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# Artificial Intelligence Readiness and AI Adoption among Small and Medium Enterprises in Bangladesh

Md Masud Rana[1*], Shree Sujit Kumar Das[1], Srikanto Mondal[2]

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## ABSTRACT

AI is viewed as a tool that is suitable for SMEs, however, it might not be feasible unless SMEs have the technological, organizational, human and environmental conditions to enable its implementation. This study investigates how to define AI readiness and its contribution to explaining the adoption of AI within the SME context in Bangladesh. 310 SME decision makers responded and provided valid answers to the survey. Structural equation modelling was used to test the proposed model. Results of the measurement models showed good model fit, factor loadings, internal consistency, convergent validity, and discriminant validity. Fit of the structural model was also excellent. Within the four constructs, technological readiness, organisational readiness, human-capital readiness, and environmental readiness all had positive and statistically significant impacts on overall AI readiness. An overall high AI readiness positively affected the adoption of AI. Another mediation analysis revealed that overall, AI readiness was a significant mediator of all four dimensions of readiness and adoption. Overall, AI readiness and AI adoption was explained by 53.2% and 45.4% of the variance in the model, respectively. The results clearly identify that the-AI readiness factor serves as a pivotal central organisational mechanism that transforms resources, capabilities, people, and conditions into implementing AI in operations. The research provides a comprehensive approach for SME digital transformation in emerging economies.

## INTRODUCTION

AI is no longer a new technology, but rather a operational tool that can revolutionize the way companies analyze data, interact with customers, predict demand, manage quality, identify risks and allocate resources. This change comes as a significant strategic opportunity for small and medium business entities (Hasan *et al.*, 2023). AI-based solutions can make up for small management capacity, speed up the time for making routine decisions, reduce information processing costs, and provide larger and more sophisticated analytics capabilities for smaller companies which are unable to maintain large expert teams (Zoubi *et al.*, 2023). But AI tools do not ensure effective adoption. SMEs need also to be equipped with appropriate ICT fabric, good quality data, managerial willing stakeholders, financial resources and ICT support, skilled employees, implementation partners, business environment that supports the use of ICT. The key issue is, whether an enterprise is prepared to move from AI availability to use in the organisation.

SMEs are often characterised by limited capital, uneven digital prowess, informal management systems and a lack of access to higher technical skills. Adopting under these circumstances can lead to unequal adoption (Ingalagi *et al.*, 2021). While some companies quickly transition from experimentation to integration, others stay in the planning phase despite the fact that they know the strategic importance of AI. SMEs in Bangladesh play a role in employment, entrepreneurship, supply chain and regional economic activities. Knowing why some enterprises are more ready to invest in technology than others can lead to better technology policy, more effective managerial investment and better planned capability-development programmes (Drydakis, 2022). A readiness perspective is beneficial because it combines both internal and external factors and not just a technological decision.

The present study considers AI readiness as a multidimensional state of the organisation. Four antecedent dimensions are explored. Technological readiness relates to infrastructure, systems integration, data quality, security and compatibility of existing processes (Lemos *et al.*, 2025). Organisational readiness refers to the commitment of senior management, organisational direction, financial resource allocation, innovative culture and cross functional cooperation. Human-capital readiness translates to employee knowledge, skills, the willingness to learn, employee training, and collaborative attitudes towards AI. Environmental readiness is seen as access to technology providers, implementation support, competitive pressure, and customer expectations, as well as supporting institutional conditions. These dimensions are likely to impact the enterprise's overall artificial intelligence readiness and, in turn, determine how widely AI is integrated with enterprise business, processes, analyses, and Digital development strategy (Sortino & Eggert, 2022).

The study also considers overall readiness to use AI

[1] MBA, School of Economics and Management, Chang'an University, China
[2] School of Economics and Management, Master's Student, Chang'an University, Xi'an, Shaanxi Province, 710064, China
[*] Corresponding author's e-mail: mdmasudrana94k@gmail.com

as a mediating mechanism. This is important because the four readiness dimensions might not only have direct impacts on adoption. Potential comes from infrastructure, legitimacy for investment comes from leadership, implementation capacity comes from people, and pressure and support come from external factors (Omrani *et al.*, 2024). However, these factors need to come together in an enterprise-ready state of readiness for widespread adoption to be possible. Thus, mediation offers a better account of how conditions and resources that are diffused get converted into implementation. The model incorporates and examines whether technological, organisational, human-capital and environmental readiness first enhance the overall AI readiness and if this readiness boosts AI adoption.

Survey responses from 310 valid SME were generated and the measure quality of the six constructs, along with the structural relationship of the constructs was evaluated by means of structural equation modelling. Analysis of Data Quality, Respondent Profiles, Descriptive Patterns, CFA, Reliability, Convergent Validity, Discriminant Validity, Global Model Fit, Direct Structural Paths, and Explained Variance and Mediated Effects are examined (Doe *et al.*, 2022). One of the key contributions of the study is an integrated empirical description of the adoption of AI in SMEs that highlights the gap between enabling conditions and operational application: overall readiness. It is also a useful logic for diagnostics for managers and policy actors: it is important to strengthen individual capabilities, but becoming more ready to implement policies is more likely if multiple capabilities can be combined to create a coherent state of organisational readiness (Adu *et al.*, 2022).

## LITERATURE REVIEW

### AI Readiness and AI Adoption

Adopting AI is not just a purchasing decision, but a change in the whole organisation. AI systems rely on data, digital connections, process reengineering, managerial decision-making, employee training, governance, and seeking external expertise (Saweo, 2023). SMEs encounter specific problems as this is generally required with lower budgets and less availability of specialist talent. Readiness thus represents how much a company has put in place the conditions needed to go from the awareness or experimentation of a service to its frequent and purposeful utilization. Readiness requires a balance of organisation capacity.

Overall, AI readiness can be thought of as the enterprise's collective capability to take up, engage in, absorb the change, manage the risks and generate the business values of introducing AI. It's wider than intent. The difference between intention and readiness lies in the ability to do something and the willingness to do so. In addition to this, the overall readiness differs from the adoption (Govori & Sejdija, 2023). A firm might be ready to adopt even without AI being used throughout the operations, and might be using one or two AI tools without the ability it needs to sustain scaling. In separating readiness from adoption, it is thus possible to explain more precisely how the transition from enabling conditions to actual use takes place (Chaudhuri *et al.*, 2022). Adoption is captured in the extent to which the technology is applied to operations, integrated into routine practices, provides support for managerial decision-making, expanded use cases, intentions to scale the technology in the future, and the perceived strategic importance of AI for digital development (Chen, 2024).

### Technological Readiness and Overall, AI Readiness

Technological readiness is the technical part of the foundation of AI implementation. SMEs need digital infrastructure, they need information systems that can communicate with new tools and they need information properly organised for analysis, prediction and use in AI tools (Binsaeed *et al.*, 2023). Data security and privacy controls also play a major role, as the application of AI often increases the amount of data collected, its sensitivity, and circulation within organisations. Compatibility is important, too. The lower the effort required to integrate new tools into existing processes, the lower the cost and easier to manage. Technological limitations lead to higher integration costs, data quality issues and other uncertainties, and a higher chance of pilots being left out of the normal course of action. Conversely, robust infrastructure, seamless integration, trustworthy data, and appropriate security measures enhance the viability of implementation and boost confidence in the opportunity to utilize AI responsibly and on a massive scale (Schkarin & Dobhan, 2022). As a result, technological readiness should lead to an increase in overall AI readiness.

**H1**: There is a positive and statistically significant relationship between technological readiness and overall AI readiness of SMEs of Bangladesh.

### Organisational Readiness and Overall AI Readiness

Organisational readiness refers to managerial and institutional circumstances which transform the technological feasibility into an authorized business endeavour. Since AI implementation is not the only thing on the plate, senior management needs to be seen as supportive (Naushad & M. M, 2020). A clear strategic direction guides employees to understand the importance and the right places of using AI. It's crucial to be ready for the financial aspect too, as implementation may include software licenses, system integration, data readiness, outside guidance, training, and process re-engineering. A culture that is oriented towards innovation further decreases the perceived cost of experimentation through the encouragement of learning and the notion of a controlled trial (Firmansyah *et al.*, 2022). Because AI applications often overlap various functions, such as operations, finance, marketing, customer service, and technology, cross-functional collaboration is crucial. Strategic direction, resources, and coordination from leaders help employees perceive AI as more of an organisational imperative than a fleeting innovation (Qu *et al.*, 2021).

**H2**: Organisational readiness positively and statistically significantly influences the overall AI readiness of SMEs in Bangladesh.

**Human-Capital Readiness and Overall AI Readiness**

Human-capital readiness includes knowledge, skills, learning orientation, and attitudes needed for working with AI enabled systems. The employees don't need to be data scientists, but they do need to know how to use the output, understand when there are boundaries of what can be achieved and communicate with technical specialists, and be able to alter processes when technology changes the boundaries of the tasks (Ahmed, 2022). Technical & Analytical expertise is particularly critical if SMEs have small in-house teams or external providers. Through training uncertainty can be reduced and confidence strengthened, while a learning mindset enables ongoing adjustment to changes in systems. Implementation is also impacted by employee attitudes (Zamani, 2022). Even in the face of robust technical conditions, resistance can impede adoption if AI is viewed as a job threat or a job replacement, or if it's viewed as an infringement on one's professional autonomy. Employees see AI as an opportunity, and they are provided with sufficient development—then, the more the organisation is able to take in new technology (Benabed *et al.*, 2022).

**H3**: Human-capital readiness is positively and significantly related to overall AI readiness of the SMEs in Bangladesh.

**Environmental Readiness and Overall AI Readiness**

Environmental readiness reflects conditions that are either facilitating or inhibiting adoption outside of the enterprise. SMEs rely on technology vendors, consultants, cloud providers, training organisations and industry partners to provide capabilities that they do not have the cost-effective capacity to support within their own organization (Bharadiya, 2023). Learning cycles can be shortened and implementation complexity can be reduced due to access to reliable providers. Additionally, competitive pressure can create a sense of urgency around the adoption, especially when competitors leverage AI to enhance their responsiveness, personalization, forecasting, or cost control (Nasrollahi *et al.*, 2021). There is a corollative pressure on the demand side, as customers demand digital service, quick customer support, customized communication, and data-driven transparency. Adoption can be further impacted by government policy and institutional programmes, including infrastructure, incentives, standards, skills and regulation. So it's an environment that boosts opportunity and confidence (Sani *et al.*, 2022).

**H4**: There is a positive and statistically significant relationship between environmental readiness and overall AI readiness among SMEs of Bangladesh.

**Overall AI Readiness and AI Adoption**

This framework's main thesis is that the overall AI readiness directly influences adoption. Organisations that are onboarding AI, have a plan around implementation, understand organisational change, manage risk and understand how to achieve business value from AI should be more open to integrating AI tools in their business (Upadhyay *et al.*, 2023). Readiness decreases the amount of uncertainty about feasibility, and provides management with a firmer foundation for committing resources to the expanded use. It also provides for continuity between pilot projects and routine operations. An enterprise could try out a stand-alone chatbot or generative AI without altering its broader digital course (Atieh *et al.*, 2023). A ready enterprise, on the other hand, is better equipped to embed AI in decision processes, expand applications of AI across functions, and embed AI in digital strategy.

**H5**: The overall AI readiness positively and statistically affects AI adoption by SMEs in Bangladesh.

**Mediating Role of Overall AI Readiness**

The four antecedent dimensions are also likely to have a mediating effect on readiness, which in turn affects adoption. The logic behaves sequentially (Sharma *et al.*, 2024). Technological resources increasing the feasibility of implementation, organisational support giving strategic legitimacy and resources, Human capital offering operational competence and environmental conditions offering support, pressure and external capabilities (Hasan *et al.*, 2023). The most important and effective are those that first of all foster a coherent organisational state in which the firm is ready to implement, manage change, deal with risk and reap value. This mediating role prevents adoption being a de facto reaction to single resources (Zoubi *et al.*, 2023).

**H6**: AI readiness significantly mediates the relationships between the individual readiness dimensions and AI adoption among SMEs in Bangladesh.

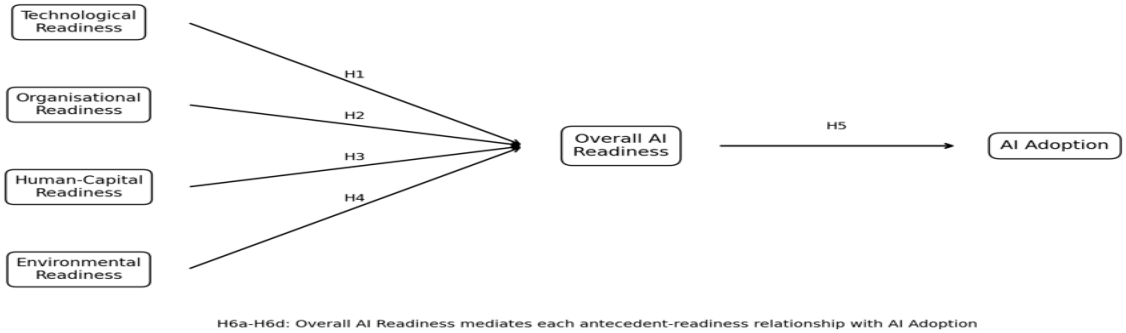



**Figure 1**: Conceptual Framework of AI Readiness and AI Adoption

## MATERIALS AND METHODS

### Research Design and Respondent Eligibility

A quantitative, cross-sectional survey design was used in this study to explore the relationships between variables of AI readiness, overall AI readiness and AI adoption in Bangladeshi SMEs. This design was suitable, as it was research model in which there are number of latent constructs for which several observed indicators were used for measuring and there was need for simultaneous estimation of direct and indirect relationships (Drydakis, 2022). The main method employed was structural equation modelling. The unit of response comprised an informed representative from an SME, not an anonymous employee who does not have decision making capacity (Wong *et al*., 2024). Participants were eligible if they were owners, managers, supervisors, executives, or decision makers in a technology or AI related area within the enterprise and had been there for over 6 months. These screening conditions were designed to make sure that the responses addressed the organisational and not general views on AI.

### Sample and Data Screening

A final, valid analytical data set of 310 was received. There were no missing measurement values nor were there any duplicate responses; all 310 initial responses were retained during data screening (Hossin *et al*., 2021). The range of observed item scores was near the expected 5-point range. The skewness values were between -1.140 and -0.596 and kurtosis values were between -0.609 and 0.654, suggesting no significant distribution issues with measured items. Respondents from various age groups, levels of education, jobs and period of service were included in the sample (Sortino & Eggert, 2022). The participating firms also differed in terms of their sector, enterprise age, number of employees, geographical dimension, the level of AI use, and the main applications of AI. This heterogeneity was helpful since the purpose of the study was to understand readiness and adoption within a broad SME context and not in any one given industry or organization (Omrani *et al*., 2024).

### Measurement Instrument

The questionnaire included demographic and enterprise-profile questions, and multi-item measures to assess six constructs. The scores for the measurement items were on a 5-point Likert scale from strongly disagree (1) to strongly agree (5). Technological readiness was assessed using five items, pertaining to digital infrastructure, systems integration, data availability, security and privacy and compatibility with business processes (Doe *et al*., 2022). Organisational readiness was assessed with five items that focused on senior-management commitment, financial resources, innovation-supportive culture, strategic vision and interdepartmental cooperation. Human-capital readiness included five items that assessed digital knowledge, access to technical or analytical knowledge, willingness to learn, training provision and positive employee attitudes towards AI. Environmental readiness was measured with 5 items including vendor access, partner support, competitive pressure, customer expectations and institutional support.

### Construct Operationalisation

The overall level of AI readiness was determined by five items, each reflecting a degree of preparedness to introduce AI, capability to manage in the implementation process, capability to manage changes in organisation, preparedness to deal with risk and uncertainty, and readiness to get business value. Six items were used to measure AI adoption. These evaluated current use of AI enabled tools, integration into current processes, management analysis and decision making, extension of applications over time, desire for more extension of AI across other functions, and importance of AI as part of the enterprise digital-development strategy (Saweo, 2023). Thus, the measurement structure separated the antecedent capabilities that bring readiness from the readiness itself on the enterprise level and the subsequent degree of AI use.

### Measurement-Model Assessment

The staged SEM for the empirical analysis was followed. Data quality and distributional characteristics were initially evaluated. Then, the respondent and enterprise profiles were summarised with frequencies and percentages, and the general level of readiness and adoption, with construct level means and standard deviations (Govori & Sejdija, 2023). Secondly, confirmatory factor analysis was performed to test the measurement model. Chi-square, degrees of freedom, ratio of chi-square to degrees of freedom, Comparative Fit Index, Tucker-Lewis Index, Root Mean Square Error of Approximation and Standardized Root Mean Square Residual were calculated to assess the global model fit. The standardised factor loadings, standard errors, z-values and significance levels were checked to ensure that each item was a good representation of its latent construct.

### Reliability and Validity Assessment

Thirdly, reliability and validity were examined prior to interpreting structural relationships. The internal consistency was measured by Cronbach's alpha and composite reliability. Convergent validity was determined using the Average Variance Extracted (AVE) and the size and significance of the factor loadings. The heterotrait-monotrait ratio matrix was used to measure the discriminant validity (Chen, 2024). A good measurement quality was assumed as necessary for structural interpretation. The measurement model was accepted and the structural model was estimated to test H1-H5. To compare the relative strength of the effects, standardised beta coefficients were used and statistical significance and the precision of the estimates were determined by

measuring the unstandardised estimates, the standard errors, the z-values, the p-values and the confidence intervals.

**Procedural and Ethical Considerations**

Participation was presented as voluntary and information to be used for academic purposes only. No individual respondent or enterprise was envisaged to be identified in the research report. This was significant due to the fact that respondents had to assess their internal capabilities, management commitment, data practices, workforce competence, and existing AI utilization (Chaudhuri *et al.*, 2022). Furthermore, the questionnaire was constructed with item codes that were simple and clear for each construct, as well as a consistent response scale, thus facilitating the process of preparing data and specifying the model. The reported data set was used for analytical decisions and not a retroactively adjusted conceptual framework. This ensured consistency between the research questions, measurement instrument, hypotheses, and structural paths, and only minimized the danger that the interpretation is based on separate statistical results rather than the theory proposed in the hypotheses.

**Structural Model and Mediation Testing**

The explanatory power of the model was tested by means of coefficient of determination of the two endogenous constructs overall AI readiness and AI adoption. H6a to H6d were tested by conducting mediation analysis using overall AI readiness as a mediator. Standard errors, z-values, p-values and confidence intervals were used to evaluate indirect-effect significance (Binsaeed *et al.*, 2023). This was considered to be supporting evidence for a hypothesis if the estimated effect was positive and statistically significant, and if the direction of the effect was as predicted in the hypothesis. The analysis hence presented a measurement validation analysis, structural-path testing, explained variance, and mediation assessment that was all integrated into one single analytical framework.

## RESULTS AND DISCUSSION

The results are presented in the order that the SEM was used. Construct descriptives and assessment of measurements are provided after data screening and sample characteristics (Schkarin & Dobhan, 2022). Evidence of reliability and validity is then examined, followed by the interpretation of fit of the structural-model, direct hypotheses, explained variance and mediation effects. Immediately after each table is a description of the statistics reported.

**Data Screening**

Table 1 shows a data set for analysis that is clean. There were no missing measurement values or duplicated responses and all 310 initial responses were valid, thus no case deletion or imputation was necessary. The item scores remained within the range (1–5) desired for the items. Distributional diagnostics were also good. Reported ranges of skewness and kurtosis were within the acceptable limits which mean that the responses observed were not too skewed or too peaked. These results are adequate for the next steps in the SEM analysis

**Table 1**: Data Screening Results

| Assessment | Result | Criterion | Decision |
|---|---|---|---|
| Initial responses | 310 | Reported | Reported |
| Valid responses | 310 | Reported | Reported |
| Missing measurement values | 0 | No serious missingness | Acceptable |
| Duplicate responses | 0 | No duplicate responses | Acceptable |
| Minimum item score | 1 | At least 1 | Acceptable |
| Maximum item score | 5 | Not more than 5 | Acceptable |
| Skewness range | -1.14 to -0.596 | Between -2 and +2 | Acceptable |
| Kurtosis range | -0.609 to 0.654 | Between -7 and +7 | Acceptable |

**Respondent Profile**

The demographic profile indicates that the majority of the respondents, namely 70.65 % were males and females made up the remaining 26.45 %. The largest age group was 25-34 years at 40.97%, followed by 35-44 years at 32.90%. The majority of the respondents were bachelor's

**Table 2:** Respondents' Demographic Profile

| Variable | Category | Frequency | Percentage |
|---|---|---|---|
| Gender | Male | 219 | 70.65 |
| Gender | Female | 82 | 26.45 |
| Gender | Prefer not to disclose | 3 | 0.97 |
| Gender | Other | 6 | 1.94 |
| Age Group | Below 25 years | 21 | 6.77 |

| | | | |
|---|---|---|---|
| Age Group | 25-34 years | 127 | 40.97 |
| Age Group | 35-44 years | 102 | 32.90 |
| Age Group | 45-54 years | 47 | 15.16 |
| Age Group | 55 years and above | 13 | 4.19 |
| Education | Secondary or below | 23 | 7.42 |
| Education | Higher secondary | 27 | 8.71 |
| Education | Diploma | 19 | 6.13 |
| Education | Bachelor's degree | 145 | 46.77 |
| Education | Master's degree | 85 | 27.42 |
| Education | Doctoral or professional qualification | 11 | 3.55 |
| Position | Owner or entrepreneur | 99 | 31.94 |
| Position | Chief executive or director | 15 | 4.84 |
| Position | Senior manager | 60 | 19.35 |
| Position | Middle-level manager | 75 | 24.19 |
| Position | Supervisor or executive | 35 | 11.29 |
| Position | IT or technology officer | 24 | 7.74 |
| Position | Other | 2 | 0.65 |
| Service Length | Less than 1 year | 32 | 10.32 |
| Service Length | 1-3 years | 114 | 36.77 |
| Service Length | 4-6 years | 93 | 30.00 |
| Service Length | 7-10 years | 44 | 14.19 |
| Service Length | More than 10 years | 27 | 8.71 |

and master's degree holders. Owners/entrepreneurs (31.94%), middle-level managers (24.19%) and senior managers (19.35%) were the largest position categories in order. The focus in terms of service length was on companies of one to six years with a wide managerial spectrum that represents a comparatively old organisation with a sufficient number of years of exposure to assess the firm's technology related capabilities (Schkarin & Dobhan, 2022).

**SME Profile**

The biggest two sectors were retail or wholesale and manufacturing, but also included were information technology, professional services, agriculture, logistics, hospitality, healthcare, education and other services. Majority of the firms were not newly created, but rather established with 32.26% of the firms being 6-10 years old and 30.33% of the firms more than 10 years old. The majority of employee size was between 10 and 99 employees. Amongst the areas, Dhaka (45.48%) and Chattogram (19.35%) had the highest shares of firms, all divisions were duly represented. The use of AI was relatively mature in the sample analysed. Fifty percent of the firms reported extensive operational use and 23.87% of the firms reported limited operational use. Marketing and sales topped the list, accounting or financial analysis

**Table 3**: Profile of Participating SMEs

| **Variable** | **Category** | **Frequency** | **Percentage** |
|---|---|---|---|
| Sector | Manufacturing | 54 | 17.42 |
| Sector | Retail or wholesale | 56 | 18.06 |
| Sector | Information technology | 42 | 13.55 |
| Sector | Financial or professional services | 43 | 13.87 |
| Sector | Agriculture or agro-processing | 33 | 10.65 |
| Sector | Hospitality and tourism | 16 | 5.16 |
| Sector | Transportation and logistics | 27 | 8.71 |
| Sector | Healthcare | 13 | 4.19 |
| Sector | Education | 13 | 4.19 |
| Sector | Other services | 13 | 4.19 |
| Enterprise Age | Less than 3 years | 39 | 12.58 |
| Enterprise Age | 3-5 years | 77 | 24.84 |

| | | | |
|---|---|---|---|
| Enterprise Age | 6-10 years | 100 | 32.26 |
| Enterprise Age | 11-15 years | 49 | 15.81 |
| Enterprise Age | More than 15 years | 45 | 14.52 |
| Employee Size | Fewer than 10 employees | 28 | 9.03 |
| Employee Size | 10-24 employees | 73 | 23.55 |
| Employee Size | 25-49 employees | 85 | 27.42 |
| Employee Size | 50-99 employees | 79 | 25.48 |
| Employee Size | 100-249 employees | 40 | 12.90 |
| Employee Size | 250 employees or more | 5 | 1.61 |
| Division | Dhaka | 141 | 45.48 |
| Division | Chattogram | 60 | 19.35 |
| Division | Rajshahi | 25 | 8.06 |
| Division | Khulna | 31 | 10.00 |
| Division | Barishal | 9 | 2.90 |
| Division | Sylhet | 22 | 7.10 |
| Division | Rangpur | 9 | 2.90 |
| Division | Mymensingh | 13 | 4.19 |
| AI Use Level | No AI use | 9 | 2.90 |
| AI Use Level | Planning to use AI | 32 | 10.32 |
| AI Use Level | Experimenting or piloting | 39 | 12.58 |
| AI Use Level | Limited operational use | 74 | 23.87 |
| AI Use Level | Extensive operational use | 156 | 50.32 |
| Primary AI Application | Customer service or chatbots | 44 | 14.19 |
| Primary AI Application | Marketing and sales | 55 | 17.74 |
| Primary AI Application | Accounting or financial analysis | 45 | 14.52 |
| Primary AI Application | Inventory and supply-chain management | 33 | 10.65 |
| Primary AI Application | Human resource management | 24 | 7.74 |
| Primary AI Application | Production or quality control | 19 | 6.13 |
| Primary AI Application | Cybersecurity or fraud detection | 28 | 9.03 |
| Primary AI Application | Business forecasting and decision support | 31 | 10.00 |
| Primary AI Application | Generative AI tools | 22 | 7.10 |
| Primary AI Application | No current application | 9 | 2.90 |

followed, then the customer service and chatbots. This sample was then a mix of different adoption phases and fields of applications.

**Descriptive Statistics**

For each of the six constructs, mean levels were found to be near and/or greater than 4.00 on the five-point scale, reflecting overall high levels of readiness and adoption. The mean of the organisational readiness was highest (4.103) with particularly high perceptions of management commitment, strategic direction, resource support, innovation orientation, and organisational cooperation. Environmental readiness averaged 4.046 and human-capital readiness averaged 4.014. Technological readiness,

**Table 4**: Descriptive Statistics of the Constructs

| Construct | Code | Items | Mean | Standard Deviation | Interpretation |
|---|---|---|---|---|---|
| Technological Readiness | TR | 5 | 3.978 | 0.813 | High |
| Organisational Readiness | OR | 5 | 4.103 | 0.833 | High |
| Human-Capital Readiness | HR | 5 | 4.014 | 0.899 | High |
| Environmental Readiness | ER | 5 | 4.046 | 0.833 | High |
| Overall AI Readiness | AIR | 5 | 3.935 | 0.813 | High |
| AI Adoption | AIA | 6 | 3.946 | 0.846 | High |

overall AI readiness and AI adoption had a mean of 3.978, 3.935, and 3.946 respectively. The standard deviations varied from 0.813 to 0.899. The pattern indicates that the readiness dimensions are reasonably well balanced and there is some variation which allows for modelling in multivariate packages (Firmansyah *et al.*, 2022).

**Measurement-Model Fit**

Confirmatory factor analysis yielded excellent measurement-model fit. The ratio of chi-square to degrees-of-freedom was 1.122, less than the accepted value of 3.00. CFI was 0.988 and TLI was 0.987 both well over 0.90. RMSEA was found to be 0.020 and SRMR was 0.040, both of which are well below the criterion of 0.08. These indices as a whole show that the proposed six factor measurement structure very well recapitulated the observed covariance pattern. The fit evidence can be followed by subsequent reliability, validity and structural testing.

**Table 5**: Measurement Model Fit

| Fit Index | Obtained Value | Recommended Value | Decision |
|---|---|---|---|
| Chi-square | 470.023 | Reported | Reported |
| Degrees of freedom | 419 | Reported | Reported |
| Chi-square/df | 1.122 | < 3.00 | Acceptable |
| CFI | 0.988 | > 0.90 | Acceptable |
| TLI | 0.987 | > 0.90 | Acceptable |
| RMSEA | 0.020 | < 0.08 | Acceptable |
| SRMR | 0.040 | < 0.08 | Acceptable |

**Factor Loadings**

All the measurement items loaded significantly onto their respective constructs as shown in the standardised loadings. Loadings varied between 0.656 and 0.819 with each being statistically significant at $p < 0.001$. Technological readiness loadings were between 0.656 and 0.750; organisational readiness loadings, 0.702 and 0.786; human-capital readiness loadings, 0.752 and 0.819; environmental readiness loadings, 0.698 and 0.774; overall AI readiness loadings, 0.689 and 0.748; and AI adoption loadings, 0.691 and 0.756. HR2 performed the highest individual loading of 0.819 with HR4 next at 0.816. The loading pattern demonstrates that the constructs have been adequately represented by each of the items.

**Table 6**: Standardised Factor Loadings

| Construct | Item | Std. Loading | SE | Z | p | Decision |
|---|---|---|---|---|---|---|
| TR | TR1 | 0.727 | 0.036 | 20.429 | <0.001 | Retained |
| TR | TR2 | 0.724 | 0.036 | 20.329 | <0.001 | Retained |
| TR | TR3 | 0.656 | 0.046 | 14.406 | <0.001 | Retained |
| TR | TR4 | 0.750 | 0.034 | 22.236 | <0.001 | Retained |
| TR | TR5 | 0.712 | 0.039 | 18.197 | <0.001 | Retained |
| OR | OR1 | 0.786 | 0.030 | 25.900 | <0.001 | Retained |
| OR | OR2 | 0.731 | 0.037 | 19.980 | <0.001 | Retained |
| OR | OR3 | 0.702 | 0.040 | 17.617 | <0.001 | Retained |
| OR | OR4 | 0.776 | 0.036 | 21.658 | <0.001 | Retained |
| OR | OR5 | 0.729 | 0.038 | 19.224 | <0.001 | Retained |
| HR | HR1 | 0.752 | 0.031 | 24.461 | <0.001 | Retained |
| HR | HR2 | 0.819 | 0.027 | 30.162 | <0.001 | Retained |
| HR | HR3 | 0.769 | 0.031 | 24.678 | <0.001 | Retained |
| HR | HR4 | 0.816 | 0.025 | 33.201 | <0.001 | Retained |
| HR | HR5 | 0.761 | 0.029 | 26.274 | <0.001 | Retained |
| ER | ER1 | 0.698 | 0.037 | 19.054 | <0.001 | Retained |
| ER | ER2 | 0.774 | 0.035 | 21.964 | <0.001 | Retained |
| ER | ER3 | 0.719 | 0.037 | 19.388 | <0.001 | Retained |
| ER | ER4 | 0.766 | 0.030 | 25.410 | <0.001 | Retained |
| ER | ER5 | 0.735 | 0.036 | 20.612 | <0.001 | Retained |

| | | | | | | |
|---|---|---|---|---|---|---|
| AIR | AIR1 | 0.689 | 0.038 | 18.046 | <0.001 | Retained |
| AIR | AIR2 | 0.720 | 0.033 | 22.134 | <0.001 | Retained |
| AIR | AIR3 | 0.709 | 0.037 | 18.993 | <0.001 | Retained |
| AIR | AIR4 | 0.748 | 0.031 | 24.100 | <0.001 | Retained |
| AIR | AIR5 | 0.747 | 0.034 | 21.837 | <0.001 | Retained |
| AIA | AIA1 | 0.749 | 0.033 | 22.494 | <0.001 | Retained |
| AIA | AIA2 | 0.756 | 0.028 | 27.477 | <0.001 | Retained |
| AIA | AIA3 | 0.718 | 0.032 | 22.243 | <0.001 | Retained |
| AIA | AIA4 | 0.735 | 0.036 | 20.348 | <0.001 | Retained |
| AIA | AIA5 | 0.691 | 0.038 | 18.268 | <0.001 | Retained |
| AIA | AIA6 | 0.745 | 0.028 | 26.769 | <0.001 | Retained |

**Reliability and Convergent Validity**

All constructs had acceptable reliability and convergent validity. Cronbach's alpha and composite reliability ranged from 0.838 to 0.888 and 0.839 to 0.889 respectively. These values show good internal consistency with no sign of item over-repetition. The variance for all the constructs was greater than 0.50, which ranged from 0.511 for technological readiness to 0.615 for human-capital readiness. This finding revealed that human-capital readiness had the highest convergent-validity evidence, whereas, technological readiness had the lowest convergent-validity evidence, but still above the fixed benchmark (Qu *et al.*, 2021). All these numbers combined represent the measurement model of structural testing

**Table 7**: Reliability and Convergent Validity

| Construct | Cronbach's Alpha | Composite Reliability | AVE | Decision |
|---|---|---|---|---|
| TR | 0.838 | 0.839 | 0.511 | Acceptable |
| OR | 0.862 | 0.862 | 0.556 | Acceptable |
| HR | 0.888 | 0.889 | 0.615 | Acceptable |
| ER | 0.857 | 0.857 | 0.546 | Acceptable |
| AIR | 0.845 | 0.845 | 0.522 | Acceptable |
| AIA | 0.874 | 0.874 | 0.537 | Acceptable |

**Discriminant Validity**

The findings of HTMT matrix indicate clear evidence of discriminant validity. All inter-construct ratios were well below commonly used conservative thresholds. Values ranged from 0.075 to 0.660. The biggest ratio was between AI readiness overall and AI adoption. Even this was below the level that would suggest construct overlap. The ratios between the four antecedent readiness dimensions was especially low, indicating the empirical distinctness of the four readiness dimensions of technological, organisational, human-capital and environmental. All six constructs thus were kept as empirically different entities.

**Table 8**: HTMT Discriminant Validity

| Construct | TR | OR | HR | ER | AIR | AIA |
|---|---|---|---|---|---|---|
| TR | 1 | 0.130 | 0.119 | 0.163 | 0.488 | 0.410 |
| OR | 0.130 | 1 | 0.075 | 0.075 | 0.385 | 0.371 |
| HR | 0.119 | 0.075 | 1 | 0.096 | 0.425 | 0.175 |
| ER | 0.163 | 0.075 | 0.096 | 1 | 0.301 | 0.226 |
| AIR | 0.488 | 0.385 | 0.425 | 0.301 | 1 | 0.660 |
| AIA | 0.410 | 0.371 | 0.175 | 0.226 | 0.660 | 1 |

**Structural-Model Fit**

The overall fit of the structural model was also very good. The chi-square to degrees-of-freedom ratio was 1.138, CFI was 0.986, TLI was 0.985, RMSEA was 0.021, and SRMR was 0.046. All principal indexes were easily passed the stated acceptance criterion. Thus, on imposing the hypothesised direction of the relationships, the structure did not deviate from the observed data (Zamani, 2022). Thus, it was appropriate for the interpretation of structural effects and mediated effects.

**Table 9**: Structural Model Fit

| Fit Index | Obtained Value | Recommended Value | Decision |
|---|---|---|---|
| Chi-square | 481.364 | Reported | Reported |
| Degrees of freedom | 423 | Reported | Reported |
| Chi-square/df | 1.138 | < 3.00 | Acceptable |
| CFI | 0.986 | > 0.90 | Acceptable |
| TLI | 0.985 | > 0.90 | Acceptable |
| RMSEA | 0.021 | < 0.08 | Acceptable |
| SRMR | 0.046 | < 0.08 | Acceptable |

**Direct Effects and Hypothesis Testing**

All five direct hypotheses obtained were confirmed. Technological readiness was the strongest of the four antecedent predictors of overall AI readiness with a standardised beta of 0.393. Human-capital readiness came in at beta = 0.339, organisational readiness beta = 0.329 and environmental readiness beta = 0.199. All effects were statistically significant, with none of the reported confidence intervals containing zero. Thus, H1 – H4 were supported. Overall, AI readiness showed the highest structural influence on the model, with beta = 0.674, p< 0.001, predicting AI adoption. H5 was thus available. The ability to implement and gain insights from AI was consequently most closely linked with the climate of preparedness for adoption.

**Table 10**: Direct-Effect Hypothesis Testing

| Hypothesis | Relationship | Estimate | Std. Beta | SE | Z | p | CI Lower | CI Upper | Decision |
|---|---|---|---|---|---|---|---|---|---|
| H1 | TR -> AIR | 0.574 | 0.393 | 0.100 | 5.736 | <0.001 | 0.384 | 0.771 | Supported |
| H2 | OR -> AIR | 0.481 | 0.329 | 0.086 | 5.566 | <0.001 | 0.311 | 0.646 | Supported |
| H3 | HR -> AIR | 0.495 | 0.339 | 0.100 | 4.933 | <0.001 | 0.304 | 0.698 | Supported |
| H4 | ER -> AIR | 0.291 | 0.199 | 0.083 | 3.524 | 0.0004 | 0.135 | 0.457 | Supported |
| H5 | AIR -> AIA | 0.624 | 0.674 | 0.072 | 8.722 | <0.001 | 0.505 | 0.786 | Supported |

**Explanatory Power**

The model accounted for 53.2% of the variance in overall AI readiness. This is a significant amount of explanatory power for a model that relies on four conceptually distinct readiness antecedents and indicates that technological, organisational, human-capital and environmental factors all play an important role in enterprise-level readiness. This model accounted for 45.4% of the variance in the adoption of AI. While this is considered a weak value on the table, it singles out that by itself almost half of the variance in the adoption was due to overall AI readiness (Benabed *et al.*, 2022). The remaining variance is due to factors such as costs, regulation, risks, owner attributes and/or application-specific restrictions.

**Table 11**: Coefficient of Determination

| Endogenous Construct | Code | R-squared | Interpretation |
|---|---|---|---|
| Overall AI Readiness | AIR | 0.532 | Moderate |
| AI Adoption | AIA | 0.454 | Weak |

**Mediation Analysis**

All four indirect effects were positive and significant. Overall readiness had the largest mediated effect on the adoption of AI with 0.358 (technological readiness). The indirect effects of human-capital readiness was 0.309, organisational readiness was 0.301 and environmental readiness was 0.182. All p values were < 0.001 and none of the intervals included 0. Thus, it was supported that H6a-H6d are true. The mediation effects show that the four readiness dimensions impact adoption by contributing

**Table 12**: Mediation Analysis

| Hypothesis | Indirect Relationship | Indirect Effect | SE | Z | p | CI Lower | CI Upper | Decision |
|---|---|---|---|---|---|---|---|---|
| H6a | TR -> AIR -> AIA | 0.358 | 0.067 | 5.324 | <0.001 | 0.237 | 0.498 | Supported |
| H6b | OR -> AIR -> AIA | 0.301 | 0.063 | 4.792 | <0.001 | 0.186 | 0.434 | Supported |
| H6c | HR -> AIR -> AIA | 0.309 | 0.060 | 5.166 | <0.001 | 0.200 | 0.437 | Supported |
| H6d | ER -> AIR -> AIA | 0.182 | 0.054 | 3.377 | 0.0007 | 0.088 | 0.302 | Supported |

to the enterprise's overall readiness to implement AI successfully. Readiness thus functions to transform the individual dispersed enabling conditions into the capacity to adopt.

**Summary of Hypothesis Tests**

Empirical evidence fully supported the proposed framework as confirmed by the hypothesis summary. The direct relationships (H1-H5) were supported and the indirect ones (H6a-H6d) were supported through the overall AI readiness. The pattern is theoretically coherent because each of the antecedent dimensions has a contribution to readiness; and the contribution to readiness is strong and also predicts adoption; and the indirect paths are statistically significant (Nasrollahi *et al.*, 2021). The evidence points to a whole-of-the-enterprise perspective, where several readiness factors together contribute to enterprise-level readiness.

**Table 13**: Summary of Hypothesis-Testing Results

| Hypothesis | Relationship | Decision |
|---|---|---|
| H1 | TR -> AIR | Supported |
| H2 | OR -> AIR | Supported |
| H3 | HR -> AIR | Supported |
| H4 | ER -> AIR | Supported |
| H5 | AIR -> AIA | Supported |
| H6a | TR -> AIR -> AIA | Supported |
| H6b | OR -> AIR -> AIA | Supported |
| H6c | HR -> AIR -> AIA | Supported |
| H6d | ER -> AIR -> AIA | Supported |

## Discussion

**AI Readiness as the Central Mechanism**

The results indicate that AI adoption by Bangladeshi SMEs can be seen as the result of a readiness building process. Each of the four antecedent dimensions was statistically significant in enhancing the overall level of AI readiness, from which readiness in turn had a significantly large positive impact on adoption (Upadhyay *et al.*, 2023). This pattern aligns with the belief that companies don't go straight from sporadic resources to continuous application of AI. They create an organisational state in which the infrastructure, leadership, people, risk management and external support can be orchestrated. The high overall AI readiness (Beta) indicates that the readiness of this set of players is key to the transitions needed from technology potential to operational use.

**Technological Readiness**

Technological readiness proved to be the leading determinant of overall readiness. This finding aligns with the AI implementation experiences. Firms cannot easily escape shallow experimentation without acceptable security controls, reliable data, and compatible infrastructure and integrated systems (Upadhyay *et al.*, 2023). The discovery does not mean that technology is everything. It had a powerful impact because it provided the reality that gave the managerial idea and worker skills something to work on. The mediation result also reveals that technological readiness itself acts as an influential factor towards adoption, not only as a technical input but as an overall readiness state.

**Human-Capital and Organisational Readiness**

Human-capital readiness was the second most influential antecedent followed by organisational readiness. The outcome demonstrates the significance of human beings in a field that is commonly referred to in technical jargon. AI systems change the way people search for information, process outputs, decide and communicate, and do routine work. This means businesses must hire staff that can learn, has a level of digital literacy and can communicate with experts or tech suppliers (Sharma *et al.*, 2024). Training plays a strategic role since capability of implementation is not something that can be acquired entirely from outside the firm. Meanwhile, organisational readiness validates the significance of senior-management commitment, strategic vision, investment of resources and cross-functional cooperation. Leadership can legitimise experimentation and provide resources for integration, and technical tools and employees could be available, but adoption could stall.

**Environmental Readiness**

The smallest, but not insignificant, direct effect on overall readiness was from environmental readiness. This is a meaningful relative magnitude. External vendors, partners, competitors, customers and institutions affect opportunity structure as it pertains to adoption, but are not a substitute for internal capability (Hasan *et al.*, 2023). The supportive provider ecosystem can decrease complexity and customer pressure and competitive intensity can create urgency. But only external conditions become valuable if there is a response of the enterprise to them. The mediated effect was deemed significant, providing supportive evidence that environmental support plays a part in adoption within the context of the firm overall being prepared.

**Mediating Effects**

The most significant theoretical contribution is the findings

of the mediation. Overall readiness indirectly influenced the adoption of AI in all four readiness dimensions. Technological readiness was the most important indirect impact, followed by human-capital readiness, and organisational readiness, while environmental readiness was still important (Ingalagi *et al.*, 2021). The sequence illustrates a balance from resources to preparedness and from preparedness to adoption is needed for SMEs. Investments in technology, skills, leadership and outside supports should thus be viewed as complementary, not competing, investments. An SME may achieve a higher value for potential by improving the value of only one domain without being able to implement the full domain. The integrated model illuminates why certain companies can have individual capabilities but still not operate at scale with AI: the capabilities are not yet integrated to an enterprise state of readiness.

**Explanatory Power of the Model**

The explained variance further shows that the framework has substantively but not comprehensively, explanatory power. Overall, the four antecedents accounted for 53.2% of the variation in AI readiness, indicating that the four antecedent areas can explain over half of the variation in readiness toward the use of AI. AI adoption accounted for 45.4% of the overall readiness. This allows for many more determinants (Sortino & Eggert, 2022). Some factors that may affect adoption include ROI, cost of implementation, industry regulations, risk tolerance of owners, data sensitivity, trust in customers, financial access, vendor lock-in issues and the maturity of specific AI solutions. These factors can be applied to future extensions, which will maintain readiness as the organizational mechanism.

**Theoretical and Practical Implications**

**Theoretical Implications**

Theoretically, the study proposes an integrated readiness architecture that explains SME AI adoption. It distinguishes between four antecedent domains and the higher order organisational state of overall readiness and the behavioural outcome of adoption. This distinction helps to clarify why it is not the same as implementation (Omrani *et al.*, 2024). The mediation paths that were statistically significant indicate that the technological and organisational conditions, as well as human capital, and the environment, become relevant due to their ability to reinforce the company's capacity to introduce AI, to manage change, to address risk, and to generate value. The model thus provides a process explanation that links the possession of a capability with the use of technology to the readiness.

**Practical Implications**

The findings offer a step-by-step process of diagnostic sequence for SME managers. Technical aspects first – Data Organisation, System Integration, Infrastructure Adequacy, and Security Controls. Secondly, leaders need to establish a clear AI direction, allocate budgets, encourage experimentation, and coordinate functions (Doe *et al.*, 2022). Third, building workforce readiness can be done through training, providing access to technical knowledge, and communication that positions AI as a tool to enhance work, not just as a threat. Fourth, companies must actively establish relationships with trustworthy suppliers, consultants, networks and institution institutions. The level of readiness should be measured, and not by the number of purchased tools. A company is truly prepared when it can deploy AI, manage related change and risk, and harness applications into value for the business.

**Limitations and Future Research**

The interpretation must be limited by several factors. The cross-sectional design shows readiness and adoption at a single time period and consequently is unable to show the advancement of firms into adoption stages. Evidence comes from perceptual survey responses of informed representatives of the organisation; not necessarily identical to audited technology expenditure, technology system log, or objective measures of performance (Adu *et al.*, 2022). There is also a relatively large share of firms in the sample reporting that they use AI for operations, meaning that the estimated relationships may be most representative of those SMEs that are already using digital technologies. Moreover, this model puts an emphasis on readiness, and it does not include financial results, productivity and innovation performance or employee consequences (Saweo, 2023). Future research should be longitudinal in design, include other comparisons between sectors or regions, include objective measures of adoption, and be able to identify if there are any measurable performance gains with readiness. Multi-group analysis might also be performed to compare the differences between the structural relations for different enterprise size, age, sector, AI-use stage, or geographical location.

## CONCLUSION

This study has proved that organisational readiness is a critical factor when it comes to AI adoption in SMEs in Bangladesh. Technological, organisational, human-capital, and environmental readiness all had significant positive effects on the overall AI readiness, which in turn positively impacted adoption. It was also clear that readiness was the mechanism through which enabling conditions were translated to use and that there were significant indirect effects. While technological foundations were a key influence, the evidence indicated that skills, leadership, organisational coordination and external support continue to be critical elements of the adoption process. The results thus challenge a narrow scope perspective on AI transformation, centered on the purchase of technologies. The strategic commitment by the SME, competent personnel, change management, risk readiness, and external support ecosystem are essential for the successful scaling of AI, alongside infrastructure and

data. The bottom line for managers and policy actors: it's not just about having access to the ever-expanding array of AI tools; it's about building enterprise-level readiness.

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