagree, 2 being slightly disagree, 3 strongly agree and

5 strongly disagree. The increased scores were indicative of a more powerful perception of the construct being measured.

The digital leadership items covered the strategic vision, leadership support, resource allocation, training, collaboration, procedural flexibility, and ethical direction. Items of the employee AI capability measures tested the elementary AI knowledge, task identification, learning confidence, digital competence, output evaluation, adaptability, privacy awareness, and ethical awareness. AI readiness items included infrastructure, connectivity, data availability, data quality, policy guidance, technical support, system integration, resources, coordination and risk management (Bhat, 2025). It was measured with service innovation items that evaluated new service approaches, speed, simplification of the process, responsiveness, digital channels, quality, decision support, transparency, citizen feedback, and personalisation.

Data Preparation

Data-screening process checked the instances of duplication, the unfinished measurement responses, the values that were beyond the acceptable scale, failure of screening questions and the consistent responses. All the cases (835) had full measurement details and were included in the analysis. Possible values of all items were between 1 and 5.

The demographic variables, individual indicators and construct level means scores were computed using descriptive statistics (Sultana *et al.*, 2026). Mean, standard deviation and skewness and kurtosis were investigated. Common method bias was evaluated using Harman, single-factor test and full-collinearity variance-inflation factors. A first-factor variance of less than half and full-collinearity VIF of less than 3.3 was considered evidence that common method bias was not acute.

PLS-SEM Procedure

All PLS-SEM was done either in R under the cSEM environment. The structural equations in the model were: Digital leadership and AI capability among employees predicted AI readiness. Digital leadership, employee AI capability and AI readiness were predicted to lead to service innovation. The bootstrapping was undertaken with 5,000 resamples in order to determine standard errors, t-values, p-values, and percentile confidence intervals.

The reflective measurement model was tested prior to the structural model. Outer loadings were used to test the reliability of the indicators (Cernat & Bercu, 2024). The 0.708 and above were deemed satisfactory loadings. Cronbach alpha and composite reliability were used to measure internal consistency. A minimum of 0.70 was deemed to be acceptable. Average variance extracted was used to measure convergent validity, with the minimum criterion of 0.50.

Evaluation of discriminant validity was done on the ratio of heterotrait-monotrait and Fornell-Larcker criterion.

The values of 'HTMT' smaller than 0.85 showed that construct distinctiveness was evident. In the case of the FornellLarcker assessment, the square root of each construct AVE had to be bigger than its correlations with other constructs.

Structural and Predictive Assessment

Inner VIF values were used to measure structural collinearity. The path coefficients were assessed in terms of their direction, magnitude, t-value, p-value, and 95 confidence intervals. Explanatory power was measured using the coefficient of determination and adjusted coefficient of determination (Kurhayadi, 2025). The effect sizes were assessed using Cohen f² with reference points of 0.02, 0.15 and 0.35 of small, medium, and large effects respectively.

Bootstrapped specific indirect effects were used to measure mediation. A mediation path was deemed relevant, when p-value was less than 0.05 and it did not contain a zero within a confidence interval. The direct and indirect effects were compared and then the type of mediation was identified.

The predictive relevance was measured by a ten-fold PLSpredict with a linear regression benchmark. Values of positive Q² predict denoted predictive relevance (Kurhayadi, 2025). The root mean square error of PLS model was compared to the corresponding benchmark error. A smaller error in PLS predictions was indicative of greater predictive out-of-sample performance.

Ethical and Reporting Position

The reported analysis did not recruit any human subjects. There were no personal or administrative records. The data is artificial and does not include any recognizable data. Subsequent empirical use must be institutionalized, consenting and data-protection-guaranteed. It must also substitute the simulated observations with confirmed field responses prior to substantial assertions in regard to the public administration in Bangladesh.

The massive simulated sample was maintained to facilitate consistent estimation of the multi-item model and to show the entire reporting chain. Subgroup comparisons, moderation tests and higher-order constructs were not presented since these were not among the objectives. This maintained the focus of the analysis to the seven hypotheses (Porrás *et al.*, 2025). It also minimized the risk of data driven model growth. The main focus was made on quality of measurement, structural relationship, mediation and predictive performance.

RESULTS AND DISCUSSION

Respondent Demographic and Professional Characteristics

The demographic and professional characteristics of the 835 cases are presented in Table 1. Gender, age group, academic qualification, employment level, length of service, type of organisation, where work is performed, AI-related training, digital government training, frequency

Table 1: Demographic and professional characteristics of the respondents

Characteristic	Category	Frequency	Percentage (%)
Gender	Female	366	43.83
	Male	458	54.85
	Other	1	0.12
	Prefer not to disclose	10	1.20
Age group	Below 25 years	52	6.23
	25–34 years	236	28.26
	35–44 years	297	35.57
	45–54 years	197	23.59
	55 years or above	53	6.35
Highest qualification	Higher secondary or equivalent	9	1.08
	Diploma	29	3.47
	Bachelor's degree	175	20.96
	Master's degree	523	62.63
	MPhil or equivalent	57	6.83
	PhD	36	4.31
	Other	6	0.72
Employment level	Entry-level employee	38	4.55
	Junior officer	171	20.48
	Mid-level officer	283	33.89
	Senior officer	204	24.43
	Manager or departmental head	89	10.66
	Senior executive or policymaking position	39	4.67
	Other	11	1.32
Length of service	Less than 1 year	27	3.23
	1–5 years	205	24.55
	6–10 years	210	25.15
	11–15 years	189	22.63
	16–20 years	113	13.53
	More than 20 years	91	10.90
Organisation type	Ministry	120	14.37
	Government department	178	21.32
	Directorate	158	18.92
	Division	59	7.07
	District administration	99	11.86
	Local government institution	78	9.34
	Autonomous or semi-autonomous public organisation	87	10.42
	Public regulatory authority	43	5.15
	Other	13	1.56
Work location	Dhaka	321	38.44
	Divisional city outside Dhaka	137	16.41
	District-level office	203	24.31
	Upazila-level office	115	13.77
	Union or local-level office	45	5.39
	Other	14	1.68

AI training	Yes	323	38.68
	No	483	57.84
	Not sure	29	3.47
Digital government training	Yes	563	67.43
	No	246	29.46
	Not sure	26	3.11
Digital-system use	Never	5	0.60
	Rarely	24	2.87
	Sometimes	142	17.01
	Often	378	45.27
	Very often	286	34.25
Previous AI-tool use	Yes	437	52.34
	No	347	41.56
	Not sure whether the tool was AI-based	51	6.11

of using digital-system, prior use of AI-based tools are all in the table.

The greatest gender category was male respondents. The sample size was 458 male respondents, who constituted 54.85% of the population. The number of female respondents was 366, which is equal to 43.83. One of the respondents who represented 0.12% was other. An even smaller percentage of 10 respondents or 1.20 percent of the total respondents did not disclose their gender. The distribution was characterized by high representation of both large gender groups, even though the majority of the respondents were males in moderation.

The greatest age group was 35–44 years. The sample size of this group was 297 respondents and it constituted 35.57 percent of the sample. The second-largest group consisted of respondents aged 25–34 years with 236 cases or 28.26. Another 197 respondents which is equivalent to 23.59 fell in the 45–54-year bracket. Respondents aged under 25 years constituted 6.23 and the respondents aged 55 years and over constituted 6.35. Generally, the sample was focussed among the persons who were at the middle age of their careers.

Majority of the respondents had a master's degree. The respondents in this category were 523, which was a percentage of 62.63 of the sample. The second-largest group is bachelor degree holders (175 respondents or 20.96). Another 57 respondents had an MPhil or other degree. PhDs represented 36 cases or 4.31%. Diploma holders constituted 3.47 and higher secondary or equivalent constituted 1.08. Results showed that the sample was mainly composed of well-educated people.

The highest number of employers was the mid-level officers. This group comprised 283 respondents, or 33.89% of the respondents. The respondents of the seniors were 204 or 24.43. Junior officers represented 20.48%. The sample was made up 10.66% of managers or departmental heads. Four point six seven (4.67) were senior executives or policymakers, whereas 4.55 were entry-level workers. Distribution involved the participation of persons at different levels of administration with the

highest number of participants in middle-level positions and senior operational positions.

The largest experience group was respondents who had 6–10 years of service. The number of respondents under this category was 210, which is 25.15 of the sample. The respondents who had between 1 and 5 years of service were almost equivalent and 205 respondents or 24.55. A further 189 respondents had 11–15 years of experience. Whites aged 16–20 years were 13.53 that showed more than 20 years were 10.90. The distribution showed that the majority of respondents had a lot of professional experience.

The largest type of organisation was the government departments. Of the total number of 178 respondents who were in government departments, this is 21.32 percent of the sample population. Directorates had 158 respondents or 18.92%. Ministries had 120 respondents and that is 14.37. The district administration offices were represented with 11.86 and autonomous or semi-autonomous public organisations were 10.42. There were also representatives of local government institutions, divisions, public regulatory authorities, as well as other organisations. Thus, the sample was very inclusive of institutions operating in the public sector.

The most common place of work was Dhaka. There were 321 respondents who were based in offices within Dhaka and this constituted 38.44% sample. The second-largest group with 203 respondents or 24.31 was district-level offices. Cities outside Dhaka that were divisional came in at 16.41%. Offices at the level of upazila constituted 13.77% and union or local level offices constituted 5.39%. The results indicated both a central plus decentralised administrative environment representation.

The majority of respondents had never been trained in AI related training. Four hundred and eighty-three respondents (57.84 percent of the sample) had no such training. Conversely, 323 or 38.68% had formal training on AI. Another 29 respondents did not know whether they were trained or not. The results of the investigations showed that there was a substantial gap in AI capability

since the majority of the interviewees had not undergone specialised training on artificial intelligence.

The most prevalent training was digital government or e-governance training as opposed to AI-specific training. Out of a sample of 563 respondents, it was found that 563 respondents (67.43 percent) had such training. A further 246 respondents or 29.46% had not received digital government training. The number of people who were in doubt was just 26. This trend suggested a significant amount of pre-exposure to digital transformation projects, but this exposure was not always transformed into specialised AI ability.

Electronic systems found extensive application in governmental work. There were 378 respondents who responded to using digital systems very frequently, which is 45.27 percent of the sample. The remaining 286 respondents, which amount to 34.25 percent, used them very frequently. Together, these categories represented 79.52% of the sample. Another 142 respondents engaged the use of digital systems occasionally. They were used

by only 24 respondents who were rarely used and five respondents had never used them. The results indicated that electronic systems were well integrated in daily administrative practice.

Over 50% of the respondents had already used AI-based tools. Four hundred and thirty-seven respondents or 52.34 percent of the sample indicated professional use in the previous use. In contrast, 347 respondents or 41.56% had no previous experience with AI-based tools. Another 51 respondents did not know whether the tools they have used were AI-based. The results showed an increasing exposure to AI applications, but with unequal access and familiarity across the sample.

Descriptive Statistics of the Constructs

Measures of central tendency, dispersion, and distribution of the four variables were obtained using construct-level descriptive statistics.

The mean was the greatest at 3.138 in digital leadership. The next capability of AI among employees was not

Table 2: Construct-level descriptive statistics

Construct	N	Minimum	Maximum	Mean	Standard deviation	Skewness	Kurtosis
Digital Leadership	835	1.00	5.00	3.138	0.999	-0.092	-0.862
Employee AI Capability	835	1.00	5.00	3.131	0.986	-0.125	-0.869
AI Readiness	835	1.00	5.00	3.085	0.955	-0.117	-0.753
Service Innovation	835	1.00	5.00	3.110	0.988	-0.092	-0.832

far behind with a mean of 3.131. The mean of service innovation was 3.110, and the lowest mean was 3.085 with AI readiness. Means of all constructs were all around the center of the five-point scale. This trend reflected on moderate perceptions of digital leadership, the ability of employees, willingness, and innovation.

Standard deviations were in the range of 0.955-0.999. There was enough variation in these values throughout

the responses. Skewness values ranged from -0.125 to -0.092, while kurtosis values ranged from -0.869 to -0.753. The values were acceptable and not a sign of serious distributional issues.

Common Method Bias Assessment

The bias of common methods was tested using Harman single-factor test and full-collinearity VIF values.

Table 3: Common method bias assessment

Assessment	Result	Threshold	Decision
Harman's first-factor variance	40.765%	Below 50%	No serious concern
Full VIF: Digital Leadership	1.540	Below 3.3	Acceptable
Full VIF: Employee AI Capability	1.458	Below 3.3	Acceptable
Full VIF: AI Readiness	2.052	Below 3.3	Acceptable
Full VIF: Service Innovation	1.690	Below 3.3	Acceptable

A single-factor test by Harman revealed that the initial factor had a total variance that was explained by 40.765. This value was also less than the recommended level of 50. Thus, most of the variance in the measurement items could not be attributed to a single factor.

The entire-collinearity VIF measures were between 1.458 and 2.052. Any value below 3.3 was considered as negative (Magsi *et al.*, 2026). The overall results revealed that the common method bias should not cause a severe issue in the analysis.

Indicator Reliability

Outer loading of the 36 measurement items was used to determine the indicator reliability.

All the outer loads were also greater than the recommended minimum of 0.708. The loadings for digital leadership ranged from 0.784 to 0.827. The loadings of AI capability among the employees were between 0.755 and 0.847. The AI readiness loadings fluctuated between 0.760 and 0.830 and service innovation loadings fluctuated between 0.776 and 0.855.

Table 4: Outer loadings of the measurement items

Construct	Item	Outer loading	Bootstrap SE	t-value	p-value	Decision
Digital Leadership	DL1	0.827	0.012	71.615	<0.001	Retained
	DL2	0.827	0.011	72.856	<0.001	Retained
	DL3	0.811	0.012	66.979	<0.001	Retained
	DL4	0.803	0.012	64.478	<0.001	Retained
	DL5	0.820	0.012	68.067	<0.001	Retained
	DL6	0.797	0.014	57.927	<0.001	Retained
	DL7	0.808	0.013	63.597	<0.001	Retained
	DL8	0.784	0.014	55.905	<0.001	Retained
Employee AI Capability	EAC1	0.809	0.012	66.366	<0.001	Retained
	EAC2	0.820	0.012	68.361	<0.001	Retained
	EAC3	0.847	0.010	88.538	<0.001	Retained
	EAC4	0.779	0.015	52.890	<0.001	Retained
	EAC5	0.827	0.012	71.237	<0.001	Retained
	EAC6	0.797	0.014	58.318	<0.001	Retained
	EAC7	0.781	0.014	54.372	<0.001	Retained
	EAC8	0.755	0.017	45.678	<0.001	Retained
AI Readiness	AIR1	0.806	0.013	64.039	<0.001	Retained
	AIR2	0.777	0.015	52.363	<0.001	Retained
	AIR3	0.830	0.011	77.796	<0.001	Retained
	AIR4	0.804	0.013	59.894	<0.001	Retained
	AIR5	0.793	0.013	59.759	<0.001	Retained
	AIR6	0.812	0.012	67.998	<0.001	Retained
	AIR7	0.775	0.015	50.523	<0.001	Retained
	AIR8	0.814	0.011	71.316	<0.001	Retained
	AIR9	0.760	0.015	52.076	<0.001	Retained
	AIR10	0.767	0.016	49.298	<0.001	Retained
Service Innovation	SI1	0.812	0.012	69.201	<0.001	Retained
	SI2	0.812	0.012	66.512	<0.001	Retained
	SI3	0.831	0.010	79.546	<0.001	Retained
	SI4	0.810	0.012	66.462	<0.001	Retained
	SI5	0.807	0.013	62.191	<0.001	Retained
	SI6	0.796	0.013	59.006	<0.001	Retained
	SI7	0.784	0.014	55.796	<0.001	Retained
	SI8	0.855	0.009	92.347	<0.001	Retained
	SI9	0.776	0.014	53.527	<0.001	Retained
	SI10	0.823	0.012	70.001	<0.001	Retained

The p-value of all the indicators was statistically significant at $p < 0.001$. The minimum loading was not below the minimum criterion. Hence, all 36 indicators were included in the final model of measurement.

Internal Consistency and Convergent Validity

Cronbachs alpha, rho A, composite and average variance extracted assessed internal consistency reliability and convergent validity.

The range of alpha values (Cronbach) was 0.921 to 0.942. The values of rho A were between 0.923 and 0.943,

and the values of composite reliability were between 0.935 and 0.950. The reliability values were all above the recommended value of 0.70. The outcomes thus indicated high internal consistency.

The AVE values ranged from 0.630 to 0.658. All the values were above the minimum of 0.50. All constructs thus shared over 50% of the variance in respective indicators. Convergent validity was determined.

Discriminant Validity

The HTMT ratio and Fornell–Larcker criterion was used

Table 5: Reliability and convergent validity

Construct	Number of items	Cronbach's alpha	rho_A	Composite reliability	AVE	Assessment
Digital Leadership	8	0.925	0.926	0.938	0.656	Acceptable
Employee AI Capability	8	0.921	0.923	0.935	0.644	Acceptable
AI Readiness	10	0.935	0.936	0.945	0.630	Acceptable
Service Innovation	10	0.942	0.943	0.950	0.658	Acceptable

to measure discriminant validity.

The HTMT values ranged from 0.346 to 0.628. The greatest value of HTMT was observed between AI readiness and service innovation, 0.628. None of the

values exceeded the conservative value of 0.85. The findings thus validated that the four constructs were empirically different.

Table 6: HTMT discriminant validity

Construct	DL	EAC	AIR	SI
Digital Leadership	—			
Employee AI Capability	0.346	—		
AI Readiness	0.600	0.576	—	
Service Innovation	0.523	0.484	0.628	—

Table 7: Fornell–Larcker criterion

Construct	DL	EAC	AIR	SI
Digital Leadership	0.810			
Employee AI Capability	0.321	0.803		
AI Readiness	0.559	0.536	0.794	
Service Innovation	0.489	0.453	0.591	0.811

Note: Diagonal values represent the square roots of AVE.

Digital leadership had the highest conjunction of 0.810, which was higher than the correlation with the remaining constructs (Kurhayadi, 2025). The diagonal values corresponding to the employee AI capability, AI readiness, and service innovation were 0.803, 0.794, and 0.811. All the diagonal values were higher than the corresponding inter-construct correlations. The FornellLarcker criterion was thus met.

Structural Collinearity Assessment

The structural relationships were tested after analyzing inner VIF values.

The inner values of VIF were between 1.115 and 1.832. All the values were low than the recommended 3.0. Thus, multicollinearity amongst the predictor constructs was not were of concern.

Table 8: Structural collinearity assessment

Endogenous construct	Predictor construct	Inner VIF	Assessment
AI Readiness	Digital Leadership	1.115	Acceptable
AI Readiness	Employee AI Capability	1.115	Acceptable
Service Innovation	Digital Leadership	1.455	Acceptable
Service Innovation	Employee AI Capability	1.404	Acceptable
Service Innovation	AI Readiness	1.832	Acceptable

Direct Effects and Hypothesis Testing

Bootstrapping was done with 5,000 resamples to test the hypothesis of direct structural relationships.

Digital leadership had a positive and significant effect on AI readiness. The path coefficient was 0.431, with a t-value of 16.253 and $p < 0.001$. The confidence interval was between 0.377 to 0.483 without including zero. H1 was thus supported.

The AI readiness was also positively influenced by the employee AI capability. The coefficient was 0.398, with a t-value of 15.409 and $p < 0.001$. The confidence interval

was between 0.349 and 0.449. H2 thus was in favor.

The AI preparedness had a positive effect on service innovation. The relationship produced a coefficient of 0.366, a t-value of 11.042, and $p < 0.001$. It had a confidence interval of 0.300 to 0.430. H3 was, therefore, supported.

Service innovation was strongly directly impacted by digital leadership. The path coefficient was 0.225, with a t-value of 7.403 and $p < 0.001$. The confidence interval was positive. H4 was supported.

Service innovation was also positively influenced

Table 9: Direct-effect hypothesis testing

Hypothesis	Relationship	Beta	Bootstrap SE	t-value	p-value	95% confidence interval	Decision
H1	DL → AIR	0.431	0.027	16.253	<0.001	[0.377, 0.483]	Supported
H2	EAC → AIR	0.398	0.026	15.409	<0.001	[0.349, 0.449]	Supported
H3	AIR → SI	0.366	0.033	11.042	<0.001	[0.300, 0.430]	Supported
H4	DL → SI	0.225	0.030	7.403	<0.001	[0.164, 0.284]	Supported
H5	EAC → SI	0.185	0.032	5.790	<0.001	[0.121, 0.249]	Supported

significantly by employee AI capability. The coefficient was 0.185, with a t-value of 5.790 and $p < 0.001$. Thus, H5 was accepted.

Explanatory Power

R² and adjusted R² were used to explain the power of the structural model.

Table 10: Explanatory power of the structural model

Endogenous construct	R ²	Adjusted R ²	Interpretation
AI Readiness	0.454	0.453	Moderate
Service Innovation	0.410	0.408	Moderate

The combined effects of digital leadership and AI aptitude of employees had a variance in AI readiness of 45.4%. The adjusted R² was 0.453. This finding was moderate explanatory power.

The combination of digital leadership, employee AI capability, and AI readiness explained 41.0% of the variance in service innovation. The adjusted R² was 0.408. This value was also a moderate explanation power (Porrás *et al.*, 2025). This model thus accounted a significant percentage of both endogenous constructs.

Effect-Size Assessment

The f^2 was calculated by Cohen, and it was utilized to assess the contribution each predictor made to the endogenous constructs.

Digital leadership created a medium impact on AI preparedness, the $f^2 = 0.306$. A medium impact of employee AI capability on AI readiness was also realized but the $f^2 = 0.260$. These results showed that the two predictors significantly contributed to the explained variance of AI readiness.

Table 11: Effect-size assessment

Relationship	f^2	Interpretation
DL → AIR	0.306	Medium
EAC → AIR	0.260	Medium
AIR → SI	0.124	Small
DL → SI	0.059	Small
EAC → SI	0.041	Small

AI preparedness created a minor impact on innovation of services, $f^2 = 0.124$. Small direct effects on service innovation were also produced by digital leadership and employee AI capability with f^2 of 0.059 and 0.041. As much as these effects were termed as small, they were statistically significant and theoretically relevant.

Mediation Analysis

The digital leadership and employee AI capability indirectly influence service innovation which was tested by means of AI preparedness.

Digital leadership had an indirect positive impact on service innovation with regards to AI readiness (0.158).

Table 12: Specific indirect effects and mediation results

Hypothesis	Indirect relationship	Direct effect	Indirect effect	Total effect	t-value	p-value	95% confidence interval	VAF (%)	Mediation type	Decision
H6	DL → AIR → SI	0.225	0.158	0.383	9.208	<0.001	[0.126, 0.192]	41.20	Complementary partial mediation	Supported
H7	EAC → AIR → SI	0.185	0.146	0.330	8.871	<0.001	[0.115, 0.179]	44.05	Complementary partial mediation	Supported

The impact was statistically significant, as t-value was 9.208 and $p < 0.001$. The confidence interval was 0.126 to 0.192 with an exclusion value of zero. The direct effect too did not change to negative and significant. Thus, the preparedness of AI created partial complementary

mediation and H6 was accepted.

This variance explained was 41.20. This finding suggested that a significant percentage of the overall impact of digital leadership on service innovation was via AI preparedness.

The indirect impact of AI capability among employees on the innovation of their services via AI preparedness was 0.146. The value of t and p were found to be 8.871 and less than 0.001 respectively, which was stat significance. The confidence was between 0.115 and 0.179. The immediate impact was also positive and significant. As a result, the partial complementary mediation was created, and H7 was proved.

The variance accounted for was 44.05%. This value indicated that AI preparedness contained an immense amount of impact of staff AI ability on service innovation.

Predictive Relevance

Q^2 predict and the PLSpredict process were used to assess the predictive relevance of the model.

The ten AI readiness indicators all gave positive Q^2 predict values. The values were between 0.257 and 0.323 and the approximate mean was 0.283. The Q^2 predict values of all the ten service innovation indicators were also positive, with high scores of 0.185 to 0.262. The approximate mean was 0.217.

The values of RMSE produced by the PLS model were less than the values of the linear regression benchmarks of all the endogenous indicators (Mergel *et al.*, 2023).

Table 13: Predictive relevance assessment

Endogenous construct	Q^2 _predict range	Mean Q^2 _predict	Indicators with $Q^2 > 0$	RMSE comparison	Assessment
AI Readiness	0.257–0.323	0.283	10 of 10	PLS RMSE lower for all items	Predictive relevance established
Service Innovation	0.185–0.262	0.217	10 of 10	PLS RMSE lower for all items	Predictive relevance established

Thus, the model exhibited good out-of-sample prediction results.

The seven hypotheses were all confirmed. Digital leadership had the greatest direct impact on AI readiness, and subsequently, employee AI capability. Service innovation was also significantly influenced by AI preparedness.

The immediate impacts of digital leadership and employee AI capability on service innovation were smaller than their impacts on AI readiness. Both relationships were however statistically significant. The mediation findings also showed that AI preparedness was a significant tool where leadership and employee abilities affected service innovation.

Table 14: Summary of hypothesis-testing results

Hypothesis	Proposed relationship	Effect	p-value	Decision
H1	Digital Leadership → AI Readiness	0.431	<0.001	Supported
H2	Employee AI Capability → AI Readiness	0.398	<0.001	Supported
H3	AI Readiness → Service Innovation	0.366	<0.001	Supported
H4	Digital Leadership → Service Innovation	0.225	<0.001	Supported
H5	Employee AI Capability → Service Innovation	0.185	<0.001	Supported
H6	Digital Leadership → AI Readiness → Service Innovation	0.158	<0.001	Supported
H7	Employee AI Capability → AI Readiness → Service Innovation	0.146	<0.001	Supported

Discussion

The research considered a readiness pathway between digital leadership, employee AI capability, AI readiness, and service innovation. Each of the proposed relationships was corroborated by the results (Ojiako *et al.*, 2024). The model as such provides a consistent description of the way in which AI-related organisational capacity can evolve in the context of the public administration.

AI readiness was the most directly impacted by digital leadership. This observation underscores the strategic positioning of top officials in terms of readying public organisations to change because of technology. The adoption of AI involves budget, infrastructure, governance, training, coordination and risk decision-making. Such decisions are usually based on leadership power (Raavi *et al.*, 2025). An enabling leader will be able to set priorities and establish legitimacy of the experimentation. Even when the technical tools exist, a

passive or unsure leader might postpone adoption.

Digital leadership medium effect size of readiness is also significant. It indicates that leadership is not solely correlated with readiness, but it contributes significantly to the variance explained. In real life, preparedness will tend to advance when leaders declare a clear transformation agenda, facilitate a more development of the employees and also set rules of responsible implementation (Misuraca *et al.*, 2024). Leadership must thus be viewed as a practical resource as opposed to an aesthetic promise. The positive impact of employee AI capability on readiness was also strong. This finding confirms the opinion that an institutional preparation is partially developed with the help of employee competence. The infrastructure is not a guarantee of effective AI utilization (Thakur, 2025). The employees should be aware of the intent of a system, know where it is to be used, consider the output and counteract mistakes. They should also

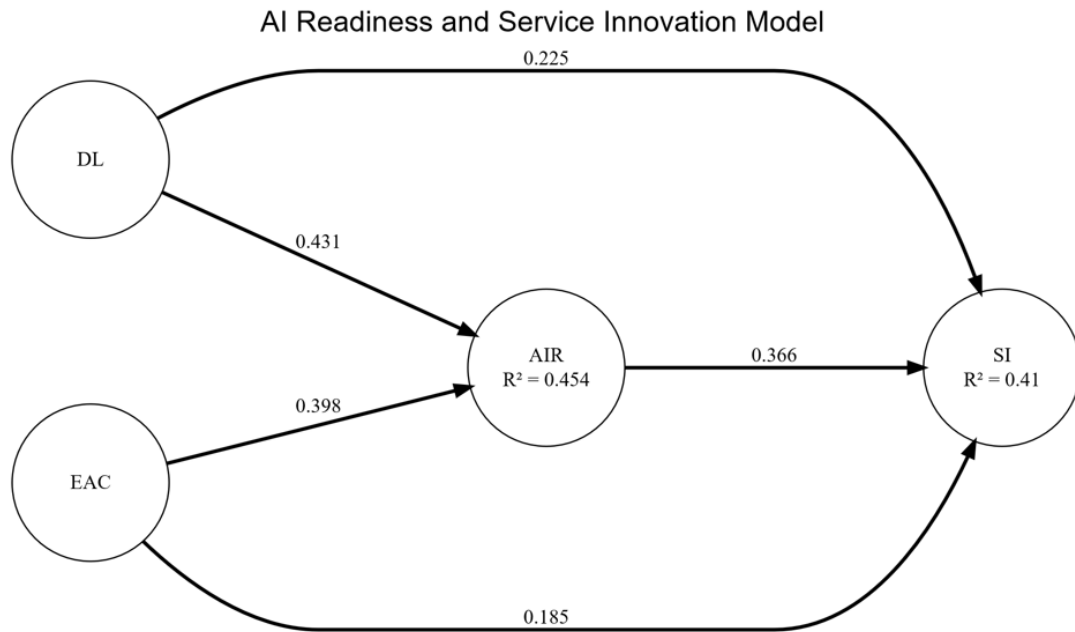


Figure 1: SEM Model Structure of the Study

be aware of privacy, security, and ethical concerns. A company that has a high level of technology and poor staff strength can be left unfunctionally ready.

The direct impacts of digital leadership and employee with AI capability on service innovation were minor compared to impact on readiness (Hossain *et al.*, 2025). This is a theoretically significant difference. New ideas could be fostered by leadership and employee capability; however, they could not be permanent services unless there are organisational arrangements. It needs data access, system integration, technical support, funding and governance. These findings thus draw a line between the presence of both strategic and human resources and the ability to convert these resources into administrative change.

The positive influence of AI readiness on innovation of services was strong (Li & Gu, 2025). This observation justifies the importance of readiness as central to the model. An organisation that is prepared is able to go beyond the solitary digital practices and bring about organised service enhancements. It is able to tie technologies to current processes, create responsibility, and uphold service quality (Rahman & Parvin, 2024a). Implementation uncertainty can also be mitigated by the preparedness since the employees are aware of where they can get support and the manner in which new systems will be led.

The mediation results give the most obvious evidence to support the proposed mechanism. The impacts of both digital leadership and employee AI capability were mediated by AI preparedness partially. The mediation was complementary due to the significant and positive effect of both direct and indirect effects (Saini, 2025). Leadership and employee capability thus impacted innovation in two ways. They both directly and indirectly

contributed to new service practices by enhancing the foundation of implementation in the organisation.

Both associations had a significant mediated proportion. The proportion of the digital leadership on services innovation and the proportion of the employee AI capability effect on service innovation were 41.20 percent and 44.05 percent accountable by AI preparedness, respectively. Such values demonstrate that preparedness is not a trifling statistical bridge. It is a key organisational procedure (Mazumder & Hossain, 2024). Reform initiatives by the public sector that involve a one-sided investment in leadership advocacy or brief training programmes can thus deliver minimal results when gaps in readiness are not bridged.

The model had a moderate explanatory power. A combination of digital leadership and employee capability accounted for 45.4% of the variance in AI readiness. The three predictors accounted 41.0 % of the variation of service innovation (Gazi *et al.*, 2024). These values are useful in the context of organisational research where organisational results are determined by numerous institutional and environmental conditions. They also indicate that the model does not purport to describe all the sources of innovation (Islam *et al.*, 2025). Additional explanatory value may be offered by policy pressure, demand by citizens, interagency cooperation, procurement systems, political support, legal frameworks and organisational culture.

The structural findings are reinforced by the predictive results. All the Q2 predict values were positive and the PLS model gave lower RMSE values compared to the benchmark of all the endogenous indicators. The model thus proved to possess predictive utility in the simulated sample configuration (Del Barone *et al.*, 2026). This matters as statistically significant coefficients may not

always result in helpful prediction. In this case, explanatory and predictive tests were on the same direction.

These findings cannot be treated as established facts about the existing Bangladeshi public agencies since the dataset is artificial (R. & Archana, 2025). They are useful in the development of models. They demonstrate that a construct structure, a questionnaire, and an analytical sequence can help to create a stable and interpretable PLS-SEM model. The research framework can be used in a future field study to investigate whether this pattern is also observed between real officials of various levels of administration.

Theoretical and Practical Implications

The model is also relevant to the research on AI-readiness as it provides a separation of strategic, human, institutional, and service outcomes. Enabling resources are digital leadership and employee AI capability. The organisational mechanism transforming those resources into innovation is considered AI readiness (Lentejas *et al.*, 2023). This difference explains why support of leadership or talent in employees might not work in case information, infrastructure, governance, and coordination continue to be poor.

The results imply a moderated preparedness approach to public-sector managers. Digital vision, ethical governance, interdepartmental coordination and resource planning should be incorporated in leadership development. The development of employees should be integrated with fundamental AI literacy and practical experience, assessment of output, privacy concerns, and responsible judgement. The training does not have to emphasize the operation of tools only.

AI preparedness ought to be evaluated prior to the mass scale implementation. Infrastructure, data quality, technical support, legal safeguards, procurement capacity, and process integration are some of the areas that can be audited as preparedness by public organisations (Sikder, 2023). The implementation of weak areas should be phased. The pilot projects must start with administrative issues that are well defined and service outputs that can be measured.

The results also indicate that service innovation is the last policy goal that should be maintained. Adoption of AI is not to be regarded as success on its own. The question that public agencies need to consider is that the use of AI-assisted changes should enhance speed, accuracy, transparency, accessibility, and citizen responsiveness (David, 2024). This results-focused structure is capable of decreasing the CSR as a symbolic practice and promoting responsible investment.

Central direction in the system must be coupled with organisational adaptability. Security, accountability, interoperability, and procurement can be facilitated with the aid of shared standards. Applications should in turn be adjustable to the service duties, manpower size, and local conditions by individual agencies.

Limitations and Future Research

The major weakness is the utilization of artificial information. The findings support the analytical design but fail to determine the true preparedness of the Bangladesh population administration. The field study is required to gather the responses of the ministries, departments, directorates, regulatory agencies, the district administration, and the local government institutions.

The cross-sectional model is also a single point in time. Longitudinal data could be used to investigate the nature of the readiness that occurs prior to innovation in future research. Other variables can be data governance, organisational culture, institutional trust, regulatory clarity, political support and citizen pressure (Bhat, 2025). The multigroup analysis may make comparisons within the administrative levels, type of organisations, training status or previous use of AI. Qualitative interviews can also be used to understand why documenting differences in ability to transform digital resources into service improvements exist in similar organisations.

Nonresponse bias, measurement invariance, and any possible endogeneity should also be tested in future field applications. Such processes would reinforce causal interpretation and demonstrate the existence of consistency in the functioning of the proposed scales among large groups within the public service.

CONCLUSION

In this work, I have been able to construct a PLS-SEM model to analyze the artificial intelligence preparedness and service innovation within the framework of the public administration in Bangladesh. The model related digital leadership, employee AI capability, and AI readiness to service innovation in five direct relationships and two mediating relationships.

The results of the simulation were in favor of all seven hypotheses. AI readiness was enhanced by digital leadership and employee AI capability. Service innovation was also supported by each of the constructs directly. AI readiness had another beneficial impact and mediated both antecedent relationships to a certain extent. The model had a moderate predictive relevance and explanatory power.

The main conclusion is that the AI transformation in the public sector cannot rely only on acquiring the technology. Leadership should offer direction, resources, organization as well as moral direction. Workers should have the adequate ability to comprehend, judge, and use AI systems in a responsible manner. A conversion of these resources to readiness is then required by organisations in terms of infrastructure, data, governance, technical support and process integration.

The framework offers a foundation of future empirical research. The following step of it has to utilize authenticated field information of government officials within Bangladesh. Until that time, such findings must be regarded as a methodological demonstration as opposed

to demonstrating administrative conditions. Despite this, the model indicates the worth of AI preparedness as the mediator between management, staff potential and service creativity.

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