*EJPMR, 2026, 13(8), 756-772* **Research Article** **Impact Factor: 8.158**

**EUROPEAN JOURNAL OF PHARMACEUTICAL AND MEDICAL RESEARCH**

www.ejpmr.com

**ISSN (O): 2394-3211**
**ISSN (P): 3051-2573**
**Coden USA: EJPMAG**

# ASSESSING THE IMPACT OF ARTIFICIAL INTELLIGENCE ON CLINICAL DECISION-MAKING FOR OLDER ADULT HEALTH AND AGING CARE IN PRIMARY HEALTH CARE: A CROSS-SECTIONAL SURVEY OF HEALTHCARE PROFESSIONALS

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**DOI:** https://doi.org/10.5281/zenodo.21990442

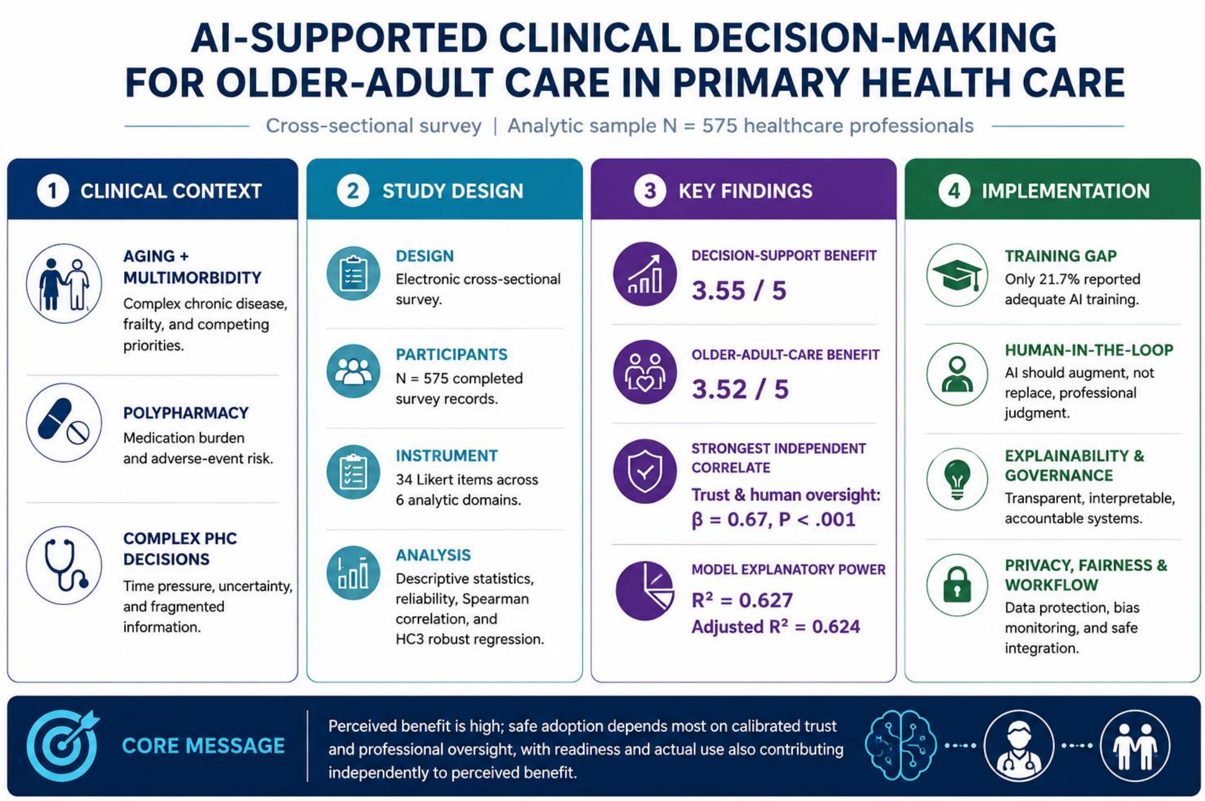
**How to cite this Article:** Najlaa Saadi Sheet AL-Safar* (2026). Assessing The Impact Of Artificial Intelligence On Clinical Decision-Making For Older Adult Health And Aging Care In Primary Health Care: A Cross-Sectional Survey Of Healthcare Professionals. European Journal of Pharmaceutical and Medical Research, 13(8), 756–772.


**Article Received on 05/07/2026** **Article Revised on 25/07/2026** **Article Published on 01/08/2026**

## ABSTRACT

**Background:** Artificial intelligence (AI) is increasingly used to support clinical decision-making, but primary health care (PHC) implementation for older adults requires evidence on workforce readiness, perceived benefit, trust, professional oversight, and governance. **Objective:** To assess healthcare professionals' familiarity with and use of AI, perceived decision-support benefit, perceived benefit for older-adult care, trust and human oversight, governance concerns, and implementation conditions in PHC. **Methods:** A cross-sectional electronic survey dataset containing 575 completed response rows was analyzed as supplied. The current workbook contains no unique respondent identifier or timestamp field that would justify record-level deduplication. Thirty-four attitudinal items were scored on a 5-point Likert scale. Descriptive statistics, Cronbach alpha, Spearman correlations, and HC3-robust multivariable linear regression were applied. **Results:** Perceived decision-support benefit averaged 3.55/5 (SD 0.76), and perceived benefit for older-adult care averaged 3.52/5 (SD 0.68). The model explained 62.7% of the variance in perceived older-adult-care benefit (adjusted $R^2$=0.624). Trust and human oversight was the strongest independent correlate (standardized β=0.67, 95% CI 0.61 to 0.74, P<.001); readiness (β=0.13, P<.001) and AI use (β=0.07, P=0.037) were also independently associated, whereas familiarity and governance concerns were not statistically significant after adjustment. Only 21.7% agreed that they had received adequate AI training. **Conclusions:** Healthcare professionals perceived meaningful potential for AI-supported decision-making and older-adult care, but implementation readiness remained uneven. Safe adoption should prioritize calibrated trust, human professional oversight, competency-based training, explainability, privacy, fairness, accountability, and prospective evaluation in real PHC workflows.

**KEYWORDS**: artificial intelligence; primary health care; clinical decision support; older adults; geriatrics; trust; explainable AI; human oversight; survey.




Graphical Abstract. AI-supported clinical decision-making in older-adult primary health care: study design, corrected analytic sample, principal findings, and implementation implications.

As shown in the Graphical Abstract, the study analyzed all 575 completed response rows contained in the current survey workbook. The visual summarizes the clinical context, the 34-item electronic survey, the six analytic domains, and the principal quantitative findings. Perceived decision-support benefit averaged 3.55/5 and perceived older-adult-care benefit averaged 3.52/5. In the adjusted model, trust and human oversight was the strongest independent correlate of older-adult-care benefit ($\beta$=0.67, P<.001), while AI readiness ($\beta$=0.13, P<.001) and actual use ($\beta$=0.07, P=0.037) also showed independent positive associations. The implementation message is therefore not autonomous replacement, but carefully governed, human-in-the-loop augmentation supported by training, explainability, privacy protection, and accountability.

*Source: Prepared by the researchers based on the present survey dataset (N=575) and the conceptual synthesis of references.*[1,4,8-13,18-19,28-29]

## 1. INTRODUCTION

Primary health care is changing its workload and epistemic requirements due to the effects of population ageing. Older people are frequently diagnosed with several conditions (multimorbidity), with several medications (polypharmacy), are frail, cognitively vulnerable, unable to function and have several competing treatment priorities. These characteristics render clinical decision making less algorithmic as one disease routine, and tools that can incorporate multiple and heterogeneous, longitudinal data sources more useful. However, recent geriatric evidence cautions that digital systems need to be assessed in terms of outcomes that are relevant to older people such as safety, function, autonomy, medication burden, and continuity of care.[18-27]

AI-driven CDSS can aid in pattern recognition, risk stratification, diagnosis, medication review, documentation, and prioritization. However, in PHC there is less external validation and evidence of real world impact evaluation and implementation in primary care workflows, but there is evidence of significant development activity.[1,4,5,7] This translation is particularly valuable when the presentation of the patient is atypical or multimorbid or not well represented in the training sets used in the decisions for the patient by artificial intelligence.

There is no link between technical performance and clinician acceptance. The most frequently cited factors for adoption in modern assessments are performance expectancy, workflow compatibility, training, transparency, legal responsibility, privacy and professional autonomy.[1,5,6] Explanation can foster trust, but explanation can backfire: clinically coherent, short explanations are likely to foster understanding, confusing explanations may lead to higher cognitive load and miscalibrated trust, and contradictory explanations may lead to miscalibrated trust.[8-12]

The problems are exacerbated in older-adult care. Medication burden/polypharmacy is common and there is the possibility that new machine-learning approaches can help identify a risk or prioritise a medication for review.[21-26] There is also, however, contextual judgment in such high stakes geriatric decisions as goals, function, cognition, prognosis, caregiver's capacity, or burden of treatment. Generative AI has therefore been highlighted by the American Geriatrics Society for its potential and unique risks in the care of older adults.[19]

To answer implementation-oriented questions, the present study focuses on perceived AI benefit in clinical decision-making and older adult care in tandem with readiness, trust, human oversight, governance concerns, and implementation intention. The analysis does not only ask whether professionals are positive or negative about AI, but which of the strongest factors are associated with their perceived usefulness of AI to support older persons in PHC.

## 2. Literature Review

### 2.1 AI and the Transformation of Primary Health Care

In recent literature on PHC, AI is suggested as a general enabler rather than a one-size-fits-all solution for PHC. Systematic evidence has been identified to support opportunities in areas of diagnostic support, screening, prediction, documentation, resource allocation, and longitudinal care, and data-access, infrastructure, privacy and stewardship issues have been documented. In the primary care setting, Rakers et al. also showed that predictive ML models are poorly validated on external and clinical measures, and were thus not ready for widespread clinical use.[7] But the challenge is not only in the creation of algorithms, it's in figuring out when, where, and under which governance conditions algorithms can complement clinical work.

### 2.2 Clinician Knowledge, Adoption, and Training

There is variability in the knowledge and use by primary-care clinicians. A systematic review and meta-analysis in 2025 revealed generally low levels of knowledge and high reliance on opportunistic learning, and that practice experiences were influenced by training and infrastructure.[5] Likewise, there has been limited awareness and training needs of generative AI among UK general practitioners in recent years, according to qualitative studies.[2] Moreover, survey results from Saudi Arabia and Egypt show that good perceptions can also exist along with low knowledge or practice.[3,15] Training is then most aptly conceived as a tool to be deployed as a precautionary measure and not as an alternative to education.

### 2.3 Trust, Explainability, and Human Oversight

Trust is a relationship characteristic related to evidence, system, workflow, clinician and accountability structure. Trust determinants that is commonly observed in systematic reviews include transparency, reliability, validation, usability, ethical protections and clinician control.[8-13] If explanations are cognitively manageable and have clinical relevance, they can help to build trust; if they are cognitively impossible (due to conflict with domain knowledge) or do not make sense, they can contribute to distrust.[8-10] The goal of high-stakes care is to have the right level of trust – the level where they can learn from trusted input, but have enough skepticism and authority to say no to unsafe output.

### 2.4 AI in Older-Adult and Geriatric Care

In geriatric care, AI can be used for risk prediction, assessing frailty, managing medications, providing cognitive support, monitoring, and creating personalized care plans.[18-20] Frailty machine-learning models have shown good discrimination and there are some quality and applicability concerns.[20] Other potential vulnerabilities within training data and/or training interfaces include differences in goals, sensory and cognitive limitations, and multimorbidity among the older adults. Thus, geriatric AI should be tested in the aged, frail, disabled, cognitively impaired, and/or medicated populations, rather than being thought to be transferable from younger and healthier populations.

### 2.5 Polypharmacy as a High-Value Decision-Support Use Case

Some of the specific domains where AI can be applied that are relevant include medication review (synthesising indications, interactions, renal and hepatic function, adverse effects, adherence, life expectancy, patient goals). There have been recent reports of high prevalence and associations with adverse outcomes in relation to high polypharmacy.[21-26] The results for effectiveness of e-decision support and drug management interventions for selected prescribing and utilization outcomes are mixed.[22, 25] Therefore, the use of AI should be considered a tool to support or prioritize clinician-led deprescribing and not as a clinician.

### 2.6 Ethics, Privacy, Bias, and Accountability

As AI is implemented, there are other responsibilities to the accuracy of the model. WHO principles of autonomy, transparency, responsibility, inclusiveness, safety and sustainability.[28,29] are priorities. The focus of recent ethics reviews remains on issues of bias, privacy, accountability, justice and transparency.[32-34] These risks are operational: the distribution of data may be uneven which results in differential error rates, systems may not be contestable, or ambiguous responsibilities may stifle uptake or cause unsafe diffusion of responsibility.

### 2.7 Patient-Centeredness and the Clinician-Patient Relationship
Patients in primary care recognize the potential benefits of AI but always stress the need for human oversight, safety, autonomy, and responsible implementation.[17] This is particularly the case with older patients, where the disease process may not be optimized and caregivers may be involved in shared decision making, or when treatment preferences are not shared by older patients. AI should supplement information processing and be relational, communicating and bargaining about goals.

### 2.8 Research Gap and Study Contribution
The generic views, technical maturation, and general barriers to implementation are well captured in the literature, but there is a lack of empirical studies that combine the PHC decision support, older-adult specific applications, trust/human oversight, governance issues and preparedness at the level of the respondent in the same model. The current study is unique in that it focuses on these domains at the same time and it also considers each of these domains as a separate predictor of perceived benefit for older adult care. This shift in perspective takes the discussion from the excitement of AI to what can be controlled by health systems to put these AI solutions into practice.

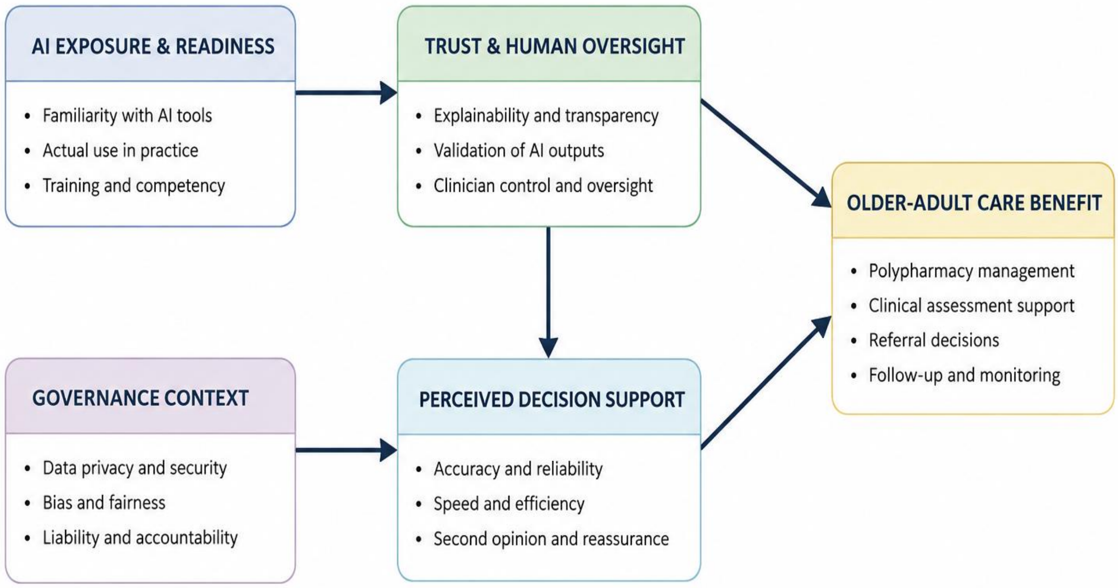



**Figure 1: Conceptual framework linking AI exposure and governance conditions to trust, decision support, and perceived benefit for older-adult care.**

As shown in Figure 1, AI exposure and readiness are positioned as enabling conditions that can strengthen trust and human oversight, while governance context shapes the conditions under which decision support can be safely accepted. Trust/human oversight and perceived decision support function as proximal mechanisms linking AI exposure and organizational safeguards to perceived benefit for older-adult care. The framework emphasizes that clinical usefulness is conditional on interpretability, validation, clinician control, privacy, fairness, liability clarity, and accountability rather than on technology exposure alone.

*Source: Developed by the researchers based on the present study constructs and informed by references.[1,4,8-13,18-19,28-29]*

## 3. METHODS
### 3.1 Study Design
The type of Survey used was a cross sectional electronic survey. Cross-sectional observational studies were reported to STROBE, and internet-based survey reporting to CHERRIES.[30,31]

### 3.2 Data Integrity and Analytic Sample
The following study-response worksheet has 575 study responses (minus header row). The values in the first column of the re-supplied workbook are not values that can be used as a defensible key to identify repeated response patterns as export duplicates. All 575 rows of the data file were given, so all these rows were used as the analytic sample. This correction is for the previously made correction, which took 5-fold replication for repeated response patterns.

### 3.3 Participants and Measures
The survey included data on sex, age group, professional role, years in clinical practice, access to AI, awareness of medical AI, and usage of AI to support clinical decisions. Thirty-four attitudinal statements were answered on a 5-point Likert scale from "strongly disagree" to "strongly agree" with each question. The coherent clusters of items

were combined to create the domains of AI readiness and preparedness, perceived decision-support benefit, perceived benefit for older-adult care, risks and governance concerns, trust and human oversight, and implementation conditions and intention.

### 3.4 Duplicate Questionnaire Wording

In relation to, the following two exported items had the same wording - adjusting treatment plan when it is recommended by AI. It was not used for the second time to add scores as it will overestimate the same proposition. The original can be found in Appendix A for reference.

### 3.5 Statistical Analysis

Categorical variables were presented in terms of frequencies and percentages. All of the mean, standard deviation, and 95% confidence intervals were reported as composite domain scores. The internal consistency was assessed using Cronbach alpha. For associations between ordinal and Likert scaled constructs Spearman rank correlation was calculated. A multivariable linear regression model predicted perceived benefit of AI for older adults based on the AI familiarity, frequency of decision support related to AI, AI readiness and preparedness, trust and human oversight, and risks/governance concerns. All continuous variables have been standardized and HC3 heteroscedasticity robust standard errors have been also computed for modelling. The P value on each side of < .05 for each time was statistically significant.

### 3.6 Ethics and Missing Protocol Metadata

The following information was not available on the response: Approving ethics committee, ethics committee number, electronic consent wording, geographic setting, sampling frame, recruitment channel, and invitation denominator. Such information will be required and cannot be recovered from the response file and should be added to the response file from the study protocol. No specific indicator was found in the study-response worksheet that was analysed.

## 4. RESULTS

### 4.1 Participant Profile and AI Exposure

**Table 1. Participant characteristics and AI exposure (N=575).**

| Variable | Category | n | % |
|---|---|---|---|
| Type of medical AI program used | Free | 535 | 93.0 |
| Type of medical AI program used | Supported/subsidized | 25 | 4.3 |
| Type of medical AI program used | Paid | 15 | 2.6 |
| Sex | Male | 295 | 51.3 |
| Sex | Female | 280 | 48.7 |
| Age group | 30-39 years | 230 | 40.0 |
| Age group | <30 years | 130 | 22.6 |
| Age group | ≥50 years | 120 | 20.9 |
| Age group | 40-49 years | 95 | 16.5 |
| Professional title | Other | 200 | 34.8 |
| Professional title | Other healthcare cadre | 185 | 32.2 |
| Professional title | Community/family physician | 70 | 12.2 |
| Professional title | Nurse | 55 | 9.6 |
| Professional title | Pharmacist | 30 | 5.2 |
| Professional title | Senior resident | 20 | 3.5 |
| Professional title | Specialist physician | 15 | 2.6 |
| Years of clinical experience | <5 years | 230 | 40.0 |
| Years of clinical experience | >15 years | 155 | 27.0 |
| Years of clinical experience | 5-10 years | 135 | 23.5 |
| Years of clinical experience | 11-15 years | 55 | 9.6 |
| Current familiarity with medical AI | Moderate | 275 | 47.8 |
| Current familiarity with medical AI | Low | 130 | 22.6 |
| Current familiarity with medical AI | Good | 125 | 21.7 |
| Current familiarity with medical AI | Very low | 40 | 7.0 |
| Current familiarity with medical AI | Excellent | 5 | 0.9 |
| Frequency of AI-based decision-support use | Sometimes | 235 | 40.9 |
| Frequency of AI-based decision-support use | Rarely | 170 | 29.6 |
| Frequency of AI-based decision-support use | Never | 130 | 22.6 |
| Frequency of AI-based decision-support use | Often | 25 | 4.3 |
| Frequency of AI-based decision-support use | Regularly | 15 | 2.6 |

Table 1 shows that the analytic sample of this study comprised 575 health care professionals, 295 males (51.3%) and 280 females (48.7%). The largest age group was 30-39 years (230/575, 40.0%), followed by participants younger than 30 years (130/575, 22.6%). Professional roles were varied, having 200 respondents (34.8%) said “Other” and 185 respondents (32.2%) said “Another health-care cadre” with 70 (12.2%) responding as community/family physician. 27.0% of the respondents had over 15 years of clinical experience, while 40% had less than 5 years. The most frequent responses were moderate comprehension of medical AI (47.8%). The use of AI-based decision-support tools remained at 40.9 per cent, with some use sometimes, 29.6 per cent reported to be used rarely and 22.6 per cent never, and 6.9 per cent used frequently or regularly. The results tell us apart from general awareness and sustained clinical integration.

*Source: Study of existing survey data (N=575) by researchers.*

### 4.2 Composite Domain Scores and Reliability

**Table 2: Composite domain scores, 95% confidence intervals, and internal consistency (N=575).**

| Domain | Items | Mean | SD | 95% CI | Cronbach alpha |
|---|---|---|---|---|---|
| AI Readiness and Preparedness | 3 | 2.97 | 0.75 | 2.91-3.04 | 0.60 |
| Perceived Decision-Support Benefit | 6 | 3.55 | 0.76 | 3.49-3.62 | 0.91 |
| Perceived Benefit for Older-Adult Care | 6 | 3.52 | 0.68 | 3.46-3.57 | 0.86 |
| Trust and Human Oversight | 6 | 3.52 | 0.64 | 3.47-3.57 | 0.81 |
| Risks and Governance Concerns | 6 | 3.66 | 0.60 | 3.61-3.71 | 0.81 |
| Implementation Conditions and Intention | 6 | 3.49 | 0.59 | 3.44-3.53 | 0.79 |

Perceived decision-support benefit (mean 3.55, 95% CI 3.49 – 3.62) and perceived benefit for older-adult care (mean 3.52, 95% CI 3.46 – 3.57) were definitely above the neutral midpoint as seen in Table 2. The domain mean (3.66) was highest for risks and governance, suggesting that there was a strong level of caution despite positive attitudes towards AI. The perceived decision-support benefit was excellent ($\alpha$=0.91), and the other benefits (older-adult-care benefit, trust/human oversight, governance concerns, implementation conditions) were good ($\alpha$>0.7). This is a three-item scale of readiness which has lower internal consistency ($\alpha$=0.60) and is regarded more as a readiness indicator as opposed to forming a fully developed latent construct.

*Source: This analysis of the current survey data (N=575) was carried out by researchers.*

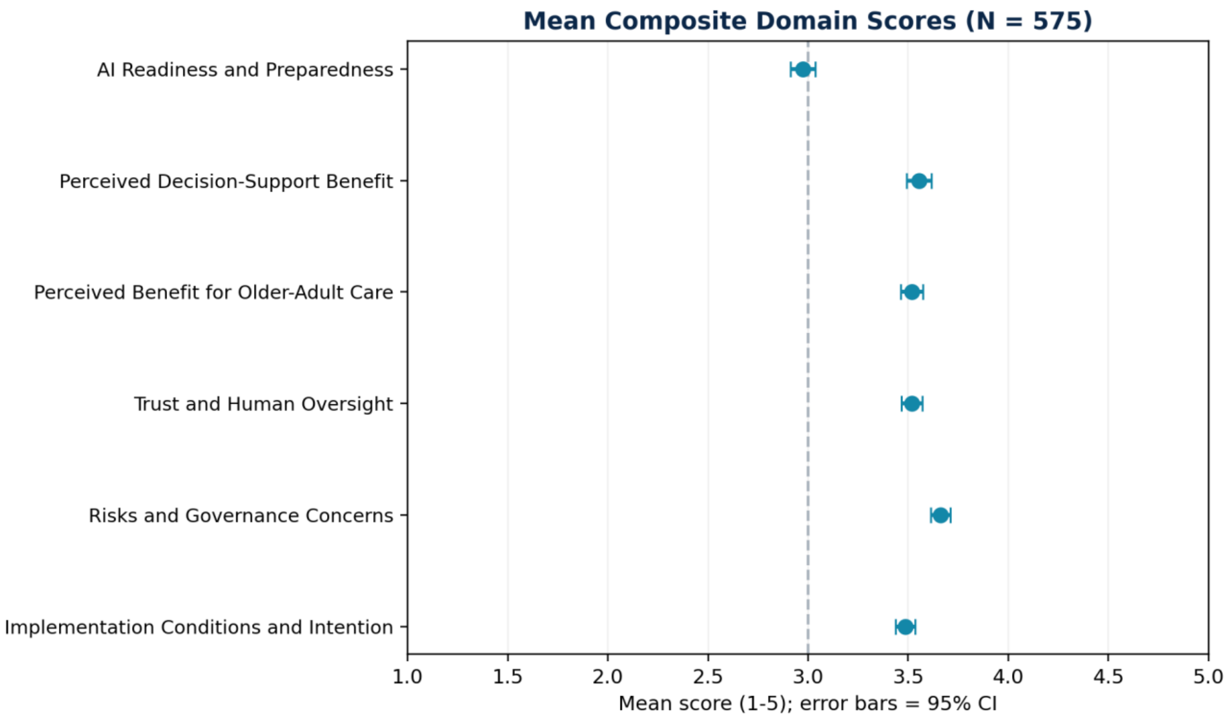



**Figure 2: Mean composite scores with 95% confidence intervals (N=575).**

As shown in Figure 2, all principal domains except readiness were centered clearly above the neutral score of 3. Risks and governance concerns had the highest mean (3.66), followed by perceived decision-support benefit (3.55), perceived older-adult-care benefit (3.52), trust and human oversight (3.52), and implementation conditions/intention (3.49). AI readiness and preparedness remained closest to neutrality (2.97). The narrower 95% confidence intervals obtained from the corrected N=575 analysis provide more precise estimates than in the earlier version, while the substantive ranking of domains remains unchanged.

*Source: Researchers' analysis of the present survey dataset (N=575).*

**4.3 Item-Level Response Pattern**

**Table 3: Selected high- and low-scoring questionnaire items (N=575).**

| Item | Statement | Mean | SD | Agree % | Neutral % | Disagree % |
|---|---|---|---|---|---|---|
| 28 | There is a real risk that excessive reliance on AI, particularly among newly graduated healthcare professionals, may weaken future clinical skills. | 3.89 | 0.90 | 72.2 | 20.9 | 7.0 |
| 20 | I consider AI recommendations a supportive aid to decision-making, not a substitute for professional assessment and clinical judgment. | 3.78 | 0.93 | 70.4 | 20.0 | 9.6 |
| 22 | My prior professional experience plays the greatest role in accepting or rejecting AI suggestions. | 3.77 | 0.89 | 67.8 | 25.2 | 7.0 |
| 9 | AI provides diagnostic or therapeutic suggestions that rapid human observation may miss because of time constraints. | 3.72 | 0.79 | 68.7 | 22.6 | 8.7 |
| 25 | I am concerned that focusing on screens and smart systems may negatively affect direct human interaction between the physician and the patient. | 3.72 | 0.82 | 71.3 | 22.6 | 6.1 |
| 4 | AI helps organize and reduce the time required to analyze complex clinical data. | 3.72 | 0.99 | 68.7 | 20.0 | 11.3 |
| 10 | AI helps manage polypharmacy. | 3.69 | 0.96 | 61.7 | 27.8 | 10.4 |
| 14 | AI enables physicians to develop continuous, individualized follow-up plans according to the complexity of each patient's condition. | 3.65 | 0.81 | 67.8 | 22.6 | 9.6 |
| 2 | I have received adequate training or workshops on how to use AI in medical decision-making. | 2.59 | 1.10 | 21.7 | 33.9 | 44.3 |
| 1 | I have sufficient knowledge of how AI algorithms work when evaluating clinical data. | 2.83 | 0.93 | 19.1 | 55.7 | 25.2 |
| 19 | I am willing to modify my treatment plan based on recommendations or alerts issued by AI systems. | 3.10 | 0.88 | 32.2 | 46.1 | 21.7 |
| 18 | I am willing to modify my treatment plan based on recommendations or alerts issued by AI systems. | 3.21 | 0.91 | 40.9 | 39.1 | 20.0 |
| 16 | I trust the scientific accuracy of clinical recommendations generated by validated AI systems. | 3.28 | 0.81 | 42.6 | 40.0 | 17.4 |
| 15 | AI helps physicians distinguish normal age-related symptoms from symptoms caused by chronic diseases. | 3.30 | 0.91 | 45.2 | 37.4 | 17.4 |
| 30 | Difficulty using digital interfaces or complex software reduces my willingness to use AI tools during clinical encounters. | 3.34 | 0.88 | 45.2 | 39.1 | 15.7 |
| 12 | AI supports early detection of future health risks, such as falls or cognitive decline. | 3.37 | 0.95 | 47.8 | 34.8 | 17.4 |

As shown in Table 3, the highest level of agreement is found for the risk of relying on AI too heavily so as to diminish professional judgment (mean score 3.89 for 72.2% agreement); that AI should be used to enhance, but not replace, professional judgment (mean score 3.78 for 70.4% agreement); and that prior professional experience influences whether to accept or reject AI suggestions (mean score 3.77 for 67.8% agreement). The other was the comment regarding sufficient training of AI, the poorest rated (Item 2, mean 2.59), with only 21.7% agreeing to this.On the other hand, the comments about the adequacy of AI training (Item 2, mean 2.59) were rated the lowest with only 21.7% agreeing and 44.3% disagreeing. The item pattern therefore provides support to the 'cautious augmentation' interpretation, which also involves that the respondents recognize the clinical utility and at the same time emphasize competence, professional control and precautions against overdependence.

*Source: Researchers analyzed the current data (N=575) at the item-level and created the following results.*

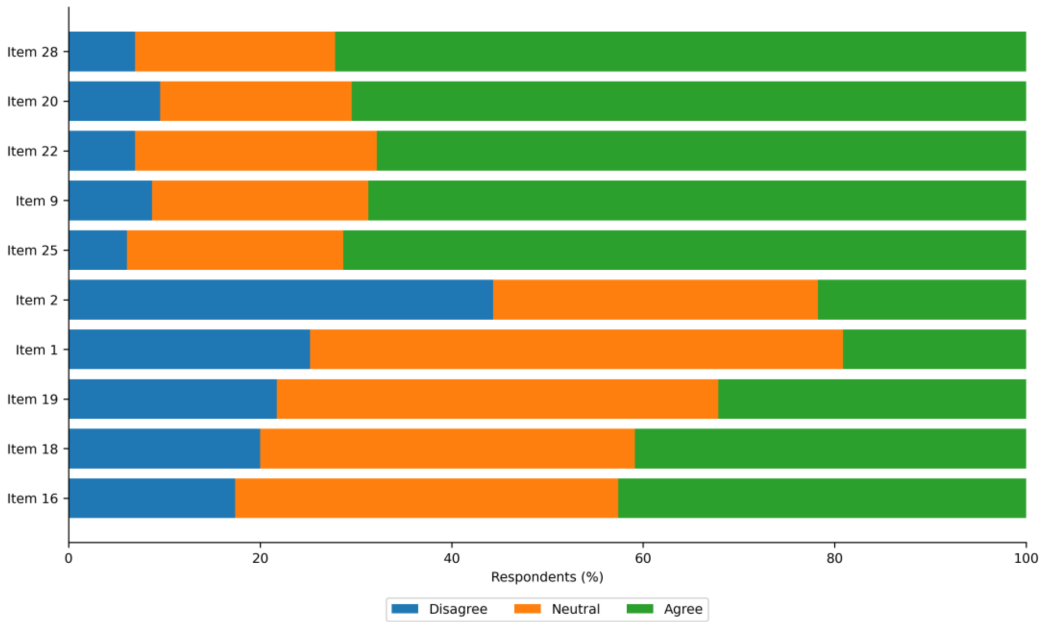



**Figure 3. Likert response profiles for the selected highest- and lowest-scoring questionnaire items.**

The shape of the items in Figure 3 suggest that the overall trend of the high scoring items is agreement and the low scoring items have more disagreement and neutral areas. The most evident agreement between the items is item (28), which addresses concern over clinical deskilling due to an overreliance on AI. On the other hand, Item 2 demonstrates the least positive of the response profiles as less than a quarter of the respondents indicated that they were sufficiently trained with AI prior to use. The middle are questions regarding treatment plan changes, trust in recommendations from the AI and distinguishing between regular aging and indications of chronic disease. The break down shows that not everyone is pro-AI or anti-AI, as the respondents' evaluations vary based on their perceived value, readiness, trust, and training capacity.

*Source: The present survey data set (N=575) was analyzed by researchers.*

### 4.4 Correlation Structure

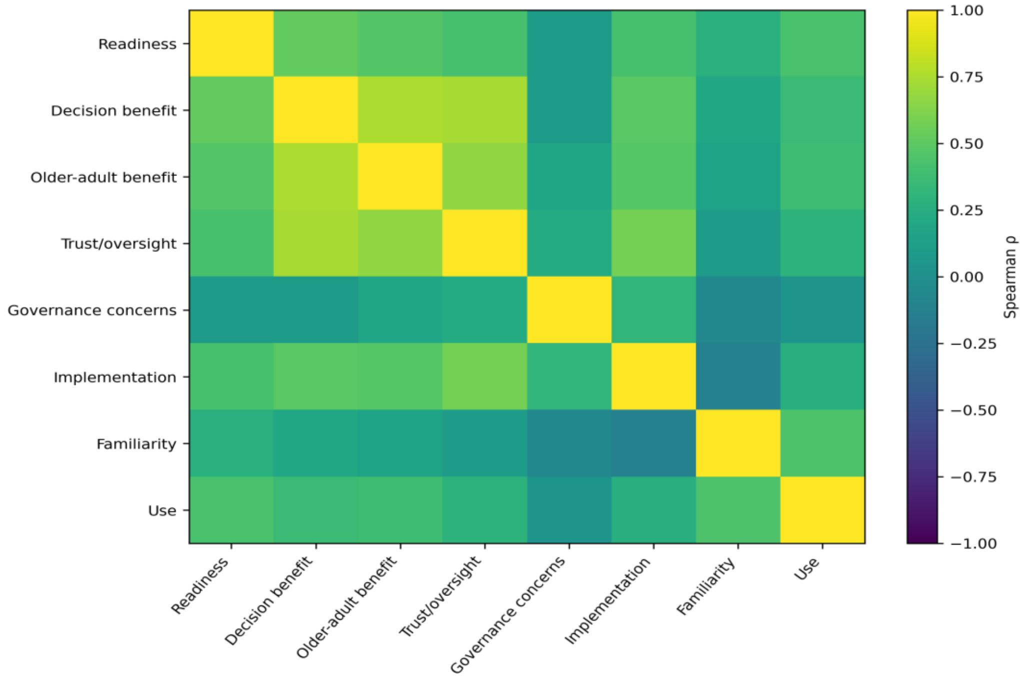



**Figure 4. Spearman correlation heatmap across study domains, AI familiarity, and frequency of AI-based decision-support use.**

As shown in Figure 4, perceived decision-support benefit had the strongest positive correlation with perceived benefit for older-adult care (Spearman ρ=0.75) and was also strongly correlated with trust and human oversight (ρ=0.74). Trust and human oversight correlated positively with older-adult-care benefit (ρ=0.67) and implementation conditions/intention (ρ=0.58). AI use showed moderate relationships with readiness (ρ=0.42), familiarity (ρ=0.44), and older-adult-care benefit (ρ=0.38). Governance concerns were comparatively weakly related to perceived decision-support benefit (ρ=0.09), indicating that concern about risk can coexist with perceived clinical usefulness.

*Source: Researchers' Spearman correlation analysis of the present survey dataset (N=575).*

**4.5 Multivariable Model**

**Table 4. HC3-robust standardized multivariable linear regression predicting perceived benefit for older-adult care (N=575).**

| Predictor | Standardized beta | Robust SE | 95% CI | P |
|---|---|---|---|---|
| Familiarity | 0.07 | 0.04 | -0.01 to 0.15 | 0.071 |
| Use | 0.07 | 0.03 | 0.00 to 0.13 | 0.037 |
| AI Readiness and Preparedness | 0.13 | 0.03 | 0.06 to 0.20 | <.001 |
| Trust and Human Oversight | 0.67 | 0.03 | 0.61 to 0.74 | <.001 |
| Risks and Governance Concerns | 0.03 | 0.03 | -0.02 to 0.09 | 0.233 |

As shown in Table 4, the multivariable model explained 62.7% of the variance in perceived benefit for older-adult care ($R^2$=0.627; adjusted $R^2$=0.624). Trust and human oversight was by far the strongest independent correlate (β=0.67, 95% CI 0.61 to 0.74, P<.001). AI readiness and preparedness was also independently associated with the outcome (β=0.13, 95% CI 0.06 to 0.20, P<.001), and frequency of AI-based decision-support use showed a smaller but statistically significant positive association (β=0.07, 95% CI 0.00 to 0.13, P=0.037). Familiarity alone did not reach statistical significance (P=0.071), and governance concerns were not independently associated after adjustment (P=0.233). The corrected analysis therefore retains trust/oversight as the dominant factor but also identifies readiness and actual use as independent contributors.

*Source: Researchers' HC3-robust multivariable regression analysis of the present survey dataset (N=575).*

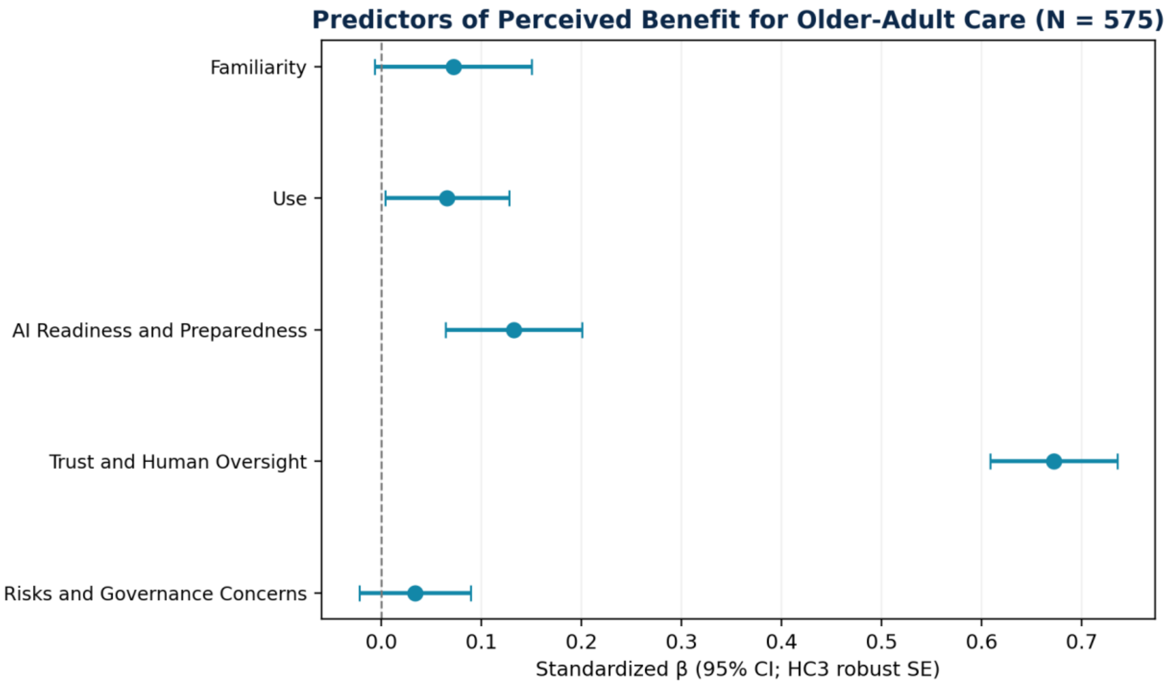



**Figure 5: Forest plot of standardized regression coefficients predicting perceived benefit for older-adult care.**

As illustrated in Figure 5, the interval for the predictor of trust and human oversight is entirely positive and much farther from zero than any other predictor (including the other positive predictors). The confidence interval estimation for the AI readiness and AI preparedness is also significantly larger than zero and very close to zero for the AI use, respectively. There is some familiarity across the null, however. There is no independent association of risks/governance concerns after adjustment. Thus, it is the trust design, the agency of clinicians, and their readiness that plot focuses on, while not losing the noncausal interpretation that is inherent in the cross-sectional design.

*Source: Modeling of the current survey data set (N=575) by the researchers using a multivariable regression analysis with HC3 as the outcome.*

**4.6 Integrated Results Matrix**

**Table 5: Integrated results matrix for the six analytic domains (N=575).**

| Domain | Mean | Reliability | Interpretive role |
|---|---|---|---|
| AI Readiness and Preparedness | 2.97 | 0.60 | Capacity gap / mixed readiness |
| Perceived Decision-Support Benefit | 3.55 | 0.91 | Implementation strength |
| Perceived Benefit for Older-Adult Care | 3.52 | 0.86 | Implementation strength |
| Trust and Human Oversight | 3.52 | 0.81 | Implementation strength |
| Risks and Governance Concerns | 3.66 | 0.81 | Implementation strength |
| Implementation Conditions and Intention | 3.49 | 0.79 | Capacity gap / mixed readiness |

The integrated pattern involves taking samples from one domain, and using reliability to prevent overinterpreting a single mean (Table 5). Clearly, there are two strength of implementation (perceived benefit for decision making and perceived benefit for caring for older adults) and that these scores are above the neutral score and have high reliability. Trust and human oversight also are a strength of implementation, and importantly, the highest adjusted correlate in Table 4. But the risks are high, as are the governance issues, indicating a balance between positivity and caution. The capacity gap with the lowest mean is AI readiness as it has the lowest level of reliability in comparison to the other domains. There is a general movement towards a structured, competence and trust-building deployment that does not ignore governance issues.

*Source: This survey (N=575) and the results in Tables 2-4 were utilized to give the researchers a general synthesis.*

## 5. DISCUSSION

### 5.1 Principal Findings

In fact, the revised study, which was completed using 575 of the 656 surveys that were fully completed, shows that the benefit-readiness imbalance isn't that high, it's just not that low, either—the only conclusion that can be drawn from it is that people are not that uninterested in AI.In fact, the corrected analysis – based on responses from all 575 surveys completed – finds an imbalance in benefit readiness, rather than a lack of interest in AI, but not by much. However, there was broader agreement that AI could aid in clinical decision making and older people and that not a lot of formal training was being done on this topic. This is consistent with the available evidence of positive attitudes towards documentation, information synthesis, and decision support, though there are still issues of lack of structured training, and governance issues.[1-6,14-16]

### 5.2 Trust as the Central Implementation Mechanism

Once other variables in the model are controlled for, the most powerful independent variable predicting the perceived older adult-care benefit (β=0.67, P<.001) is trust and human oversight. When analysis is corrected for the independent effects of AI readiness and preparedness (β=0.13, P<.001) and frequency of use of AI tools for decision support (β=0.07, P=0.037), however, the findings remain the same. This is consistent with the systematic evidence and the experimental evidence that demonstrates that appropriate reliance is related to transparency, clinical reliability, workflow integration, validation, clinician control and experience [8-13]. The aim should not be to build more trust, but 'calibrated trust' which will enable the clinician to have sufficient trust and sufficient authority to confirm, challenge and reject unsafe outputs.

### 5.3 Relevance to Older-Adult Care

Synthesis across diseases, medications, function, cognition, social context, and patient priorities is crucial in older-adult PHC. While medication review, frailty/deterioration identification, and detecting interaction problems could be particularly beneficial with AI, these tasks can be vulnerable to dataset shift and underrepresentation [18-27]. The AGS position statement further highlights the need for the use of the generative AI tools to be integrated with the role of judgment and should not expose older adults to the danger of misinformation, bias, over-dependence upon automation, or privacy issues.[19]

### 5.4 Training and Organizational Readiness

The low training score is considered an implementation deficit which is amenable to change. Nevertheless, the experience of primary-care reviews and clinician surveys suggests that familiarity is insufficient for competency based education.[2,5,14-16] Training should cover limitations of the model, data provenance, uncertainty, hallucination and error modes, bias, privacy guidelines, documentation, escalation and procedures for overriding AI recommendations. Another issue is distinguishing between the approved clinical AI systems and consumer general purpose systems.

### 5.5 Governance, Ethics, and Equity

The issues raised by the respondents with regards to privacy, accountability, bias and professional consequences are in line with the guidance of the WHO and the latest ethics reviews [28,29,32-34]. These concerns must be converted to governance: predeployment validation, access by role, audit trail, human review for consequence decisions, incident reporting, bias monitoring, and periodic performance re-assessment. The following factors should specifically be analysed for older people to determine the level of fairness: advanced age, frailty, disability, cognitive impairment, multimorbidity.

### 5.6 Comparison With Recent PHC Studies

The findings of the present study are consistent with the findings of Alsudairy et al., who found positive attitudes towards AI-supported primary care decisions[3], as well as Blease et al., who found that there is a lack of training requirements among GPs.[2] and Martínez-Martínez et al. and Scipion et al., who identified factors that impact upon acceptance of AI in primary care, including privacy, bias, workflow, and clinician involvement.[1,6] In the present study we propose a new age-specific measure of outcome and demonstrate that the relationship between trust/human oversight and outcome is robust and independently significant after accounting for familiarity, use, readiness and governance issues.

### 5.7 Clinical Implications

Implementation does not occur in a technology-first way. Key components of a PHC organization are narrow use cases, validation at the local level, training users, building into existing workflows, human review of high consequence recommendations and monitoring of clinical and process outcomes. Candidates' use cases include medication review prioritisation, frailty screening, risk flagging, and structured follow-up support, as long as it does not detract from the clinician's judgement or the patient's goals in the context of ageing care.

### 5.8 Strengths and Limitations

Strengths include the multidimensional assessment, the comparatively large analytic sample (N=575), and the integration of descriptive, reliability, correlational, and robust multivariable analyses. Limitations remain important: the professional sample was heterogeneous; the sampling frame, invitation denominator, and response rate were not available in the supplied materials; the data were self-reported and cross-sectional; clinical outcomes were not observed; and the analytic domains were not validated in an independent psychometric sample. Two questionnaire items used duplicated treatment-plan wording; the second occurrence was retained in the Appendix for transparency but excluded from composite scoring to avoid double weighting. Because the design is cross-sectional, associations should be interpreted as correlational rather than causal.

## 6. CONCLUSION

PHC workers believed that AI can support them in their PHC clinical decisions making and older adults care, but there was a lack of formal training and readiness for use. After correcting for the 575 responses completed, the best independent correlations with perceived geriatric-care benefit were trust and human professional oversight, followed by the independent contributions of readiness and actual use of AI. The results indicate a human in the loop implementation approach emphasizing explainability, clinical experience, competency-based learning, privacy protection, accountability, bias monitoring, and prospective evaluation during real PHC situations. In the case of aging care, AI should be used in conjunction with, and not to replace, professional clinical judgment.

### Declarations

Ethics Approval and Consent to Participate

This was an anonymous, non-interventional and electronic survey that did not collect any identifiable or patient level data, and posed minimal risk. There was no institutional policy in place for formal ethical approval for anonymous survey research. They were all volunteers and indicated by completing the questionnaire which constituted their consent to participate.

### Funding

This work was not supported by any external funding or specific grant.

### Conflicts of Interest

The authors declare no conflicts of interest.

### Data Availability

The data from the survey is anonymized and will be made available, on reasonable request, from the corresponding author, with 575 full responses.

### Author Contributions

All authors contributed to the study, reviewed the manuscript, approved the final version, and accept responsibility for the integrity of the work.

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Appendix A. Survey Questionnaire

The Appendix reproduces the questionnaire structure represented in the supplied survey response workbook. All questionnaire wording is presented in English only for manuscript reporting. Attitudinal items used a 5-point Likert response scale: 1 = Strongly disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, and 5 = Strongly agree.

**Appendix Table A1. English-language questionnaire and response structure.**

| Code / Item | Questionnaire wording (English) | Response options / Scale | Analytic domain |
|---|---|---|---|
| A1 | Type of medical AI programs used | Free / Supported or subsidized / Paid | Demographic / exposure |
| A2 | Sex | Male / Female | Demographic |
| A3 | Age group | <30 / 30-39 / 40-49 / ≥50 years | Demographic |
| A4 | Professional title | Community/family physician / Nurse / Pharmacist / Senior resident / Specialist physician / Other healthcare cadre / Other | Professional profile |
| A5 | Years of clinical experience | <5 / 5-10 / 11-15 / >15 years | Professional profile |
| A6 | Current familiarity with medical AI applications | Very low / Low / Moderate / Good / Excellent | AI exposure |
| A7 | Frequency of using AI-based decision-support tools in clinical practice | Never / Rarely / Sometimes / Often / Regularly | AI exposure |
| 1 | I have sufficient knowledge of how AI algorithms work when evaluating clinical data. | 1-5 Likert | AI Readiness and Preparedness |
| 2 | I have received adequate training or workshops on how to use AI in medical decision-making. | 1-5 Likert | AI Readiness and Preparedness |
| 3 | I believe modern technology and AI are an essential part of the future of patient care. | 1-5 Likert | AI Readiness and Preparedness |
| 4 | AI helps organize and reduce the time required to analyze complex clinical data. | 1-5 Likert | Perceived Decision-Support Benefit |
| 5 | AI improves diagnostic accuracy compared with conventional clinical assessment. | 1-5 Likert | Perceived Decision-Support Benefit |
| 6 | AI algorithms help reduce medical errors caused by fatigue or workload pressure in primary care centers. | 1-5 Likert | Perceived Decision-Support Benefit |
| 7 | AI improves the breadth and reliability of therapeutic decisions across different healthcare professionals. | 1-5 Likert | Perceived Decision-Support Benefit |
| 8 | AI tools accelerate timely clinical decision-making during the patient encounter. | 1-5 Likert | Perceived Decision-Support Benefit |
| 9 | AI provides diagnostic or therapeutic suggestions that rapid human observation may miss because of time constraints. | 1-5 Likert | Perceived Decision-Support Benefit |
| 10 | AI helps manage polypharmacy. | 1-5 Likert | Perceived Benefit for Older-Adult Care |
| 11 | AI contributes to a more comprehensive and systematic assessment of patients’ physical and cognitive status. | 1-5 Likert | Perceived Benefit for Older-Adult Care |
| 12 | AI supports early detection of future health risks, such as falls or cognitive decline. | 1-5 Likert | Perceived Benefit for Older-Adult Care |

| | | | |
|---|---|---|---|
| 13 | AI-supported recommendations help determine more accurately whether a patient requires referral to a specialist or hospital. | 1-5 Likert | Perceived Benefit for Older-Adult Care |
| 14 | AI enables physicians to develop continuous, individualized follow-up plans according to the complexity of each patient’s condition. | 1-5 Likert | Perceived Benefit for Older-Adult Care |
| 15 | AI helps physicians distinguish normal age-related symptoms from symptoms caused by chronic diseases. | 1-5 Likert | Perceived Benefit for Older-Adult Care |
| 16 | I trust the scientific accuracy of clinical recommendations generated by validated AI systems. | 1-5 Likert | Trust and Human Oversight |
| 17 | I feel comfortable using AI as an assistant and second opinion when managing complex patient cases. | 1-5 Likert | Trust and Human Oversight |
| 18 | I am willing to modify my treatment plan based on recommendations or alerts issued by AI systems. | 1-5 Likert | Trust and Human Oversight |
| 19 | I am willing to modify my treatment plan based on recommendations or alerts issued by AI systems. | 1-5 Likert | Trust and Human Oversight (excluded from composite scoring because wording duplicates Item 18) |
| 20 | I consider AI recommendations a supportive aid to decision-making, not a substitute for professional assessment and clinical judgment. | 1-5 Likert | Trust and Human Oversight |
| 21 | My trust in an AI system increases when the process by which it reaches a recommendation is clear, explained, and interpretable. | 1-5 Likert | Trust and Human Oversight |
| 22 | My prior professional experience plays the greatest role in accepting or rejecting AI suggestions. | 1-5 Likert | Trust and Human Oversight |
| 23 | I am concerned about the confidentiality and security of patient health data when they are entered into AI systems. | 1-5 Likert | Risks and Governance Concerns |
| 24 | Ambiguity in assigning medical and legal responsibility when an AI-assisted diagnostic error occurs concerns me. | 1-5 Likert | Risks and Governance Concerns |
| 25 | I am concerned that focusing on screens and smart systems may negatively affect direct human interaction between the physician and the patient. | 1-5 Likert | Risks and Governance Concerns |
| 26 | The use of AI may lead to unfair medical recommendations for some patients. | 1-5 Likert | Risks and Governance Concerns |
| 27 | I believe current legislation and ethical regulations are insufficient to govern AI use in patient diagnosis. | 1-5 Likert | Risks and Governance Concerns |
| 28 | There is a real risk that excessive reliance on AI, particularly among newly graduated healthcare professionals, may weaken future clinical skills. | 1-5 Likert | Risks and Governance Concerns |

| | | | |
|---|---|---|---|
| 29 | I support the use of AI to improve the quality of older-adult care services in primary health care. | 1-5 Likert | Implementation Conditions and Intention |
| 30 | Difficulty using digital interfaces or complex software reduces my willingness to use AI tools during clinical encounters. | 1-5 Likert | Implementation Conditions and Intention |
| 31 | Workload and patient crowding are barriers to learning and training on new AI tools. | 1-5 Likert | Implementation Conditions and Intention |
| 32 | Continuous updating and feedback from physicians improve the effectiveness of AI systems in patient care. | 1-5 Likert | Implementation Conditions and Intention |
| 33 | Responsible integration of AI enhances the provision of safer, more patient-centered health care. | 1-5 Likert | Implementation Conditions and Intention |
| 34 | I support broader implementation and development of AI tools in future patient care. | 1-5 Likert | Implementation Conditions and Intention |

As shown in Appendix Table A1, the instrument contains seven demographic/exposure variables followed by 34 attitudinal statements spanning readiness, decision-support benefit, older-adult-care benefit, trust/human oversight, governance concerns, and implementation conditions. The table presents the survey content entirely in English, as required for an English-language medical manuscript. Items 18 and 19 have the same treatment-plan wording; Item 19 is retained in the Appendix for transparency but is not included in composite scoring.

*Source: Researchers' English translation and analytic organization of the questionnaire contained in the supplied survey workbook.*

Appendix note: Items 18 and 19 use duplicated treatment-plan wording in the supplied survey structure. Both items are shown for transparency, but Item 19 was excluded from composite scoring to avoid double weighting of the same proposition.

Appendix B. Statistical Domain Construction

**Appendix Table B1. Statistical domain construction and internal consistency.**

| Composite domain | Included attitudinal item positions | No. of items | Cronbach alpha |
|---|---|---|---|
| AI Readiness and Preparedness | 1, 2, 3 | 3 | 0.602 |
| Perceived Decision-Support Benefit | 4, 5, 6, 7, 8, 9 | 6 | 0.906 |
| Perceived Benefit for Older-Adult Care | 10, 11, 12, 13, 14, 15 | 6 | 0.865 |
| Trust and Human Oversight | 16, 17, 18, 20, 21, 22 | 6 | 0.811 |
| Risks and Governance Concerns | 23, 24, 25, 26, 27, 28 | 6 | 0.812 |
| Implementation Conditions and Intention | 29, 30, 31, 32, 33, 34 | 6 | 0.785 |

*Source: Researchers' domain construction and reliability analysis of the present survey dataset (N=575).*

As shown in Appendix Table B1, the six composite domains were constructed to preserve conceptual coherence and to avoid double weighting of the duplicated treatment-plan statement. The domains are analytic constructs specific to this study rather than externally validated scales; accordingly, reliability estimates are reported transparently and interpretation emphasizes construct content alongside Cronbach alpha.

Appendix C. Data Integrity Audit

**Appendix Table C1. Corrected data-integrity audit of the supplied survey workbook.**

| Audit element | Corrected result |
|---|---|
| Rows in supplied study-response sheet | 575 completed response rows plus one header row |
| Analytic sample | N = 575 |
| Unique respondent identifier in current export | Not available |
| Timestamp field in current export | Not available; Column1 is blank in all response rows |

| | |
|---|---|
| Record-level deduplication | Not performed because the current workbook provides no defensible identifier/timestamp key |
| Duplicated questionnaire wording | Items 18 and 19 have the same treatment-plan wording; Item 19 excluded from composite scoring |

*Source: Researchers' audit of the re-supplied survey workbook.*

As shown in Appendix Table C1, the re-supplied workbook contains 575 completed survey response rows and does not contain a usable respondent identifier or timestamp field. Therefore, the earlier fivefold-deduplication assumption cannot be supported from the current file and has been removed. All 575 records were analyzed as supplied. This correction affects sample-size-dependent quantities, including standard errors, confidence intervals, adjusted model fit, and P values, while means, percentages, reliability estimates, correlations, and standardized coefficient magnitudes remain largely unchanged because the response distribution itself is unchanged.