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Artificial Intelligence Readiness and Technology Adoption among Healthcare Professionals in Bangladesh: Evidence from Partial Least Squares Structural Equation Modeling

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ABSTRACT

Artificial intelligence (AI) presents possibilities of enhancing healthcare information processing, documentation, professional decision support, and coordination within an organization. However, the presence of technology is not always associated with readiness or long-term professional application. This paper looks into the associations between perceived AI literacy, organizational support, inadequacy of technological infrastructure, perceived usefulness, perceived risk, AI readiness, and self-reported AI technology adoption behavior among healthcare professionals in Bangladesh. The quantitative cross-sectional survey design was modelled through analysing partial least squares structural equations modelling (PLS-SEM). The results of the analysis include 460 respondents, seven reflective constructs, and 28 measurement indicators. The measurement model has reasonable internal consistency, convergent validity and discriminant validity. The reported estimates support all the seven specified structural hypotheses. AI readiness is positively related to perceived AI literacy (β = 0.257), organizational support (β = 0.219), technological infrastructure (β = 0.186), and perceived usefulness (β = 0.224) and is negatively related to perceived risk (β = 0.222). There exists a positive relationship between AI readiness and technology adoption (β = 0.489), and a direct correlation between the adoption and perceived usefulness (β = 0.270). The structural model describes 45.1 % of difference in preparedness and 42.9 % in the adoption behavior. There exist five statistically significant indirect relationships between readiness and organizational, individual, and technological perceptions and reported professional AI use. Its findings indicate that responsible adoption needs to be supported by concomitant investments in workforce capabilities, implementation support, infrastructure, and risk management. Self-reported data at one point in time restricts the ability to make causal interpretations and must be generalized carefully.

INTRODUCTION

Artificial intelligence is a more and more topical element of modern healthcare renewal. Information classification systems, pattern recognition systems, text generation systems and systems that can aid professional judgments have the capacity to impact clinical and nonclinical operations. They are not only of great practical importance in the field but also in documentation, services administration, information search, communications, and normal working process organization (Denecke & Baudoin, 2022). These functions could be of help in personnel working under great time limitations or in organizations whereby dependable information has to be handled within a short duration of time. Availability of an AI-enabled application, however, is not the only criteria of a meaningful professional adoption. Another factor of successful integrations is the understanding of the healthcare workers with the technology, organizational encouragement, appropriate infrastructure, and recognition of the value and risks of the technology (Wang *et al.*, 2023).

Another good location to study these interdependent conditions is Bangladesh. Healthcare services are provided in a combination of a public, private, nonprofit, and community-based setting that vary in resources, professional roles, managerial styles, and technological access (Wiljer *et al.*, 2021). Medical technologists, pharmacists, nurses, physicians, and allied health personnel as well as administrators might get various opportunities to utilize AI-enabled systems. Therefore, what one professional group experienced cannot be presupposed to be the experience of another. A description of AI adoption would be very narrow-minded and fail to acknowledge infrastructure and institutional constraints (Chalutz Ben-Gal, 2023). In contrast, an account that considers organizational investment only might overlook knowledge, professional confidence, perceived utility, and worries regarding patient protection.

There should also be a gap between the acceptance of technology, preparedness and actual utilization. Acceptance can be taken to indicate a positive appraisal of a system and readiness is about being ready to integrate it in a responsible manner in the regular professional activities. Adoption behavior can be defined as the reportedly expressed engagements with AI applications as opposed to overall beliefs about their relevance in the future. These notions are interrelated, yet not equivalent. A person might think that AI enhances efficiency in working without necessarily being qualified to oversee its results. The other might have technical knowledge but be in an institution whose infrastructure is not appropriate (Altamimi *et al.*, 2023). Current research balances AI

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preparedness between a number of hypothesized antecedents and reported adoptions to explore the relationship between preparedness and the translation of positive perceptions into professional practice.

The perceived AI literacy construct deals with the practical knowledge needed to identify AI-enabled applications, the general functionality of them, and the constraints of material generated. In the case of healthcare professionals, this insight is particularly consequential since even what appears to be a persuasive output can still have errors or lack in clinical context (Sharma *et al.*, 2022). Managerial encouragement, learning and leadership commitment are encapsulated in organizational support. Technological infrastructure sufficiency deals with the dependability and appropriateness of the digital resources. Perceived usefulness is expected efficiency, quality improvement in work and information processing. The perceived risk is an opinion about the accuracy, confidentiality, explainability, and professional accountability. The five variables are a combination of personal, organizational, and technological and governance-related aspects of preparedness.

The behavior of AI technology adoption is the result of the study, which is operationalized in the form of self-reported professional use over the past three months (Alami *et al.*, 2020). This working definition is also narrower and more behaviorally oriented as compared to an intention to embrace an AI system at an unspecified point in the future. This difference is especially applicable when positive attitudes are accompanied with low operational opportunities. The result however remains self-reported as opposed to the independent verification of the results through software usage logs (Nitiéma, 2023). Its interpretation should thus be considered with a view of the likelihood of recall error, the familiarity with AI applications, and also the difference in what the respondents define as AI-enabled technology.

The analytical phraseology has seven latent constructs, which are documented by four reflective manifestations, and seven directional hypotheses (Hameed *et al.*, 2023). AI preparedness is a positioned endogenous regulator that is foreseen by literacy, backing, infrastructure, utility, and risk. Ready and perceived usefulness are directly related to adoption behavior. This model then makes two complementary questions to be investigated: what conditions are linked to professional preparedness, and to what extent is professional preparedness related to reported adoption? Additional indirect-effect estimates also measure whether readiness mediates statistical relationships among its five antecedents to adoption behavior. It is possible to consider these associations within the boundaries of a cross-sectional research design.

There are four objectives of the study which are interrelated. First, it explores the associations between perceived AI literacy, organizational support, technological infrastructure, perceived usefulness and perceived risk and AI readiness. Second, it estimates the relationship between readiness and reported adoption behavior. Third, it evaluates the extra direct correlation between usefulness and adoption once the readiness is taken into account. Fourth, it assesses the indirect relationships of the five antecedents with adoption using readiness (Novak *et al.*, 2023). These goals address a practical question that the use of professional AI has a closer relationship with individual capacity or organizational circumstances, perceived benefit, risk-related cautiousness, or the readiness that results when they are combined.

LITERATURE REVIEW

Hypothesis Development

AI Readiness as a Distinct Form of Professional Preparedness

AI readiness refers to how professionals understand themselves to be ready to apply approved AI-enabled applications in well-established work practices. It also involves readiness to change its habits, trust in implementing relevant protective measures, and ability to embrace technological transformation (Kennedy & Gallego, 2021). Preparation is more extensive than knowledge since preparation of a profession needs not only conceptual grasp. It is also less broad than successful organizational implementation in that it does not show that an institution has attained a better quality, safety, or productivity. The measure that is taken here is purposefully focused on the personal understanding of readiness and supervision responsibility (Zając *et al.*, 2023). This concentration would be suitable in research that requires healthcare professionals to report their working conditions and experiences elicited.

Perceived AI Literacy and AI Readiness

Perceived AI literacy is awareness of useful applications, knowledge in the key principles of technology, awareness of possible errors, and the distinction between AI-based systems and traditional software (Malerbi *et al.*, 2023). These skills can guide practitioners on the right activities to be assisted by AI and establish achievable expectations of system performance (Gillan *et al.*, 2021). In the medical field, effective involvement must also be sensitive to the fact that the advice can be partial, statistically skewed, or unreasonable to a specific patient or institutional context. Knowledge can thus underpin preparedness by alleviating doubt and enhancing trust in professional supervision as opposed to promoting unregulated dependence on automated products (Yoo *et al.*, 2023).

Professionals reporting higher AI literacy could be more competent to assess demonstrations, be involved in training, understand what is needed to implement it, and when the human review is needed. This literacy can also cool the fear of dealing with the technical language that one might not be familiar with (Lai *et al.*, 2021). Nevertheless, current measures reflect perceived competence, rather than external, digital or clinical, capability. High literacy score ought not to be as evidence that one can implement a system without extra instruction. In the conceptual framework suggested, the expected relationship will be positive since the perceived understanding will be used

to promote professional preparedness (Gama *et al.*, 2022). In this regard, H1 is that perceived AI literacy has a positive relationship with AI readiness amongst healthcare professionals in Bangladesh.

Organizational Support and AI Readiness

Organizational support presents the idea of whether institutional leadership promotes responsible AI usage, learning, and environment that contribute to technological integration (Tulk Jesso *et al.*, 2022). The healthcare labour is entrenched in the set roles, professional chains of command, information control processes, and operational anticipations (Terry *et al.*, 2022). The surrounding institution is thus of a factor in individual preparedness. When employees feel that the management understands the importance of AI and encourages cautious experiment, they might be more open to obtaining new skills and changing their work. An enabling environment can also help in minimising ambiguity in terms of whether appropriate use is regarded or institutionally opposed (Thakkar & Bharathi, 2023).

The concept of support is not the blind encouragement of digital systems. Responsible managerial aid in the healthcare industry must entail transparency in regards to allowable uses, oversight, error amplification, patient privacy, and accountability (Priyadarshini, 2023). Fashioning these circumstances, organizational motivation might create pressure to utilize tools that are not ready to be evaluated by workers. The current indicators of organizational support include encouragement of the management and positive learning climate in the organization, and formal policies and audit practices are not directly measured (Cheng *et al.*, 2022). The framework however anticipates that support will be positively related to readiness. H2 thus hypothesizes a good correlation between perceived organizational support and AI readiness.

Technological Infrastructure Adequacy and AI Readiness

Technological infrastructure comprises the workplace resources to run digital applications on a regular basis and amalgamate them into daily activities. Appropriate dimensions can be computing equipment, network connection, system reliability, compatibility between platforms and the availability of the right software environments (Yin *et al.*, 2021). The significance of these is relative to different institutions and professions. A person can be educated and eager but still cannot prepare to do ordinary AI-contained jobs in case of the lack of the required technological requirements (Nasr *et al.*, 2021). On the other hand, trustworthy online materials can render training, guided experimentation, and gradual integration more practical.

The construct of operationalized infrastructure is perceptual (Hossain *et al.*, 2022). It offers the statements about whether or not respondents think that their working place is sufficiently equipped and technologically suitable to do the work to work with the AI. It does not audit network performance, cybersecurity arrangements, database interoperability, and computing capacity alone. However, the perceived infrastructural sufficiency is likely to be a significant correlate of preparedness since it determines the plausibility of AI application in typical work practices. According to H3, there is a positive correlation between perceived technological infrastructure adequacy and AI readiness in healthcare professionals in Bangladesh (Ogaga & Zhao, 2023).

Perceived Usefulness and AI Readiness

Perceived usefulness is about whether the AI-enabled applications can enhance the effectiveness and efficiency of the professional activities (Secinaro *et al.*, 2021). The research quantifies the projected gains in accomplishing tasks, in processing information relating to healthcare and in enhancing the quality of work and also in decreasing the time spent in performing routine functions. Such decisions can help to prepare by creating a specific rationale to put their effort into acquiring new practices (Choudhury, 2022). In situations where a technology is viewed as pertinent to important professional matters, prospective users can be more likely to learn how to use the technology and what protections are required to responsibly integrate it.

Perceived Risk and AI Readiness

Applications powered by AI present issues that are of especially valid importance within healthcare settings. Outputs can be imprecise, sensitive data of patients can be compromised, technical suggestions can be hard to clarify, and accountability of mistakes can be disputed (Khan, 2023). These issues may influence the willingness of the professionals to implement new tools that are not familiar to the usual practice. Regarding risk perception, it may deter the premature adoption in which the impact of a wrong or poorly controlled output seems to be high (Asif Naveed, 2023). It can also underscore valid governance, training and oversight needs that are supposed to go hand in hand with the implementation processes.

In this research, the risk construct will mean the degree of the concerns of the respondents. An increased value means more interaction with concerns on accuracy, privacy, explainability, and professional accountability (Denecke & Baudoin, 2022). The only reason why items are not reverse-coded is because the hypothesized coefficient is negative. A negative sign would imply that the greater the concern, the less prepared is conditional upon the other predictors that would be allowed to appear in the model (Wang *et al.*, 2023). It would not mean that risk awareness per se would be a bad thing and that prudent skepticism would be abolished. H5 predicts that perceived risk is negatively associated with AI readiness among healthcare professionals in Bangladesh.

AI Readiness and Technology Adoption Behavior

The shift to readiness to use is at the focus of the proposed model. Professionals who have the ability to oversee AI-generated content and reorganize the processes can perhaps be more inclined to use AI-enabled applications

in their work (Wiljer *et al.*, 2021). The relationship is conceivable since preparedness embodies self-assessed practical training, and not just the abstract appraisal of technological capability (Chalutz Ben-Gal, 2023). It could also affect confidence required in transitioning between viewing a technology and using it in activities like documentation, information review, communication, planning, and decision support.

Here, adoption behavior is assessed by how often a professional activity related to AI took place within the past three months. This time-validated definition of behavior is aimed at dividing the present reported use and the future intentions (Altamimi *et al.*, 2023). However, readiness and utilization can be mutually strengthening: confidence can be enhanced by repetitive exposure to AI and better utilization can be enhanced by confidence. Cross-sectional evidence is not able to assert the process of the first (Sharma *et al.*, 2022). The given model quantifies the expected positive correlation without any temporal causality. H6 proposes that AI readiness is positively related to AI technology adoption behavior.

Direct Usefulness and the Mediating Role of Readiness

The perceived usefulness can result in adoption behavior via a different channel compared to readiness. When other institutional preparation areas are not ready yet, professionals with expectations of instant efficiency or information gains can adopt appropriate applications (Alami *et al.*, 2020). On the other hand, users, who do not think that a tool has much value, may not consider using it even with sufficient capability and infrastructure. A direct usefulness-to-adoption path will enable the analysis to differentiate this performance-related relationship with the indirect relationship that functions through readiness. H7 thus anticipates a positive direct relationship between perceived usefulness and actual behavior of adoption of AI technology.

The model also allows the evaluation of five additional indirect effects (Nitiéma, 2023). It is expected that positive indirect relationships exist between literacy, support, infrastructure, and usefulness since each of these is supposed to be related to increase readiness, which in turn is supposed to have a positive relationship with adoption. A negative indirect relationship is anticipated for risk. Out of such statistical effects there is no mediation, as causal chain of action, without temporal sequence or experimental proof (Hameed *et al.*, 2023). They come in handy, though, to consider whether the estimated path structure is congruent with the suggested bridging role of readiness. The conceptual model illustrates five antecedents leading to readiness and two predictors of adoption.

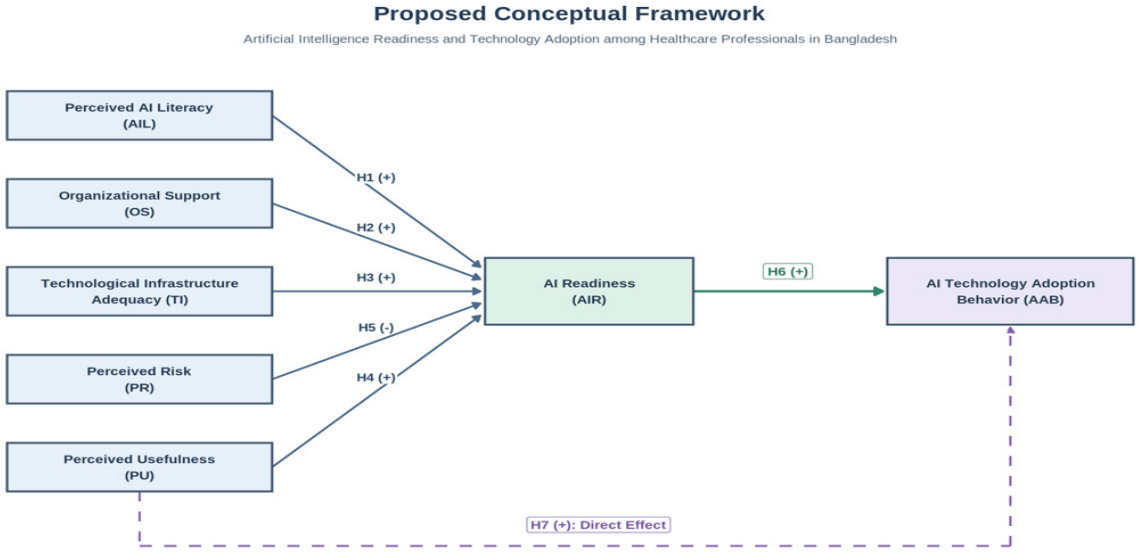


Figure 1: Proposed conceptual framework and hypothesized directions

MATERIALS AND METHODS

Research Approach and Analytical Scope

The study has been described as a quantitative cross-sectional survey study on the professional perceptions and reported AI-based behaviour in Bangladesh. The method chosen to estimate the relationships between multiple latent variables and test a model with both direct and indirect paths as an analytical tool was partial least squares structural equation modeling (Kennedy & Gallego, 2021). The result of the analytical results is 460 observations. The available analytic documentation does not specify the dates of recruitment, response rates, institutional permissions, or the cleaning of raw-data; no unverified procedures are claimed in this regard.

The unit of analysis is the individual healthcare professional. The questionnaire was designed to include physicians, nurses, pharmacists, medical technologists, allied healthcare practitioners, and healthcare administrators. Diversity within these categories was deemed significant since the work of professionals is characterized by varied workflow and exposure to AI-enabled tools. Employment setting, geographical location,

previous training, and frequency of use of digital are also included in the questionnaire. The given characteristics enable the description of the analyzed sample, but no structural comparisons of multigroups or demographic effects are adjusted. They are thus not offered as moderators or control variables that were tested.

Target Population, Eligibility, and Sample

The population of interest will be healthcare workers in Bangladesh. The survey design indicated three eligibility criteria that include; the respondent should be aged 18 years and should be professionally involved in healthcare services in Bangladesh and should have three months of experience related to healthcare. Previously, the use of AI was not a criterion (Zając *et al.*, 2023). This rule of exclusion is relevant since narrowing the sample to defined users of AI would eliminate non-adopters and may provide an overestimation of usage in the population under study. The reported 28 measurement items all have a consistent 460 observations at the end of the analytic tables and the sum of the reported demographics is 460. The sample cluster comprises of respondents of varied professional backgrounds, kind of institution, places of work, and administrative department. It is heterogeneous, in other words, descriptively composed. Diversity of reported categories should however not be confused with statistical representativeness. The materials available do not provide a probability-based sampling frame, response rate, and national population weights (Malerbi *et al.*, 2023). Based on this, findings cannot be understood as the estimated relationships across the entire population of all healthcare professionals in Bangladesh; instead, they should be understood as estimated relationships in the sample analyzed. Such limitations do not mean the analysis is pointless, but limit the extent of inference.

Questionnaire Structure and Operational Definitions

The structured questionnaire included the eligibility screening, demographic and professional questions as well as 28 indicators organized into seven constructs. Four reflective statements were used to represent each construct. Perceived AI literacy involved identifying AI applications, knowledge of its underlying concepts, awareness of constraints and distinguishing AI technology and standard digital technologies. Organizational support covered institutional encouragement and commitment to leadership (Gillan *et al.*, 2021). Technological infrastructure adequacy measured the adequacy, appropriateness, and dependability of digital resources of the workplace. Perceived usefulness was related to performance and efficiency expectations whereas perceived risk was related to the questions of accuracy, privacy, explainability and accountability.

The operationalization of AI readiness involved the perceived readiness to use approved AI applications, alter current procedures, employ protective measures, and address the changes in professional activity. The dependent construct was the self-reported frequency of professional activity over the last three months that involved AI usage. Its four indicators dealt with AI-assisted work, consultations of AI generated information, use of AI functionality within the working application, and AI-assisted documentation, communication, planning, or decision support. This definition does not include normal software that is not AI-enabled. It does not also consider positive attitudes or intentions as the evidence of the observed behavior adoption (Yoo *et al.*, 2023).

Measurement Scales and Instrument Considerations

The binary agreement responses of five points (strongly disagree to strongly agree) were utilized in the first six constructs. The dependent construct of adoption adopted a different five-point frequency scale of never to very often. Those respondents who did not use professional AI during the reference period were asked to choose never on all four adoption items. This design will enable the representation of respondents with various levels of usage without requiring AI experience as a condition to participate (Lai *et al.*, 2021). The tool also differentiated between existing professional AI usage and general digital technology usage, and minimized the risk of conceptualizing as AI usage ordinary software familiarity.

The research tool perceives the indicators to be researcher-created and theoretically driven as opposed to pre-determined validated measures. The protocol used in instrument development suggests that it be reviewed by experts, administered by pilots, and, in some cases, translated and back-translated. The reported analytical outputs cannot be used to determine completion of these activities. This means that empirical construct statistics in the results may reinforce the measurement performance of the indicators under analysis, but it cannot be explained that all the content-validity, language-equivalence, or procedural validation steps were fulfilled (Gama *et al.*, 2022). This difference is preserved in the evaluation of evidence of the quality of instruments.

Model Specification

There are five predictors of AI readiness and two predictors of adoption behavior present in the structural model. Its first equation can be represented as $AIR = \beta1(AIL) + \beta2(OS) + \beta3(TI) + \beta4(PU) + \beta5(PR) + \varepsilon1$. The second equation is $AAB = \beta6(AIR) + \beta7(PU) + \varepsilon2$. In this case AIL indicates the perceived AI literacy, OS organizational support, TI technological infrastructure adequacy, PU perceived usefulness, PR perceived risk, AIR AI readiness, and AAB adoption behavior. The disturbance terms entail unexplained variation in respective endogenous constructs. The expected signs of the coefficients will be positive with the exception of risk and readiness.

The survey plan indicated that all seven sets of indicators were reflective. Indicators are considered under this specification as a manifestation of their underlying constructs and not as an independent component

which jointly defines a formative index. Evaluation of outer loadings, shared variance, internal consistency and discriminant validity are justified by reflective measurement assumptions (Tulk Jesso *et al.*, 2022). Large and imbued directed loadings indicate that the indicators are related content constructs. However, positive loadings do not suffice to determine the substantive completeness of a construct, especially so in the case of a wide concept like healthcare AI readiness that may encompass the institutional, regulatory, and technical aspects not discussed in the four items.

Measurement Model Assessment

The quality of the measurement was determined based on the measured outer loadings (documented), indicator reliability, Cronbachs alpha, rho A, composite reliability and average variance extracted (Terry *et al.*, 2022). Fornell-Larcker matrix, heterotrait-monotrait ratios and bootstrapped confidence intervals of HTMT estimates were also analyzed. Practical benchmarks used were outer loadings of about 0.708 and above and average variance extracted of at least 0.50. Essentially, estimates of reliability of at least 0.70 were considered to denote adequate internal consistency. In the case of discriminant validity, the analysis assessed the existence of square roots of AVE that were higher than between-construct correlations, as well as, the presence of HTMTs that were lower than traditional values.

Structural Model and Predictive Assessment

In the structural analysis, collinearity between predictors was taken into account along with standardized path estimates, bootstrap-standardized path estimates, coefficient of determination, adjusted coefficient of determination and f-squared effect sizes. The estimated coefficients were understood based on their direction, magnitude, reported confidence bounds and approximate levels of significance (Thakkar & Bharathi, 2023). Since the numerical p-value cells are represented as zero in the findings by rounding, the manuscript presents them as $p < .001$ with supporting test statistics, instead of using them as literal zero-probability values. Evaluations allowed the assessment of the variance inflation factors to determine the possible overlapping of the predictors of the same endogenous construct as a problem.

Ethical and Inferential Considerations

The questionnaire will contain a voluntary participation statement, a consent option, a prohibition of gathering patient-identifying data, and a guarantee that the answers will be summarized in aggregate. The reason such provisions are suitable is that they are placed in a survey that is researching the perceptions of professionals and not clinical outcomes at the patient level. Institutional ethical approval and the implementation of consent procedures, as well as a review of the confidentiality of responses, are not, however, reported in the source materials. Any journal submission must be confirmed by those administrative details before they are allowed to submit the actual research records. The research, therefore, does not purport to have had an approval identifier or a completed oversight process that is not substantiated by the research records (Priyadarshini, 2023).

Being a cross-sectional observational analysis, the model approximates statistic associations in keeping with the conceptual structure proposed. It does not rule out reciprocal relationships, missing determinants or common-method effects and particularly since the explanatory and dependent constructs were measured using the same questionnaire. The terminology of mediation here is indicative of the estimated indirect paths within the given model and should not be used to define the causal time-dependent mechanisms. These constraints guide the language of results and discussion, with reported relationships differentiating between reported effects of an organizational intervention or AI implementation program.

RESULTS AND DISCUSSION

Demographic and Professional Profile

The sample to be analyzed consists of 460 healthcare professionals. The largest age group was 25–34 years (39.35%), followed by 35–44 years (30.22%). Patients between the ages of 18 and 24 were 12.83% then there were the patients between 45 and 54 years of age who were 13.04% and at least 55 years of age 4.57. Fifty percent (50.00%) of the sample consisted of men and 48.70% of female. There were small proportions of other category and non-disclosed gender. Forms of education were bachelor degrees, professional medical degrees,

Table 1: Demographic and professional characteristics

Variable	Category	n	%
Age group	18–24	59	12.83
	25–34	181	39.35
	35–44	139	30.22
	45–54	60	13.04
	55 years or above	21	4.57
Gender	Female	224	48.70
	Male	230	50.00
	Other	2	0.43
	Prefer not to disclose	4	0.87

Education	Bachelor's Degree	179	38.91
	Diploma	89	19.35
	Doctoral Degree	17	3.70
	Master's Degree	64	13.91
	Professional Medical Degree	111	24.13
Profession	Allied Healthcare Professional	43	9.35
	Healthcare Administrator	20	4.35
	Medical Technologist	62	13.48
	Nurse	147	31.96
	Pharmacist	56	12.17
	Physician	132	28.70
Experience	1–3 years	126	27.39
	4–6 years	116	25.22
	7–10 years	96	20.87
	Less than 1 year	49	10.65
	More than 10 years	73	15.87
Institution type	Government	190	41.30
	NGO/Nonprofit	31	6.74
	Other	3	0.65
	Private	236	51.30
Workplace type	Clinic	68	14.78
	Community Healthcare Facility	27	5.87
	Diagnostic Centre	54	11.74
	Healthcare Administration Office	10	2.17
	Hospital	259	56.30
	Other	1	0.22
	Pharmacy	41	8.91
Workplace location	Rural	68	14.78
	Semi-urban	122	26.52
	Urban	270	58.70
Division	Barishal	38	8.26
	Chattogram	88	19.13
	Dhaka	140	30.43
	Khulna	54	11.74
	Mymensingh	26	5.65
	Rajshahi	40	8.70
	Rangpur	30	6.52
	Sylhet	44	9.57
Formal AI training	No	300	65.22
	Yes	160	34.78
Digital technology use	Never	20	4.35
	Often	128	27.83
	Rarely	111	24.13
	Sometimes	142	30.87
	Very Often	59	12.83
Professional AI use, past 3 months	No	82	17.83
	Yes	378	82.17

Note: Percentages are based on N = 460 and may differ slightly from 100% owing to rounding.

diplomas, masters and doctoral degrees. The variety of qualifications suggests that the sample consists of professionals that can apply AI in various work situations. The most common (31.96%) consistent with professional group was nurses, then physicians (28.70%), medical technologists (13.48%), pharmacists (12.17%), allied healthcare professionals (9.35%), and administrators (4.35%). The number of respondents in the private sector was 51.30% however, 41.30% worked in government institutions. The most commonly reported type of work place was in a hospital (56.30%). The proportion of urban environments gave 58.70% of the responses, with Dhaka taking 30.43% of the sample. 34.78% of the respondents reported formal AI-related training and 65.22% reported none. Worth noting, 82.17 % responded yes on the independent screening question of professional AI use in the last three months; this numerical percentage needs to be differentiated with the multi-indicator adoption score adopted by the structural model.

Descriptive Statistics of Measurement Indicators

The item-level descriptives indicate a significant difference in the seven constructs. The AI literacy item has ranged at 3.141 to 3.496 whilst organizational support has a range of 2.772 to 2.878. Technological infrastructure items had means of 2.741-2.978 implying an adverse reported condition as compared to the usefulness indicators whose means were 3.487-3.596. These trends can be seen as descriptive comparisons and not adjusted comparisons, yet they indicate that participants might realize that professional benefits might be reached even when they describe that they have doubts about institutional conditions, technological provision.

The range of means of the perceived risk items was 3.304-3.696 with the largest mean value being an issue of explainability of the AI-generated recommendations. Readiness = 2.907 to 3.207: There is variability in perceived preparedness. The frequency of adoption was between 2.750 and 3.109. The four items of adoption

Table 2: Descriptive statistics of measurement indicators

Construct	Item	N	Mean	SD	Skew.	Kurt.
AIL	AIL1	460	3.215	1.120	-0.123	-0.860
AIL	AIL2	460	3.365	1.095	-0.142	-0.752
AIL	AIL3	460	3.141	1.116	-0.092	-0.757
AIL	AIL4	460	3.496	1.086	-0.239	-0.691
OS	OS1	460	2.878	1.146	0.091	-0.826
OS	OS2	460	2.772	1.123	0.216	-0.676
OS	OS3	460	2.850	1.150	0.174	-0.780
OS	OS4	460	2.828	1.118	0.229	-0.646
TI	TI1	460	2.772	1.117	0.204	-0.662
TI	TI2	460	2.741	1.132	0.320	-0.583
TI	TI3	460	2.852	1.091	0.264	-0.582
TI	TI4	460	2.978	1.114	0.090	-0.718
PU	PU1	460	3.596	1.146	-0.417	-0.681
PU	PU2	460	3.517	1.117	-0.291	-0.742
PU	PU3	460	3.487	1.103	-0.200	-0.848
PU	PU4	460	3.583	1.116	-0.282	-0.794
PR	PR1	460	3.411	1.121	-0.170	-0.825
PR	PR2	460	3.304	1.106	-0.070	-0.848
PR	PR3	460	3.696	1.074	-0.396	-0.668
PR	PR4	460	3.385	1.103	-0.159	-0.736
AIR	AIR1	460	2.961	1.092	0.137	-0.719
AIR	AIR2	460	3.111	1.162	-0.008	-0.830
AIR	AIR3	460	3.207	1.086	0.023	-0.652
AIR	AIR4	460	2.906	1.144	0.157	-0.776
AAB	AAB1	460	2.996	1.300	-0.140	-1.034
AAB	AAB2	460	3.109	1.304	-0.289	-0.974
AAB	AAB3	460	2.898	1.247	-0.049	-0.881
AAB	AAB4	460	2.750	1.216	0.100	-0.927

Note: N = 460 for every indicator. The minimum and maximum for every item are 1 and 5. AAB uses frequency responses; other constructs use agreement responses.

were all based on a frequency scale and not directly on an agreement scale so the numerical value of these items should not be directly understood as an agreement score. The standard deviations of the item tend to reflect significant variance in responses. The values of skewness and kurtosis recorded do not show extremely deviant univariate distributions, but the descriptive characteristics alone do not prove multivariate normality or lack of response bias.

Indicator Loadings and Construct Reliability

The loadings of outer measurements of the reflective measurement model were positive and significant. Among 28 indicators, the loadings ranged between 0.800 (TI3) and 0.908 (AAB2) in case of three-decimal approximation. All the time the loads recorded were above the practical threshold of 0.708. The squared loading values are used to compute the indicator reliability values and the values also indicate that every manifest variable has a large amount of variance in common with the relevant construct. All loadings have confidence intervals that are positive and not indicative of individual weak points. Holding all 28 items thus seems to be in line with evidence of loading that has been reported.

The statistics of reliability provide a supplementary evaluation. Alpha values of Cronbach lie between 0.858 and 0.924 in the case of infrastructure adequacy and adoption behavior respectively. Composite reliability is between 0.904 and 0.946 and estimates of rho A exhibit similar trends. The average variance extracted is between 0.702, on the infrastructure, and 0.814 on the adoption behavior. All constructs are, thus, greater than the

Table 3: Outer loadings and indicator reliability

Construct	Indicator	Loading	Reliability	CI
AIL	AIL1	0.848	0.719	[0.817, 0.875]
AIL	AIL2	0.859	0.738	[0.831, 0.884]
AIL	AIL3	0.826	0.682	[0.789, 0.858]
AIL	AIL4	0.854	0.730	[0.825, 0.879]
OS	OS1	0.864	0.746	[0.833, 0.889]
OS	OS2	0.872	0.760	[0.845, 0.894]
OS	OS3	0.832	0.691	[0.794, 0.861]
OS	OS4	0.868	0.754	[0.841, 0.892]
TI	TI1	0.854	0.729	[0.824, 0.879]
TI	TI2	0.868	0.754	[0.838, 0.892]
TI	TI3	0.800	0.639	[0.753, 0.839]
TI	TI4	0.827	0.684	[0.783, 0.861]
PU	PU1	0.843	0.710	[0.809, 0.870]
PU	PU2	0.866	0.750	[0.840, 0.889]
PU	PU3	0.835	0.698	[0.800, 0.864]
PU	PU4	0.852	0.726	[0.823, 0.876]
PR	PR1	0.846	0.716	[0.810, 0.875]
PR	PR2	0.847	0.717	[0.813, 0.877]
PR	PR3	0.881	0.776	[0.858, 0.900]
PR	PR4	0.855	0.731	[0.826, 0.880]
AIR	AIR1	0.848	0.719	[0.820, 0.874]
AIR	AIR2	0.899	0.809	[0.881, 0.915]
AIR	AIR3	0.820	0.672	[0.779, 0.853]
AIR	AIR4	0.892	0.796	[0.872, 0.909]
AAB	AAB1	0.903	0.816	[0.883, 0.921]
AAB	AAB2	0.908	0.824	[0.886, 0.924]
AAB	AAB3	0.891	0.793	[0.868, 0.911]
AAB	AAB4	0.906	0.822	[0.889, 0.922]

Note: Indicator reliability equals the squared outer loading. CI indicates the reported bootstrap interval.

frequently utilized minimums of internal consistency and convergent validity. The tendency towards high reliability of the adoption construct can be attributed to the high level of agreement of the four behavioral-frequency scales that its indicators denote, yet the potentiality of similar wording of items is to be taken into account when

evaluating the instrument substantively.

The results substantiate the internal consistency of the constructs of reflectiveness in this dataset under analysis. They fail to establish that the measures measure all the features of AI competence or readiness which matter and are powerless to check the validity of individual self-ratings. This difference matters in healthcare uses, in which technical confidence and actual capability to identify a misleading AI output can be different. In general, the statistics presented allow the interpretation of subsequent structural estimates without an evident loading or reliability problem with seven blocks of measurements described (Cheng *et al.*, 2022).

Table 4: Internal consistency and convergent validity

Construct	α	rho_A	CR	AVE
AIL	0.869	0.872	0.910	0.717
OS	0.882	0.885	0.918	0.738
TI	0.858	0.862	0.904	0.702
PU	0.871	0.873	0.912	0.721
PR	0.880	0.885	0.917	0.735
AIR	0.888	0.891	0.923	0.749
AAB	0.924	0.924	0.946	0.814

Note: rho_A represents the reliability coefficient; CR denotes composite reliability; AVE denotes average variance extracted.

Discriminant Validity

According to the FornellLarcker matrix, the square root of AVE of each construct is higher than its correlations with other constructs. The diagonal scores are between 0.838 and 0.902 (technological infrastructure and adoption behavior) respectively. The highest reported off-diagonal latent correlation is between readiness and adoption behavior (0.608) and falls short of the corresponding diagonal values of 0.866 and 0.902. There is a positive correlation as well between usefulness and adoption of 0.485. These correlations are substantively plausible, but the reported matrix does not imply the relevant constructs to be statistically indistinguishable.

Table 5: Fornell–Larcker discriminant validity matrix

Construct	AIL	OS	TI	PU	PR	AIR	AAB
AIL	0.847	—	—	—	—	—	—
OS	0.232	0.859	—	—	—	—	—
TI	0.167	0.307	0.838	—	—	—	—
PU	0.235	0.206	0.312	0.849	—	—	—
PR	-0.087	-0.171	-0.165	-0.232	0.857	—	—
AIR	0.410	0.419	0.402	0.439	-0.364	0.866	—
AAB	0.396	0.314	0.325	0.485	-0.306	0.608	0.902

Note: Diagonal entries represent the square root of AVE; below-diagonal entries are interconstruct correlations.

This is supported by the HTMT results. The range of ratios is between 0.102 and 0.671 between perceived literacy and risk and readiness and adoption. All the pairs stand under 0.85 and 0.90 as traditional screening standards. Readiness and adoption present the highest HTMT ratio, which should occur since preparedness and reported use are theoretically connected. However, the

Table 6: Heterotrait–monotrait ratios (HTMT)

Construct	AIL	OS	TI	PU	PR	AIR	AAB
AIL	—	—	—	—	—	—	—
OS	0.263	—	—	—	—	—	—
TI	0.193	0.353	—	—	—	—	—
PU	0.268	0.232	0.362	—	—	—	—
PR	0.102	0.193	0.187	0.264	—	—	—
AIR	0.465	0.472	0.457	0.497	0.410	—	—
AAB	0.442	0.346	0.365	0.540	0.338	0.671	—

Note. Entries are HTMT ratios for unique pairs of constructs.

value is lower than the chosen thresholds, which confirms their consideration as independent latent variables in this measurement framework. Some other moderately correlated pairs are usefulness and adoption (0.540) and usefulness and readiness (0.497).

Further evidence is reported bootstrapped HTMT intervals. In all 21 pairs of constructs, upper bounds are below 1.000; with the largest upper bound of 0.724 on readiness and adoption. Therefore, no pair of the confidence intervals signify an HTMT ratio of one. A combination of the Fornell-Larcker, HTMT point estimates and HTMT intervals validates discriminant validity in the model analyzed. The outcomes are to be taken in conjunction with the conceptual definitions and not to be utilized as an assumption that covariance in methods has been removed completely.

Table 7: Bootstrap intervals for HTMT estimates

Construct pair	HTMT	Lower CI	Upper CI
AIL–OS	0.263	0.163	0.363
AIL–TI	0.193	0.095	0.296
AIL–PU	0.268	0.169	0.362
AIL–PR	0.102	0.050	0.202
AIL–AIR	0.465	0.372	0.546
AIL–AAB	0.442	0.345	0.520
OS–TI	0.353	0.252	0.441
OS–PU	0.232	0.132	0.328
OS–PR	0.193	0.101	0.291
OS–AIR	0.472	0.389	0.554
OS–AAB	0.346	0.256	0.434
TI–PU	0.362	0.272	0.450
TI–PR	0.187	0.086	0.288
TI–AIR	0.457	0.368	0.538
TI–AAB	0.365	0.276	0.452
PU–PR	0.264	0.165	0.360
PU–AIR	0.497	0.413	0.575
PU–AAB	0.540	0.466	0.608
PR–AIR	0.410	0.320	0.494
PR–AAB	0.338	0.244	0.430
AIR–AAB	0.671	0.613	0.724

Note: All reported interval upper bounds are below 1.000.

Collinearity and Hypothesis Testing

Inner-model collinearity of predictors of readiness and adoption was evaluated before interpretation of the structural coefficients. The variance inflation factors were reported to have a range of between 1.080 to 1.239 which is way below the usual screening threshold of 3.3 or 5.0. These values show that multicollinearity can hardly be the main reason behind reported magnitudes of the coefficient. The fact that the VIF is low does not refute the presence of omitted predictors or common-source bias but it indicates that the predictors included in each estimated equation are numerically apart.

Table 8: Structural collinearity assessment

Endogenous	Predictor	VIF
AIR	AIL	1.103
AIR	OS	1.168
AIR	TI	1.198
AIR	PU	1.199
AIR	PR	1.080
AAB	AIR	1.239
AAB	PU	1.239

Note: VIF denotes the variance inflation factor for predictors of the indicated endogenous construct.

All of the five relationships between AI readiness and the five proposed antecedents are backed by the results. The standardized coefficients of perceived AI literacy are positive: 0.2566 (t = 7.024), organizational support 0.2187 (t = 5.909), technological infrastructure adequacy 0.1855 (t = 4.720), and perceived usefulness 0.2243 (t = 6.017). Ready is negatively correlated with the perceived risk (β = -0.2221 = t 6.239). All of the reported confidence intervals of these paths are non-zero. According to conditional standardized terms, the highest positive antecedent coefficient is associated with literacy though there is no need of interpreting differences between coefficients as statistically significant differences unless this is explicitly tested.

Table 9: Structural coefficients and hypothesis tests

H	Path	β	t	p	CI	Decision
H1	AIL → AIR	0.257	7.024	< .001	[0.184, 0.327]	Supported
H2	OS → AIR	0.219	5.909	< .001	[0.147, 0.291]	Supported
H3	TI → AIR	0.185	4.720	< .001	[0.105, 0.264]	Supported
H4	PU → AIR	0.224	6.017	< .001	[0.152, 0.295]	Supported
H5	PR → AIR	-0.222	6.239	< .001	[-0.293, -0.156]	Supported
H6	AIR → AAB	0.489	15.497	< .001	[0.426, 0.550]	Supported
H7	PU → AAB	0.270	7.768	< .001	[0.204, 0.339]	Supported

Note: Coefficients are standardized. Approximate p-values are reported as p < .001 in place of rounded zero entries in the tabulated analysis. CI denotes the reported bootstrap interval.

The correlation between readiness and adoption behavior is positive and it has a relatively high value (β = 0.4894; t = 15.497). After adding readiness, perceived usefulness also positively correlates directly with adoption (β = 0.2704; t = 7.768). Both confidence intervals reported do not have zero. Such estimations propose that preparedness and anticipated professional advantage bring about separate links to what is reported using AI. They fail to demonstrate how a proportional outcome would inevitably be achieved by the increasing readiness as a result of intervention due to the use of the standardized coefficients to explain conditional relationships in the observed cross-sectional model.

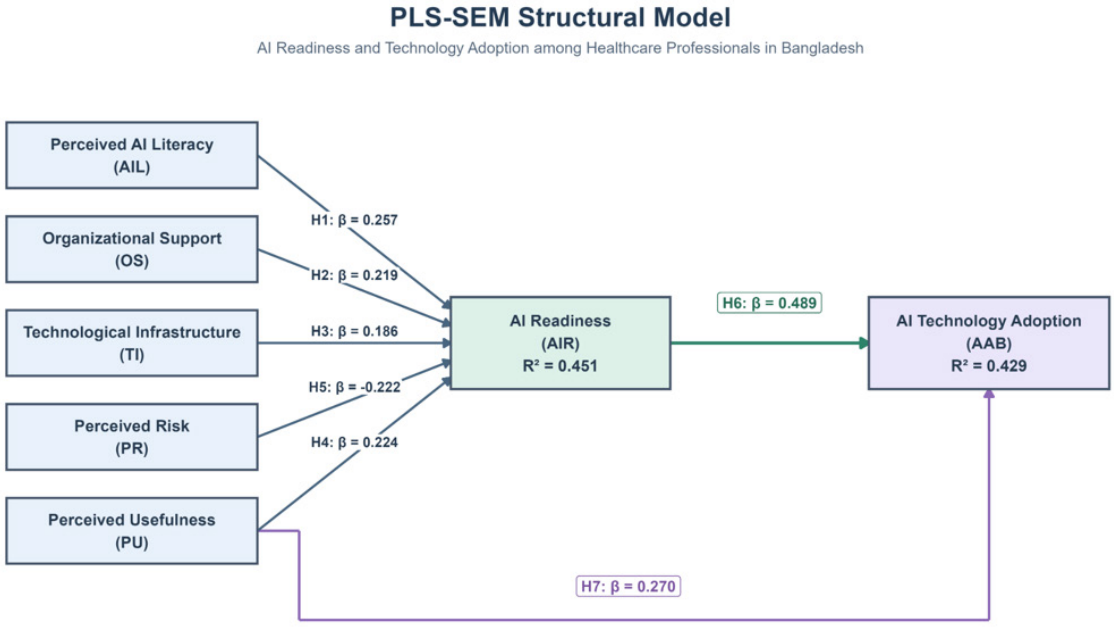


Figure 2: Estimated structural model, standardized coefficients, and R^2 values.

Explanatory Power and Effect Sizes

The given antecedents explain together 45.11% of reported AI readiness, and the adjusted R-squared is 0.4450. The predictors of 42.89% variance of the adaptation behavior are readiness and perceived usefulness with adjusted R-squared of 0.4264. These values mean significant within-sample explanatory power as well as they show that over half of the variance of each outcome is not accounted by the equations given. The remaining variation could be attributed to unmeasured competencies, system availability, institutional policy, professional activity, maturity of implementation, or

circumstances in a situation, but these alternatives were not directly examined during the analysis.

Results of the f-squared give a more localised picture of predictor contributes. The reported effect sizes of readiness infrastructure, literacy, and so on have an antecedent effect with a range of 0.0524 to 0.1087,

Table 10: Coefficients of determination

Outcome	Predictors	R^2	Adj. R^2
AIR	AIL, OS, TI, PU, PR	0.4511	0.4450
AAB	AIR, PU	0.4289	0.4264

Note: R^2 represents explained variance in the endogenous construct.

which are considered small. The direct usefulness-to-adoption effect falls under small (0.1031, as well). By contrast, the contribution of readiness to adoption (f2 0.3383) falls under the medium category used in the analysis. This tendency indicates that readiness is the most consequential predictor in its equation with the two variables, which in turn are the contributions, which can be found in a number of antecedents.

Table 11: Predictor effect sizes (f^2)

Structural path	f^2	Classification
AIL → AIR	0.1087	Small
OS → AIR	0.0743	Small
TI → AIR	0.0524	Small
PU → AIR	0.0763	Small
PR → AIR	0.0831	Small
AIR → AAB	0.3383	Medium
PU → AAB	0.1031	Small

Note: Effect-size classifications follow the reported assessment.

Indirect Relationships Through AI Readiness

The additional indirect-effect findings indicate positive relationships between adoption and four enabling variables via readiness. It has an indirect estimate of literacy 0.1256, organization support 0.1070, infrastructure 0.0908 and usefulness 0.1098. There is a negative indirect relationship between perceived risk and adoption via readiness (−0.1087). All five confidence intervals do not include zero and the test statistics logically reflect the significance assignments registered in the analysis. These approximations are in line with the hypothesized statistical bridging role of readiness.

Table 12: Indirect relationships through AI readiness

Indirect path	Effect	t	CI
AIL → AIR → AAB	0.1256	5.982	[0.0855, 0.1693]
OS → AIR → AAB	0.1070	5.556	[0.0716, 0.1475]
TI → AIR → AAB	0.0908	4.530	[0.0514, 0.1306]
PU → AIR → AAB	0.1098	5.710	[0.0733, 0.1483]
PR → AIR → AAB	-0.1087	5.631	[-0.1476, -0.0733]

Note: CI denotes the reported bootstrap interval; every listed indirect effect has an interval excluding zero.

These indirect effects have implications, which can only be interpreted through consideration of the path structure of the model. Usefulness has a direct path to adoption, and an indirect path to adoption via readiness; the indirect estimate will not substitute the former association (Yin *et al.*, 2021). The other four antecedents have no separately specified direct arrows to adoption in the specified structural framework. The important indirect estimates that they give thus fail to determine whether a direct relationship that was omitted would persist on adding such a direction. In addition, readiness and adoption were measured at the same time, thus the analysis cannot show that the readiness changed preceding the adoption. The results reported can be best characterized as statistically significant indirect relationships in the model presented.

Indicator-Level Predictive Assessment

PLS-based and linear-model benchmark errors are compared in the predictive table of eight endogenous indicators, which include four readiness items and four adoption items. The PLS root mean squared error of all the reported indicators is less than the linear-model. Directional advantage also exhibits the same directionality when it comes to mean absolute error. The variation in RMSE is quite low with an absolute value of about 0.009 to 0.030. So, the predictive comparison gives preference to the given PLS procedure on the basis of the following reported indicators, but the numerical changes cannot be

overestimated.

Predictive evaluation is useful as a model can describe relationships in a sample without showing similar behaviour on novel observations. The results of the reported indicators are positive evidence in comparison to the chosen benchmark. Nevertheless, the documentation of the analysis lacks all the procedural information to recreate the exact prediction exercise and no external validation sample is reported (Nasr *et al.*, 2021). These results in turn endorse a narrow argument of comparatively reduced reported prediction errors, rather than an argument of decision-support accuracy validation in clinical settings. The differences in the prediction error that are observed do not either prove the safety or effectiveness of any particular application of AI.

Table 13: PLSpredict error comparison with linear-model benchmark

Item	PLS RMSE	LM RMSE	Δ RMSE	PLS MAE	LM MAE
AIR1	0.9206	0.9412	-0.0205	0.7469	0.7655
AIR2	0.9220	0.9372	-0.0152	0.7460	0.7547
AIR3	0.9233	0.9537	-0.0304	0.7387	0.7631
AIR4	0.9094	0.9336	-0.0242	0.7253	0.7472
AAB1	1.0493	1.0688	-0.0194	0.8600	0.8747
AAB2	1.0613	1.0770	-0.0157	0.8712	0.8843
AAB3	1.0287	1.0379	-0.0092	0.8505	0.8565
AAB4	0.9660	0.9767	-0.0107	0.7835	0.7914

Note: RMSE is root mean squared error; MAE is mean absolute error. Differences are reported as PLS RMSE minus linear-model RMSE.

Discussion

Interpretation of the Main Structural Relationships

The main conclusion is that the readiness to use AI demonstrates a significant positive correlation with the self-reported adoption behavior of the discussed healthcare professionals. The standardized coefficient of 0.4894 is larger than the direct usefulness coefficient in the adoption equation and has the highest f-squared value in the structural results. This trend aligns with the hypothesis that professional use is partially based on the belief that AI is useful but the feeling that they can incorporate it into their working practice (Hossain *et al.*, 2022). Preparedness is thus a beneficial analytical point of focus in implementation debates especially where technological enthusiasm can surpass professional preparation.

Perceived AI literacy is the predictor of readiness with the highest positive standard association with the other four. This finding implies that practitioners who report higher levels of awareness on AI-related uses and constraints are also more likely to report high preparedness. The literacy construct in question is being measured by outlining the false outputs, and this is significant as the readiness cannot be related to unblinking trust (Ogaga & Zhao, 2023). The skills acquired with the help of training programs that form the ability to differentiate AI functions, assess restrictions, and find the most suitable applications could thus prove more applicable to responsible adoption than the ones aimed at general awareness only. This is not a tested training intervention, and is an implication based on observed associations.

There are two relationships between perceived usefulness. It has a positive relationship with readiness, which is a strong indication that anticipated professional benefit might be the motivator of preparation and adjustment (Secinaro *et al.*, 2021). The fact that its remaining direct relationship with adoption also implies that the perceived performance gains could also be associated with use that is not covered by readiness. This two-fold pattern serves as one of the explanations of why AI adoption cannot be simplified to just one psychological determinant. By efficiency and improvement of routine work, one can expect their relevance, but the results do not quantify whether the improvements have been really met (Choudhury, 2022). The implementation assessments are to differentiate between the perceived utility and the confirmed changes in accuracy, timeliness, safety, workload, and service quality.

Positive associations are observed between organizational support and technological infrastructure and readiness, albeit their standardized coefficients and f-squared are smaller as compared to literacy. These findings show that preparedness is institutionalized in situations and not solely on individual attitudes (Khan, 2023). The encouragement of management can provide the permission and opportunity to learn and appropriate digital infrastructure can make responsible use practically feasible. Both variables are not enough alone to determine successful implementation. A healthcare organization can have the right equipment but lack specific accountability regulations, or speak managerial support without offering employees systems to use and professional advice.

The readiness is negatively related to perceived risk. The finding is especially important since the issues of accuracy, privacy, explainability, and accountability are associated with justifiable clinical and professional duties. The increased risk perception can be accompanied by an unwillingness to use AI tools in the everyday workflows. However, the goal of responsible implementation should not be to squash worry (Asif Naveed, 2023). Risk

awareness can encourage the requisite scrutiny, enhance escalation behaviors, and reinforce the use of professional safeguards. The problem at hand is how to manage the risk that can be identified by use of governance and technical controls without undermining the critical judgment that is necessary to practice safe healthcare.

Readiness as a Statistical Linking Construct

The five supported indirect relationships imply that the readiness plays a significant role in the statistical network proposed. The positive relationships between literacy, support, infrastructure, and usefulness with adoption are propagated along the described readiness paths whereas risk is linked with decreased adoption via low readiness. These results provide a more jointed meaning than a row of discrete bivariate associations (Wang *et al.*, 2023). The individual capability, institutional support, technological support, and perceived usefulness seem to coincide with a shared dimension of preparedness that is, in turn, closely related to use.

However, the structure of analysis should not be confused with the indication of a seen sequence of implementation. The literacy of respondents, their perceived support, readiness and adoption were measured in one cross-sectional set up. The approximate associations cannot determine their temporal order. Reported literacy, perceived usefulness and confidence may be reinforced by adoption per se. Moreover, the fact that a number of antecedents have no direct relationships to adoption in the given model limits the inferences about the possibility of readiness being the sole process through which the relationships between said variables can lead to behavior (Wiljer *et al.*, 2021). The current indirect coefficients should not be interpreted as ultimate causal processes to carry out future analyses, where alternative model structures and longitudinal measurement should be taken into account.

Descriptive Context and Implementation Gaps

The descriptive results provide practical background to the structural model. Over three-fifths of the sample had received no formal AI training, and usefulness ratings tended to be better than organizational support and technological infrastructure ratings (Sharma *et al.*, 2022). This constellation implies that there may be a lack of fit between perceived technological promise and institutional preparation among the understudied group. The result must not be systematically applied to all healthcare facilities since the sample is not reported to be representative of the nation. It still establishes a topical question of implementation: do the expectations regarding the AI capabilities find a reflection in the systematic professional education, appropriate digital resource, and specific procedures of the responsible use?

Measurement and Predictive Interpretation

The obtained results of the measurements reinforce the belief that the seven sets of indicators are coherent statistically and show significant differences within the sample analyzed. The reported benchmarks are met by loadings, reliability, convergent validity and discriminant validity (Alami *et al.*, 2020). These findings are significant as an outcome of a structural model of poorly differentiated constructs would hardly be interpretable. However, positive coefficients fail to provide a criterion validity with observed workplace behavior. The literacy indicators have the perceived understanding, and the adoption indicators with the self-reported frequency. The ability to assess skills and system generated activity logs objectively might be valuable complementary evidence in future research.

Practical and Policy Implications

Professional Development and AI Literacy

The existence of relationship between perceived literacy and readiness justifies relevance of structured professional development. The training must not ignore detecting authentic AI functionality, the fundamentals and constraints of typical systems, how to interpret the uncertain results, and the difference between support and professional judgement. Examples can be specific to the tasks of healthcare personnel, like reviewing documents, retrieving information, supporting image-analysis, pharmacy-information processing, or administrative planning (Nitiéma, 2023). This training must contain clear explanation of conditions according to which outputs must be verified or are not to be used. Learning should be measured in terms of what is known and not the attendance or confidence.

Organizational Preparation and Governance

Companies that contemplate implementing AI should ensure that managerial support goes hand in hand with operational norms. The most believable conditions that support the concept of supportive leadership are the clarity of the professional roles, training access, allowable uses, reporting relationships, and ultimate decision-making authority. Applications that are approved, but need administrative support, and those that need a more detailed clinical governance can be differentiated pursuant written procedures (Hameed *et al.*, 2023). Before broader deployment can take place, pilot implementations can also uncover workflow disruptions, documentation overheads, and information security issues. The stated correlation on organizational support and readiness offers a motivator to examine these institutional circumstances, yet the comparative efficacy of specific governance measures would be an empirical question to be answered in future studies.

Infrastructure and Equity of Access

Adequacy of infrastructure is positively related to preparedness in the estimated model. Sustainable adoption also involves consideration of equipment reliability, network access, software compatibility, maintenance, and security of institutional information systems. Investments

must be aligned to the work that professionals really do and not solely by the fact that an application has become commercially visible (Novak *et al.*, 2023). The disparities between urban, semi-urban, and rural environments are a topic of special interest in the implementation planning. Due to the fact that the current analysis does not estimate subgroup-specific effects, one local self-specific resource limitation should be assessed and only then should one uniform investment strategy be used across institutions.

Risk Management and Professional Accountability

The aversarial correlation between perceived risk and preparedness points to the fact that the fears related to AI are not to be swept under the carpet, but perceived as an opposition to change. Organizations ought to put up precautions against inaccurate information, unjustified dissemination of information, low explainability, and dubious responsibility. Reviewing of consequential outputs by humans, appropriate access controls, role-based permissions, cautious data treatment, and definite escalation processes might hold pertinent elements of responsible implementation. The policies must also determine the decisions that are left under professional authority (Malerbi *et al.*, 2023). It is not an aim to make maximum use of AI in all activities, but rather make use of it in circumstances that are protective of patients, health care workers, and institutional liability.

Monitoring Adoption and Evaluating Outcomes

The result of the current research is self-reported use, rather than confirmed performance improvement. Where possible, the adoption surveys should hence be combined with measures of appropriate use, user competency, error recognition, processing time, quality of service, and pertinent safety indicators, by decision-makers. Monitoring must be able to differentiate between frequent but of low value use and selective use that enhances a clearly defined task. Implementation costs, workload effects and unintended consequences should also be documented in evaluation designs (Lai *et al.*, 2021). This evidence would aid in establishing whether the positive perceptions and readiness relationships identified in the current dataset will result in a significant organizational or clinical value in the long run.

CONCLUSION

This research paper discussed a seven-item model of AI preparedness and self-reported use of technology using a sample of 460 healthcare professionals included in the cross-sectional survey of Bangladesh analysis. The indicator loadings, internal consistency, convergent and discriminant validity of the measurement are satisfactory as shown by the measurement results. All the seven structural paths suggested are justified in the reported estimates. Ready is positively correlated with perceived AI literacy, organizational support, technological infrastructure, and perceived usefulness and negatively correlated with perceived risk. Both adoption behavior and usefulness have a positive relationship with readiness, and readiness has a stronger standardized relationship in the equation of adoption.

The model explains about 45 % of the variance in the readiness and 43 % of the variance in adoption. Considerable indirect effects also imply that preparedness bridges the five mentioned antecedents with reported AI use. These results support the combined approach to comprehending adoption where personal knowledge, organizational support, technological factors, role of anticipated utility, and risk-related issues are taken into account. Practically, the need to increase the application of responsible AI should consider education of professionals, trusted infrastructure, appropriate institutional governance, and long-term evaluation instead of implementing AI as the installation of a software package only.

The contribution of the study is that it explores the notion of preparedness in a systematic way as a statistically significant construct in the relationship between professional perceptions and reported AI-enabled activity. However, the findings cannot be turned into evidence of causal effect, national representative prevalence and clinical outcome improvements. More longitudinal and independent-validated research of this nature should be conducted in the future to identify how these shifts in organizational circumstances and professional competence affect the use of AI appropriately as time goes on. These limits yield an empirical foundation of coherence in the findings to use these findings to further investigate and plan responsibly on the adoption of AI in healthcare in Bangladesh.

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