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Original Article

# Artificial Intelligence in Strengthening Primary Healthcare Delivery in Pakistan: A Feasibility and Application Assessment

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## ABSTRACT

Background: Primary healthcare facilities in Pakistan may benefit from artificial intelligence (AI)-supported triage and clinical decision support, but provider readiness and contextual barriers remain uncertain. Objective: To assess AI readiness, perceived clinical utility, triage potential, ease of use, and implementation barriers among primary healthcare providers in Southern Punjab, Pakistan, and to compare outcomes across professional cadres. Methods: This cross-sectional survey included 96 medical officers, lady health supervisors, and allied health professionals working in Basic Health Units and Rural Health Centers between August and December 2025. Participants were recruited through non-probability purposive sampling. Readiness and technology acceptance were assessed using a modified Artificial Intelligence Readiness Scale for Medical Professionals and adapted Technology Acceptance Model domains. Descriptive statistics, Pearson correlations, one-way analysis of variance, and Tukey post-hoc comparisons were used. Results: The response rate was 91.4%. Mean AI readiness was 3.12 ± 0.64, perceived clinical utility was 3.78 ± 0.58, triage efficiency potential was 3.85 ± 0.61, perceived ease of use was 2.64 ± 0.72, and perceived barriers were 4.15 ± 0.53. Awareness differed across cadres ($F = 8.14$, $p < 0.001$), with medical officers reporting higher scores than lady health supervisors and allied health professionals. Technological competence correlated positively with triage-tool acceptance ($r = 0.64$, $p < 0.001$). Conclusion: Providers perceived substantial potential value in AI-supported primary care, but cadre-specific readiness gaps and infrastructural and ethical barriers may constrain implementation. Workforce preparation and infrastructure development should precede prospective pilot evaluation.
Keywords: Artificial Intelligence; Attitude of Health Personnel; Cross-Sectional Studies; Pakistan; Primary Health Care; Technology Acceptance.

EDITORIAL INFORMATION

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## INTRODUCTION

Primary healthcare constitutes the first level of contact between individuals and the health system and plays a central role in disease prevention, early identification of illness, initial management, and referral. In Pakistan, Basic Health Units and Rural Health Centers provide essential services to rural and underserved populations; however, their capacity may be constrained by shortages of trained personnel, limited diagnostic resources, high patient volumes, fragmented records, and uneven digital infrastructure. Similar structural challenges across low- and middle-income countries have increased interest in technological approaches that may support healthcare professionals and improve the organization of frontline services (1,2).

Digital health interventions, including telemedicine and mobile health applications, have shown potential to improve communication, service access, clinical coordination, and continuity of care in resource-limited settings, although their successful implementation remains dependent on local infrastructure and workforce capacity (3). Artificial intelligence represents a further development within this field and includes computational systems capable of supporting pattern recognition, risk classification, clinical documentation, and decision-making. In primary care, AI-assisted tools may support preliminary triage, identification of high-risk patients, standardized clinical decision support, and prioritization of referrals. Nevertheless, evidence concerning these potential applications has largely emerged from settings with more developed digital systems, and the transferability of such technologies to low-resource healthcare environments remains uncertain (4,5).

The implementation of AI is not determined solely by algorithmic performance. Availability of electricity and internet connectivity, compatibility with existing information systems, data quality, privacy protections, regulatory oversight, and the technical competence of intended users can influence whether a digital tool is accepted and used appropriately. Health professionals' perceived usefulness, confidence in using technology, perceived ease of use, and willingness to adopt AI-supported systems are therefore important components of implementation readiness (6). Evidence from other resource-constrained clinical contexts also indicates that healthcare innovations and standardized decision-support approaches must be adapted to the skills of frontline personnel, available resources, referral pathways, and local service-delivery conditions (7,8).

These considerations are particularly relevant to primary healthcare because medical officers, lady health supervisors, and allied health professionals differ in professional education, clinical responsibilities, exposure to digital technologies, and expected interaction with decision-support systems. Differences in baseline technological competence may consequently be associated with differences in AI awareness, perceived ease of use, and willingness to adopt AI-guided triage. At the same time, positive perceptions of clinical utility cannot be interpreted as evidence of operational feasibility or improved patient outcomes unless the technology is prospectively implemented and evaluated. Provider surveys can instead offer preliminary evidence about workforce readiness, perceived applications, and barriers that should be addressed before implementation is attempted.

Existing literature has primarily discussed the broad potential of AI and digital health in developing countries or examined technology within disease-specific and comparatively specialized settings. Limited empirical evidence is available regarding how different cadres of frontline primary healthcare providers in Southern Punjab perceive AI-assisted clinical tools. In particular, uncertainty remains regarding providers' baseline AI awareness, technological self-efficacy, perceived clinical utility, perceived ease of use, acceptance of AI-supported triage, and concerns about infrastructural and ethical barriers. Addressing this gap is necessary to determine whether future pilot implementation should initially prioritize workforce training, digital infrastructure, governance mechanisms, or profession-specific support.

Accordingly, this cross-sectional study aimed to assess AI readiness and awareness, perceived clinical utility, perceived triage potential, ease of use, and infrastructural and ethical barriers among medical officers, lady health supervisors, and allied health professionals working in Basic Health Units and Rural Health Centers in Southern Punjab, Pakistan. It further aimed to compare selected outcome scores across professional cadres and examine the association between baseline technological competence and willingness to adopt AI-guided triage tools. The study evaluated provider perceptions and readiness rather than the clinical effectiveness or operational performance of an implemented AI system.

## MATERIALS AND METHODS

A quantitative cross-sectional survey was conducted to characterize healthcare providers' awareness, readiness, acceptance, and perceived barriers regarding the potential use of artificial intelligence in primary healthcare. This design was selected because the study aimed to measure provider perceptions and examine associations among technology-related variables at a single period without implementing an AI intervention. The study was conducted from August to December 2025 in Basic Health Units and Rural Health Centers in Southern Punjab, Pakistan. This setting was selected because its predominantly rural primary healthcare facilities serve populations experiencing socioeconomic and healthcare-access constraints and were considered relevant for evaluating provider readiness for resource-dependent digital technologies.

The target population comprised licensed medical officers, lady health supervisors, and allied health professionals providing clinical services in participating primary healthcare facilities. Healthcare providers were eligible if they were currently working in a Basic Health Unit or Rural Health Center and had completed at least six months of continuous primary healthcare experience. Providers working exclusively in tertiary-care hospitals and individuals employed solely in nonclinical administrative positions were excluded. Eligible providers were recruited through non-probability purposive sampling across the participating facilities. The target sample of 96 participants was selected with reference to the sample range used in a comparable feasibility survey of digital-health adoption among rural healthcare providers in South Asia. Participation was voluntary, and written informed consent was obtained before questionnaire administration.

Data were collected once from each participant using a structured, self-administered questionnaire. The instrument recorded demographic and professional characteristics, including age, sex, professional cadre, facility type, duration of primary-care experience, and previous digital-health training. It also assessed baseline technological competence and multiple AI-related outcomes. The same questionnaire format and administration procedure were used for all participants.

Provider readiness and awareness were assessed using a modified version of the Artificial Intelligence Readiness Scale for Medical Professionals. The instrument generated an overall readiness score and scores related to baseline AI knowledge and technological self-efficacy. Perceptions regarding AI adoption were assessed using items adapted from the Technology Acceptance Model. The assessed domains included perceived clinical utility, perceived potential to improve triage efficiency, perceived ease of use, willingness to adopt AI-guided triage tools, and perceived infrastructural and ethical barriers. Items were rated on five-point Likert scales, and the resulting composite domain scores ranged from 1.00 to 5.00. Higher readiness, knowledge, self-efficacy, utility, triage, ease-of-use, and acceptance scores indicated more favorable perceptions, whereas a higher barrier score indicated greater perceived infrastructural and ethical constraints.

Before the main survey, the questionnaire underwent pretesting and content review by a panel with expertise in medical informatics and public health. The modified instrument was used to ensure that the terminology and proposed AI applications were relevant to primary healthcare practice in the study setting. The use of a structured self-administered format minimized variation in interviewer administration. Questionnaires complete for the study variables were included in the final analysis, whereas incomplete questionnaires were excluded; therefore, the reported analysis constituted a complete-case analysis. No clinical intervention, diagnostic algorithm, or AI-assisted triage system was implemented, and all outcomes represented participants' self-reported perceptions and readiness during the survey period.

Statistical analysis was performed using IBM SPSS Statistics version 26.0. Categorical variables were summarized as frequencies and percentages, while continuous variables and composite scale scores were summarized as means and standard deviations.

Mean scores were accompanied by 95% confidence intervals where applicable. The distribution of continuous outcome scores was evaluated using the Shapiro–Wilk test, visual inspection of normal quantile–quantile plots, and assessment of skewness and kurtosis. Differences in readiness and technology-acceptance scores across the three professional cadres were examined using one-way analysis of variance. When an omnibus difference was detected, Tukey's post-hoc procedure was used for pairwise comparisons. Pearson correlation coefficients were calculated to examine bivariate association

## RESULTS

A total of 105 questionnaires were distributed, of which 96 were fully completed and included in the analysis, corresponding to a response rate of 91.4%. The analytical sample included 42 medical officers (43.8%), 28 lady health supervisors (29.2%), and 26 allied health professionals (27.1%). Participants had a mean age of 34.6 ± 6.8 years and a mean primary-care experience of 7.2 ± 4.1 years. Women accounted for

54 participants (56.3%), and 58 participants (60.4%) worked in Basic Health Units. Previous digital-health training was reported by 21 participants (21.9%) (Table 1).

The mean overall AIRS-MP readiness score was 3.12 ± 0.64, with a baseline-knowledge score of 2.95 ± 0.71 and a technological self-efficacy score of 3.29 ± 0.68. Among the technology-acceptance outcomes, perceived triage-efficiency potential had a mean score of 3.85 ± 0.61 and perceived clinical utility had a mean score of 3.78 ± 0.58. The mean perceived ease-of-use score was 2.64 ± 0.72, while the mean infrastructural and ethical-barrier score was 4.15 ± 0.53 (Table 2).

*Table 1. Demographic and Professional Characteristics of Participants (N=96)*

| Characteristic | Category | Value |
|---|---|---|
| **Age, years** | — | 34.6 ± 6.8 |
| **Sex** | Male | 42 (43.8) |
| | Female | 54 (56.3) |
| **Professional cadre** | Medical officer | 42 (43.8) |
| | Lady health supervisor | 28 (29.2) |
| | Allied health professional | 26 (27.1) |
| **Facility type** | Basic Health Unit | 58 (60.4) |
| | Rural Health Center | 38 (39.6) |
| **Primary-care experience, years** | — | 7.2 ± 4.1 |
| **Previous digital-health training** | Yes | 21 (21.9) |
| | No | 75 (78.1) |

Values are presented as n (%) or mean ± SD.

*Table 2. Artificial Intelligence Readiness and Technology-Acceptance Scores (N=96)*

| Outcome | Scale range | Mean ± SD | 95% CI |
|---|---|---|---|
| **AIRS-MP total readiness** | 1.00–5.00 | 3.12 ± 0.64 | 2.99–3.25 |
| **AIRS-MP baseline knowledge** | 1.00–5.00 | 2.95 ± 0.71 | 2.81–3.09 |
| **AIRS-MP technological self-efficacy** | 1.00–5.00 | 3.29 ± 0.68 | 3.15–3.43 |
| **Perceived clinical utility** | 1.00–5.00 | 3.78 ± 0.58 | 3.66–3.90 |
| **Perceived triage-efficiency potential** | 1.00–5.00 | 3.85 ± 0.61 | 3.73–3.97 |
| **Perceived ease of use** | 1.00–5.00 | 2.64 ± 0.72 | 2.49–2.79 |
| **Perceived infrastructural and ethical barriers** | 1.00–5.00 | 4.15 ± 0.53 | 4.04–4.26 |

AIRS-MP, Artificial Intelligence Readiness Scale for Medical Professionals; CI, confidence interval; SD, standard deviation.

*Table 3. Bivariate Associations Among Technology-Readiness and Acceptance Variables (N=96)*

| Variable 1 | Variable 2 | Pearson r | 95% CI | p-value |
|---|---|---|---|---|
| **Baseline technological competence** | Perceived clinical utility | 0.41 | 0.23–0.56 | <0.001 |
| **Baseline technological competence** | AI-guided triage acceptance | 0.64 | 0.50–0.74 | <0.001 |
| **Baseline technological competence** | Perceived ease of use | 0.58 | 0.43–0.70 | <0.001 |
| **Baseline technological competence** | Perceived infrastructure barriers | −0.31 | −0.48 to −0.12 | 0.002 |
| **Perceived clinical utility** | AI-guided triage acceptance | 0.52 | 0.36–0.65 | <0.001 |
| **Perceived clinical utility** | Perceived ease of use | 0.33 | 0.14–0.50 | 0.001 |
| **Perceived clinical utility** | Perceived infrastructure barriers | −0.12 | −0.31 to 0.08 | 0.244 |
| **AI-guided triage acceptance** | Perceived ease of use | 0.46 | 0.29–0.60 | <0.001 |
| **AI-guided triage acceptance** | Perceived infrastructure barriers | −0.22 | −0.40 to −0.02 | 0.031 |
| **Perceived ease of use** | Perceived infrastructure barriers | −0.48 | −0.62 to −0.31 | <0.001 |

Confidence intervals were calculated using Fisher's z transformation. All p-values are two-tailed.

*Table 4. Comparison of Outcome Scores Across Professional Cadres (N=96)*

| Outcome | Medical officers (n=42), mean ± SD | Lady health supervisors (n=28), mean ± SD | Allied health professionals (n=26), mean ± SD | F(2,93) | p-value | $\eta^2$ |
|---|---|---|---|---|---|---|
| **AIRS-MP awareness** | 3.45 ± 0.52 | 2.88 ± 0.61 | 2.84 ± 0.65 | 12.07 | <0.001 | 0.206 |
| **Perceived clinical utility** | 3.86 ± 0.54 | 3.71 ± 0.62 | 3.73 ± 0.59 | 0.71 | 0.496 | 0.015 |
| **Perceived ease of use** | 2.91 ± 0.68 | 2.42 ± 0.70 | 2.45 ± 0.73 | 5.47 | 0.006 | 0.105 |
| **Perceived barriers** | 4.08 ± 0.55 | 4.22 ± 0.51 | 4.19 ± 0.52 | 0.68 | 0.508 | 0.014 |

One-way analysis of variance was calculated from the reported group sizes, means, and SDs. AIRS-MP, Artificial Intelligence Readiness Scale for Medical Professionals; $\eta^2$, eta squared.

*Table 5. Tukey–Kramer Pairwise Comparisons for Outcomes with Significant Omnibus Differences*

| Outcome | Comparison | Mean difference | 95% CI | Adjusted p-value |
|---|---|---|---|---|
| **AIRS-MP awareness** | Medical officers vs lady health supervisors | 0.57 | 0.23–0.91 | <0.001 |
| | Medical officers vs allied health professionals | 0.61 | 0.26–0.96 | <0.001 |
| | Lady health supervisors vs allied health professionals | 0.04 | −0.34 to 0.42 | 0.966 |
| **Perceived ease of use** | Medical officers vs lady health supervisors | 0.49 | 0.08–0.90 | 0.014 |
| | Medical officers vs allied health professionals | 0.46 | 0.04–0.88 | 0.026 |
| | Lady health supervisors vs allied health professionals | −0.03 | −0.48 to 0.42 | 0.986 |

Mean difference was calculated as the meaning of the first group minus the meaning of the second group. Confidence intervals and adjusted p-values were calculated using the Tukey–Kramer procedure.

Baseline technological competence was positively correlated with AI-guided triage acceptance (r=0.64; 95% CI: 0.50–0.74; p<0.001), perceived ease of use (r=0.58; 95% CI: 0.43–0.70; p<0.001), and perceived clinical utility (r=0.41; 95% CI: 0.23–0.56; p<0.001). Perceived infrastructure barriers were inversely correlated with perceived ease of use (r=−0.48; 95% CI: −0.62 to −0.31; p<0.001), baseline technological competence (r=−0.31; 95% CI: −0.48 to −0.12; p=0.002), and AI-guided triage acceptance (r=−0.22; 95% CI: −0.40 to −0.02; p=0.031). The association between perceived clinical utility and infrastructure barriers was not statistically supported (r=−0.12; 95% CI: −0.31 to 0.08; p=0.244) (Table 3).

AIRS-MP awareness scores differed across professional cadres (F(2,93)=12.07; p<0.001; $\eta^2$=0.206). Medical officers had higher mean awareness scores than lady health supervisors (mean difference=0.57; 95% CI: 0.23–0.91; adjusted p<0.001) and allied health professionals (mean difference=0.61; 95% CI: 0.26–0.96; adjusted p<0.001). Awareness scores did not differ between lady health supervisors and allied health professionals (mean difference=0.04; 95% CI: −0.34 to 0.42; adjusted p=0.966).

Perceived ease-of-use scores also differed across cadres (F(2,93)=5.47; p=0.006; $\eta^2$=0.105). Medical officers had higher scores than lady health supervisors (mean difference=0.49; 95% CI: 0.08–0.90; adjusted p=0.014) and allied health professionals (mean difference=0.46; 95% CI: 0.04–0.88; adjusted p=0.026). No corresponding difference was observed between lady health supervisors and allied health professionals (mean difference=−0.03; 95% CI: −0.48 to 0.42; adjusted p=0.986). The cadre comparisons did not provide evidence of differences in perceived clinical utility (F(2,93)=0.71; p=0.496; $\eta^2$=0.015) or perceived barriers (F(2,93)=0.68; p=0.508; $\eta^2$=0.014) (Tables 4 and 5).

## DISCUSSION

This study identified a consistent contrast between favorable perceptions of the potential usefulness of artificial intelligence and limited readiness for its immediate adoption in primary healthcare. Providers generally perceived AI-supported clinical and triage functions positively, whereas ease of use was rated less favorably and infrastructural and ethical barriers remained prominent. Readiness and ease-of-use scores also varied by professional cadre, while greater technological competence was associated with stronger acceptance of AI-guided triage.

Medical officers reported greater AI awareness and perceived ease of use than lady health supervisors and allied health professionals. These differences may reflect variation in professional education, access to digital resources, exposure to clinical decision-support technologies, and opportunities for continuing professional development. However, these explanations remain provisional because the present analysis did not adjust for previous digital-health training, professional experience, age, facility type, or other potentially relevant characteristics. Wider literature on AI-informed healthcare similarly emphasizes that successful adoption depends on role-specific knowledge, trust, and the ability of healthcare professionals to interpret and supervise algorithm-supported decisions rather than on the availability of the technology alone (9). The absence of a meaningful difference between lady health supervisors and allied health professionals may indicate comparable levels of exposure, but the broad allied-health category and relatively small subgroup sizes limit more specific interpretation.

Perceived clinical utility and triage potential were favorable across all three professional cadres. This pattern is compatible with literature describing the potential of AI-assisted technologies to support risk classification, clinical documentation, health communication, and service organization in resource-constrained settings (1,4). Nevertheless, favorable perceptions do not demonstrate that AI will improve diagnostic accuracy, referral quality, waiting times, or patient outcomes in the participating facilities. Provider acceptance represents an early implementation condition rather than evidence of clinical effectiveness. The coexistence of favorable utility ratings and substantial implementation concerns is also consistent with an assessment of digital hypertension interventions in India, which identified infrastructure, workforce capacity, workflow integration, and health-system readiness as interconnected determinants of implementation (10).

The positive association between baseline technological competence and acceptance of AI-guided triage suggests that providers who are more comfortable with digital technology may be more willing to incorporate AI-supported tools into clinical workflows. A plausible explanation is that technological competence improves self-efficacy, reduces the anticipated effort required to operate unfamiliar systems, and enables providers to evaluate algorithmic recommendations with greater confidence. Conversely, limited familiarity may increase uncertainty regarding reliability, professional responsibility, and the practical value of AI-generated advice. This interpretation is consistent with broader digital-health implementation literature emphasizing the importance of workforce capability and organizational readiness (6,9). Because the study was cross-sectional, the direction of this relationship cannot be established; greater willingness may encourage technological engagement, technological competence may promote acceptance, or both may arise from previous training and access to digital systems.

Perceived infrastructure barriers were inversely associated with ease of use and, to a lesser extent, with AI-guided triage acceptance. This finding is relevant because acceptable and technically sound AI tools require dependable data capture, compatible information systems, connectivity, maintenance, governance, and trained personnel. Digital-health experience in other clinical fields has similarly shown that data quality, interoperability, workflow integration, clinical oversight, and institutional governance are necessary for responsible implementation (11). Evidence from digital solutions for paediatric sepsis further demonstrates that technologies developed in well-resourced settings may not transfer directly to facilities with different staffing, information systems, patient populations, and technical capacity (12). Accordingly, the present findings support a staged approach in which workforce preparation, infrastructure assessment, privacy protection, and local workflow evaluation precede any large-scale deployment. Implementation should then be evaluated prospectively through measures of usability, adoption, clinical performance, safety, equity, and patient outcomes rather than provider perception alone. Similar attention to accessibility, user support, and context-specific implementation has been emphasized for digital-health interventions intended to reduce gaps in preventive care (13).

The findings have practical relevance for primary healthcare planning in Southern Punjab. The broadly favorable perception of clinical utility suggests that frontline providers may be receptive to carefully designed pilot programs, while the lower ease-of-use scores among non-physician cadres indicate that a single training strategy may not be appropriate for all professional groups. Role-specific education should address basic AI concepts, interpretation of outputs, recognition of errors, data confidentiality, and maintenance of professional accountability. Any pilot system should complement rather than replace clinical judgment and should be designed around the capabilities of Basic Health Units and Rural Health Centers. These implications remain preparatory because the study did not test an AI system, assess actual use, or measure effects on clinical care.

The study included medical officers, lady health supervisors, and allied health professionals from both Basic Health Units and Rural Health Centers and achieved a high questionnaire completion rate. The assessment of readiness, utility, ease of use, acceptance, and barriers provided a multidimensional view of provider perceptions. However, several limitations should be considered. Purposive sampling and recruitment within one region limit representativeness and prevent generalization to all primary healthcare providers in Pakistan. The cross-sectional design precludes temporal or causal interpretation. Self-reported responses may have been affected by social-desirability and common-method bias, while providers' stated willingness may not predict actual technology use. The broad allied-health category may conceal important differences among professions. The subgroup sizes were modest, and the unadjusted analyses could not separate professional-cadre effects from differences in previous training, experience, age, sex, or facility characteristics. Exclusion of incomplete questionnaires may also have introduced selection bias. Finally, the modified readiness and technology-acceptance measures require clear documentation of their adaptation, scoring, cultural validity, and reliability before the magnitude of the reported scores can be interpreted confidently.

## CONCLUSION

Primary healthcare providers surveyed in Southern Punjab perceived potential clinical and triage-related value in artificial intelligence, but their readiness and perceived ease of use varied across professional cadres, and infrastructural and ethical barriers remained substantial. Greater technological competence was associated with stronger acceptance of AI-guided triage, indicating that workforce capability and implementation context are important considerations for future pilot testing. These findings describe provider perceptions and preliminary readiness rather than the feasibility, clinical effectiveness, or safety of an implemented AI system.

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