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Development and Field Testing of an Explainable Artificial Intelligence Clinical Decision Instrument for Stunting Prevention

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ABSTRACT: Artificial intelligence (AI) is increasingly integrated into clinical decision-making, yet its adoption in public health nutrition programs remains constrained by algorithmic opacity and limited healthcare professionals' trust. This study aims to develop a human-centered Explainable Clinical Decision Intelligence framework to support trustworthy AI adoption in clinical decision-making for stunting prevention. The preparation and pilot-testing phase integrates Human–AI Trust Theory, Socio-Technical Systems Theory, Clinical Decision Intelligence, Information Processing Theory, Human-Centered AI, and Organizational Learning Theory. Twelve hypotheses were formulated for future covariance-based structural equation modeling (CB-SEM). A 35-item measurement instrument, purposive sampling strategy, informed consent protocol, and data collection procedures were developed and pilot-tested with 260 healthcare professionals from hospitals and primary healthcare centers. Descriptive statistics and preliminary reliability analyses revealed inadequate internal consistency across all seven constructs, indicating that the instrument required revision and re-validation before confirmatory factor analysis (CFA) and structural model testing. Consequently, no structural relationships were reported. Potential measurement deficiencies were examined, and a methodological roadmap for subsequent CFA and SEM analyses was established. The proposed framework integrates platform quality, explainable AI quality, decision transparency, healthcare professionals' trust, decision acceptance, intervention quality, and stunting prevention effectiveness. Despite the current reliability limitations, this study establishes a theoretical and methodological foundation for future confirmatory research and offers guidance for ministries of health, healthcare institutions, clinicians, and health information system developers in implementing trustworthy explainable AI for clinical decision-making and stunting prevention.

1. INTRODUCTION

Childhood stunting remains one of the most persistent public health problems in low- and middle-income countries. Chronic undernutrition during the first one thousand days of life produces deficits in linear growth and cognitive development that carry lifelong consequences for human capital formation and national productivity. In Indonesia, national nutrition surveys have documented a stunting prevalence that continues to exceed policy targets despite a declining trajectory, prompting a national strategy that increasingly relies on digital technologies to strengthen early detection, growth monitoring, and targeted intervention at the primary healthcare level. Digital tools and mobile applications supporting caregiver engagement and cadre-led monitoring have been reported across several Indonesian regions, illustrating a broader shift toward digitally mediated public health delivery.

Within this shift, artificial intelligence is being progressively introduced into clinical workflows as a means of augmenting the judgment of healthcare professionals who conduct growth screening, risk stratification, and referral decisions. Predictive models can flag children at elevated risk of stunting before anthropometric thresholds are formally crossed, allowing earlier intervention.

Yet the clinical value of such predictions is contingent on a condition that purely statistical performance metrics do not guarantee: healthcare professionals must be willing to trust, interpret, and act upon algorithmic recommendations within real clinical and administrative constraints. A substantial body of evidence indicates that artificial intelligence in the healthcare sector delivers measurable benefits but continues to face adoption barriers rooted in opacity, workflow misalignment, and limited practitioner trust[1], and structured reviews of artificial intelligence across healthcare more broadly report similar adoption constraints even where predictive performance is strong[2]. Scoping reviews of clinician perceptions further show that willingness to adopt artificial intelligence tools depends heavily on perceived transparency and fit with existing clinical reasoning rather than on accuracy metrics alone[3].

The problem of opacity has led to the emergence of explainable artificial intelligence, which aims to make model outputs interpretable to human users without sacrificing predictive performance[4]. A widely cited survey of the field considers explainability to be the key unresolved problem separating high-performing, yet opaque models and their safe deployment in high-stakes domains such as healthcare[4]. A comprehensive survey of explainability in healthcare artificial intelligence finds that the terminology, design choices, and evaluation strategies for explanation remain fragmented, and that explainability functions as a precondition for trustworthiness rather than a stylistic add-on[5]. Ethical and social analyses of artificial intelligence-based medical decision support similarly emphasize that opacity raises accountability concerns that purely technical accuracy cannot resolve[6]. A systematic review of trust in artificial intelligence-based clinical decision support systems among healthcare workers, synthesizing studies published between 2020 and 2024, identifies transparency, usability, prior validation, and alignment with clinical judgment as the principal enablers of trust, while algorithmic opacity, insufficient training, and unresolved accountability are identified as the principal barriers[7]. Qualitative work using think-aloud protocols with clinical decision support users similarly finds that explanations are used chiefly to verify whether a recommendation makes clinical sense, and that many existing explanation techniques are perceived as technically dense and poorly integrated into workflow[8]. These findings converge on a consistent message: explainability is not a cosmetic feature of clinical artificial intelligence, but a structural precondition for the trust that determines whether a system is used at all.

Despite this convergence of evidence, the literature on clinical artificial intelligence adoption remains fragmented across disconnected streams. A first stream investigates clinical decision support largely from a technology acceptance perspective, applying the unified theory of acceptance and use of technology to explain adoption intention[9], but this framework was developed for general-purpose information systems and does not theorize explanation, transparency, or professional accountability as distinct constructs. A second stream, situated in biomedical informatics, is dominated by black box artificial intelligence and prediction accuracy studies that report model performance without examining how end users interpret, trust, or act on those predictions. A third stream evaluates machine learning performance and explainability techniques from a purely algorithmic standpoint, treating interpretability as a property of the model rather than an outcome co-produced with the professional who must use it; evidence on discrepancies between clinician perceptions and actual acceptance of decision support recommendations illustrates how this gap manifests in practice[10]. A fourth stream addresses digital health platforms broadly, emphasizing infrastructure and coverage, with limited attention to the cognitive and relational processes through which platform outputs are translated into clinical action.

Very few studies simultaneously theorize explainable artificial intelligence, clinical decision intelligence, healthcare professionals' trust, decision acceptance, intervention quality, and public health outcomes within a single human-centered structural model. This fragmentation constitutes a theoretical gap, because no existing framework specifies the causal ordering through which platform-level and explanation-level qualities propagate into professional trust and, subsequently, into measurable public health effectiveness. It constitutes an empirical gap, because the trust-enabling role of explainability has been documented largely through qualitative and scoping methodologies[11][12], with covariance-based structural testing of the full explainability-to-outcome chain remaining scarce in maternal and child health contexts in Southeast Asia. It constitutes a methodological gap because prior digital health for stunting studies have relied predominantly on partial least squares structural equation modeling, quasi-experimental designs, or narrative reviews, leaving covariance-based structural equation modeling validation of a multi-construct explainability trust acceptance outcome chain largely unexplored in this domain. It constitutes a practical gap because ministries of health, hospitals, and primary healthcare centers currently lack an evidence-based, human-centered specification of which platform and explanation attributes should be prioritized when procuring artificial intelligence-based clinical decision intelligence tools for nutrition programs.

This study addresses these gaps by proposing a human-centered explainable clinical decision intelligence framework that models a sequential chain running from platform quality to explainability quality, from explainability quality to decision transparency, from decision transparency to healthcare professionals' trust, from trust to decision acceptance, from decision acceptance to intervention quality, and from intervention quality to stunting prevention effectiveness. What clinicians want from explanation has been shown to depend on contextualized, task-relevant meaning rather than raw technical detail[13], which motivates the framework's separation of explainability quality from decision transparency as sequentially related but conceptually distinct constructs. The framework extends prior clinical decision support literature in four respects. First, it disaggregates explainability from generic system quality, allowing identification of where in the explanation pipeline trust is actually built. Second, it positions trust as a socio-technical outcome jointly shaped by platform-level and explanation-level qualities rather than as a static individual disposition. Third, it extends the causal chain beyond behavioral intention, the customary endpoint of technology acceptance studies, through to intervention quality and stunting prevention effectiveness, connecting an information systems construct chain to a public health outcome. Fourth, it is deliberately theorized using a plurality of foundations rather than relying solely on technology acceptance formulations, to capture the cognitive, relational, organizational, and ethical dimensions that a purely acceptance-oriented lens omits.

This study has three objectives, corresponding to the preparation phase of a larger research program. The first is to develop and theoretically justify a human-centered explainable clinical decision intelligence framework and twelve associated hypotheses suitable for evaluating explainable artificial intelligence-based clinical decision intelligence platforms used in stunting prevention. The second is to design, operationalize, and field-test a thirty-five-item measurement instrument for this framework, including a purposive sampling design, an informed-consent protocol, and a structured data-collection procedure, and to report the resulting respondent profile, descriptive statistics, and reliability diagnostic from an actual field test with N = 260 healthcare professionals. The third is to translate the reliability diagnostic into a concrete instrument-revision roadmap and a set of ready-to-use analysis templates, so that the subsequent confirmatory phase of the research program, the empirical test of the twelve hypotheses through covariance-based structural equation modeling, can proceed directly to data collection and analysis once a revised instrument has demonstrated adequate reliability. This manuscript therefore does not report a completed hypothesis test; it reports the theoretical, instrumental, and empirical preparation required before that test can be conducted validly, and this scope is flagged explicitly throughout the manuscript.

2. MATERIALS AND METHODS

2.1 Theoretical Foundations

The proposed framework integrates six theoretical foundations that jointly address the technological, cognitive, relational, organizational, and ethical dimensions of explainable clinical artificial intelligence, deliberately extending beyond the technology acceptance model and the unified theory of acceptance and use of technology[9] that dominate prior digital health adoption research.

Human-AI trust theory extends classical models of organizational and interpersonal trust, which identify ability, benevolence, and integrity as antecedents of trust[14], and cross-disciplinary syntheses of trust as a psychological state involving willingness to accept vulnerability based on positive expectations[15], to the specific case of algorithmic decision aids, where trust must additionally accommodate the non-human, statistical, and often opaque nature of the trustee. Within the proposed framework, this theory grounds the healthcare professionals' trust construct and specifies that trust is a downstream product of transparency and justification rather than an independent starting point.

Socio-technical systems theory holds that information system outcomes are jointly determined by the technical subsystem and the social subsystem, and that sustainable performance requires the joint optimization of both[16]. Applied to clinical decision intelligence, this perspective cautions against treating explainability as a purely technical property; an explanation is functionally transparent only if it is compatible with the professional's role, cognitive load, and clinical workflow. This theory underpins the framework's treatment of platform quality and explainability quality as jointly necessary antecedents of decision transparency.

Clinical decision intelligence is understood in this study as an evolution beyond conventional clinical decision support systems: whereas clinical decision support emphasizes rule-based or predictive alerts, clinical decision intelligence integrates predictive analytics, explanation generation, contextual patient information, and organizational feedback loops into a coherent decision

support ecosystem oriented toward continuous learning and accountability. This repositions explainability and transparency as core, structural components of the intelligence platform itself, rather than as add-on features of a static tool.

Information processing theory conceptualizes organizational and individual decision-making as constrained by the capacity to acquire, interpret, and act upon information under uncertainty[17]. Applied to artificial intelligence-assisted clinical decisions, the theory implies that raw predictive output, however accurate, imposes a processing burden on the healthcare professional unless it is accompanied by explanation that reduces interpretive uncertainty. This foundation informs the framework's specification of explainability quality as the mechanism that converts algorithmic output into processable clinical information.

Human-centered artificial intelligence reframes the design objective of intelligent systems from maximizing autonomous machine performance toward maximizing human understanding, control, and appropriate reliance, arguing that reliable, safe, and trustworthy systems must be designed around human oversight and explainability rather than around algorithmic performance alone[18]. This orientation is reinforced by human-centered explainable artificial intelligence scholarship, which argues for moving beyond merely opening the technical black box toward supporting situated human sensemaking[19], and by broader ethical frameworks for artificial intelligence in society that emphasize accountability and human oversight as design principles rather than afterthoughts[20]. Human-centered artificial intelligence supplies the overarching design philosophy motivating the framework's treatment of explainability and transparency as first-class constructs.

Organizational learning theory holds that organizations improve performance through cycles of action, feedback, and reflection that update shared routines and mental models[21]. Applied to a clinical decision intelligence platform embedded in a primary healthcare center or hospital, this theory implies that decision acceptance and intervention quality are reinforced or eroded by organizational feedback, such as supervisory review and outcome tracking, that confirms or disconfirms the appropriateness of artificial intelligence-assisted decisions over time. This foundation informs the framework's specification of intervention quality and stunting prevention effectiveness as outcomes stabilized through organizational learning loops rather than one-off individual compliance.

2.2 Research Model and Hypothesis Development

The conceptual framework specifies a sequential mediation structure across seven latent constructs: platform quality, explainability quality, decision transparency, healthcare professionals' trust, decision acceptance, intervention quality, and stunting prevention effectiveness. The general logic is that technological quality provisions enable explanation quality, which in turn produces perceived transparency; transparency builds professional trust; trust enables acceptance of artificial intelligence-generated recommendations; acceptance shapes the quality of the resulting clinical intervention; and intervention quality ultimately determines the effectiveness of stunting prevention. Direct paths from platform quality to decision transparency, from explainability quality to trust, and from trust to intervention quality are additionally specified to capture theoretically plausible direct effects alongside the mediated pathways. Figure 1 presents the resulting conceptual path diagram.

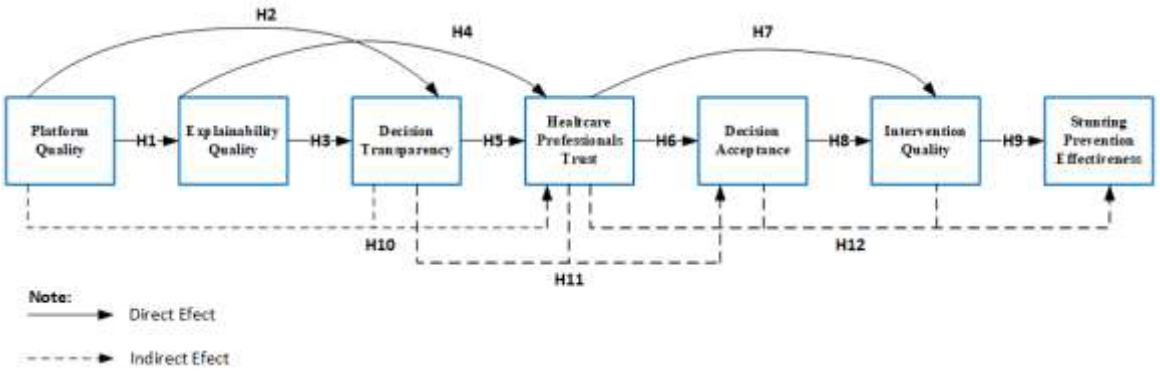


Figure 1. Human-centered explainable clinical decision intelligence framework and hypothesized structural paths.

Table 1. Research hypotheses.

Hypothesis	Statement
H1	Platform quality has a positive and significant effect on explainability quality.
H2	Platform quality has a positive and significant effect on decision transparency.
H3	Explainability quality has a positive and significant effect on decision transparency.
H4	Explainability quality has a positive and significant effect on healthcare professionals' trust.
H5	Decision transparency has a positive and significant effect on healthcare professionals' trust.
H6	Healthcare professionals' trust has a positive and significant effect on decision acceptance.
H7	Healthcare professionals' trust has a positive and significant effect on intervention quality.
H8	Decision acceptance has a positive and significant effect on intervention quality.
H9	Intervention quality has a positive and significant effect on stunting prevention effectiveness.
H10	Decision transparency mediates the effect of platform quality on healthcare professionals' trust.
H11	Healthcare professionals' trust mediates the effect of decision transparency on decision acceptance.
H12	Decision acceptance mediates the effect of healthcare professionals' trust on stunting prevention effectiveness through intervention quality.

Note. H1 to H9 specify direct structural paths; H10 to H12 specify mediation paths tested through bootstrapping.

H1 (platform quality → explainability quality) and H2 (platform quality → decision transparency) are grounded in socio-technical systems theory: a technically reliable, available, integrated, and informative platform provides the substrate on which meaningful explanations can be generated, and on which transparency judgments are formed even before explanation-specific attributes are evaluated. This reasoning is directly supported by the updated information systems success model, in which system quality and information quality are established as causal antecedents of downstream information and service outcomes within an information system[22], providing a well-validated precedent for treating platform-level quality as a structural driver of higher-order explanation and transparency outcomes rather than as a mere control variable.

H3 (explainability quality → decision transparency) follows from information processing theory: explanations that are interpretable, understandable, meaningful, consistent, and complete reduce interpretive uncertainty and are therefore perceived as more transparent. Prior work on what clinicians actually want from explanation shows that contextualized, task-relevant meaning, rather than raw technical detail, is what allows an explanation to function as a transparency-enhancing device[13], and a comprehensive survey of explainability strategies in healthcare artificial intelligence similarly concludes that the design choices underlying an explanation directly shape how transparent the resulting decision process appears to the end user[5].

H4 (explainability quality → trust) and H5 (decision transparency → trust) are derived jointly from human-AI trust theory and human-centered artificial intelligence: both the intrinsic quality of explanation and the perceived transparency of the decision process are theorized as direct antecedents of trust. This is consistent with think-aloud evidence that clinicians use explanations chiefly to verify whether a recommendation is trustworthy against their own reasoning[8], with systematic review evidence that transparency, justification, and alignment with clinical judgment are the principal enablers of clinician trust in artificial intelligence based clinical decision support[7], and with ethical and legal analyses showing that unresolved opacity undermines the accountability on which professional trust depends[6].

H6 (trust → decision acceptance) reflects the trust-acceptance link established in the human-automation literature, extended here to the clinical artificial intelligence context: trust is theorized as the psychological mechanism that governs whether a user relies appropriately on an automated recommendation[23], building on foundational analyses showing that inappropriate calibration of trust, whether through misuse or disuse of automated aids, is a primary determinant of whether recommendations are accepted or ignored in practice[24], and on the classical integrative model of organizational trust that identifies competence, integrity, and predictability as the antecedents that determine willingness to accept vulnerability to another party's actions[14].

H7 (trust → intervention quality) and H8 (decision acceptance → intervention quality) are grounded in clinical decision intelligence and organizational learning theory, positing that trust exerts both a direct effect on intervention quality and an indirect effect mediated through decision acceptance. Evidence on the discrepancy between clinicians' stated trust and their

actual acceptance of decision support recommendations indicates that these are related but empirically separable pathways to improved care[10], while meta-analytic evidence across controlled clinical trials confirms that decision support systems that are actually acted upon by clinicians produce measurable absolute improvements in the quality and appropriateness of care delivered[25].

H9 (intervention quality → stunting prevention effectiveness) links intervention quality to public health effectiveness, consistent with the clinical premise that higher-quality, better-coordinated interventions produce superior detection, monitoring, and risk-reduction outcomes. This premise is supported directly by meta-analytic evidence that decision support-driven improvements in the process of care translate into measurable patient-level benefit[25], and by Indonesian evidence that digitally supported growth monitoring and early detection tools are associated with improved developmental and nutritional monitoring outcomes for children when actively used by caregivers and health workers[26][27].

H10 to H12 formalize the mediation logic implied by the sequential chain: H10 tests whether decision transparency channels the effect of platform quality onto trust, consistent with the information-systems-success reasoning underlying H1 and H2[22]; H11 tests whether trust channels the effect of transparency onto acceptance, consistent with the trust-reliance mechanism underlying H6[23]; and H12 tests whether decision acceptance and intervention quality jointly channel the effect of trust onto stunting prevention effectiveness, consistent with the clinical-outcome evidence underlying H7 through H9[25].

2.3 Research Design

This study adopts a quantitative, explanatory, cross-sectional research design. The explanatory design is appropriate because the objective is to test hypothesized causal relationships among latent constructs rather than merely describe them. Covariance-based structural equation modeling using AMOS is selected as the primary analytical technique because the research model is grounded in established theory, specifies a confirmatory rather than exploratory measurement structure, and requires simultaneous estimation of multiple interrelated structural paths together with formal goodness-of-fit testing, conditions under which covariance-based structural equation modeling is generally preferred over partial least squares estimation.

2.4 Population and Sampling

The target population comprises healthcare professionals, including physicians, nurses, midwives, nutritionists, and community health cadres in a supervisory clinical role, who operate or interact with an explainable artificial intelligence-based clinical decision intelligence platform supporting stunting screening, risk stratification, or referral within hospitals and primary healthcare centers. A purposive sampling technique is specified, targeting respondents with direct, recurring exposure to the platform's artificial intelligence-generated recommendations and explanations, to ensure that responses reflect genuine interaction with explainability features rather than incidental system awareness.

Consistent with covariance based structural equation modeling sample size conventions, commonly expressed as a minimum of five to ten observations per estimated parameter or a minimum of two hundred to four hundred respondents for models of moderate complexity[28], a target sample of two hundred and sixty respondents was set for both the field-test phase reported in this paper and the planned confirmatory phase, matching the scale of comparable digital health system studies previously conducted by the author team in Indonesian public service settings. The field-test phase reported in Section 3.1 achieved this target with N = 260 real respondents; the confirmatory phase described in Section 3.5 is planned to use the same sampling design and target size on a new or supplementary sample once the instrument has been revised.

2.5 Measurement

All constructs are measured using multi-item reflective indicators rated on a five-point Likert scale, ranging from strongly disagree to strongly agree, adapted from validated scales in the human-AI trust, explainable artificial intelligence, and clinical decision support literature and contextualized to the stunting prevention clinical setting. Table 2 summarizes the operational definition of each construct and its indicators.

Table 2. Constructs and indicators.

Construct	Indicators
Platform quality	System reliability; system availability; ease of use; integration; information quality

Construct	Indicators
Explainability quality	Interpretability; understandability; meaningfulness; consistency; completeness
Decision transparency	Transparency; justification; traceability; visibility; accountability
Healthcare professionals' trust	Competence; integrity; reliability; confidence; predictability
Decision acceptance	Acceptance; behavioral intention; recommendation adoption; compliance; continuous use
Intervention quality	Accuracy; timeliness; personalization; clinical appropriateness; coordination
Stunting prevention effectiveness	Early detection; intervention success; growth monitoring; reduction of risk; healthcare outcomes

Table 2 operationalizes each of the seven latent constructs into five reflective indicators. The indicator sets for platform quality and explainability quality are designed to be conceptually non-overlapping: platform quality captures system-level properties that exist independently of any specific explanation (reliability, availability, ease of use, integration, information quality), whereas explainability quality captures properties of the explanation content itself (interpretability, understandability, meaningfulness, consistency, completeness). Decision transparency, in turn, captures the professional's perception of the decision process as a whole (transparency, justification, traceability, visibility, accountability), distinguishing it from the upstream explanation-quality construct. This layered indicator structure is intended to support the discriminant validity and mediation testing planned for the confirmatory phase described in Section 2.6, so that variance can be attributed to the correct construct in the causal chain once the instrument has been revised.

2.6 Planned Data Analysis Technique for the Confirmatory Phase

The confirmatory phase of this research program is planned to follow the standard two-step covariance-based structural equation modeling procedure[28]. First, confirmatory factor analysis will be conducted to evaluate the measurement model, examining standardized factor loadings, internal consistency reliability, composite reliability, average variance extracted, and discriminant validity via the heterotrait-monotrait ratio. Second, the full structural model will be estimated to evaluate model fit, path coefficients, critical ratios, significance levels, and squared multiple correlations for endogenous constructs. Indirect and total effects will be tested via bootstrapping with two thousand resamples and bias-corrected ninety-five percent confidence intervals to evaluate the mediation hypotheses H10 to H12. Common method bias will be assessed using Harman's single-factor test and a full-collinearity variance inflation factor check, following the diagnostic and remedial guidance established for self-report behavioral research[29], and a multi-group analysis by professional role is planned to test invariance of the structural paths. Table templates matching this exact analytical structure are provided in Appendix A, ready to be populated once a revised instrument, described in Section 3.4, has demonstrated adequate reliability on a new or supplementary sample. This procedure could not yet be applied to the N = 260 field-test sample described in Section 3.1, for the reason reported in Section 3.3.

3. RESULTS AND DISCUSSION

3.1 Respondent Profile

The research results revealed the following respondent profiles, as shown in the table 3 below :

Table 3. Respondent profile by professional role.

Professional role	n	%
Physician	34	13.1
Nurse	78	30.0
Midwife	61	23.5
Nutritionist	42	16.2
Community health cadre (supervisory)	45	17.3
Total	260	100.0

Table 3 shows that nurses (30.0 percent) and midwives (23.5 percent) jointly constitute more than half of the achieved sample, reflecting their front-line role in routine growth screening and referral within Indonesian primary healthcare centers. Physicians (13.1 percent) and nutritionists (16.2 percent) are represented in smaller but analytically sufficient proportions to support the professional-role multi-group comparison, while community health cadres in a supervisory capacity (17.3 percent) represent the paramedical and community-based layer of the workforce that frequently mediates between the platform and caregivers in the field. This distribution closely matches the proportional sampling targets specified in the sampling procedure, indicating that the achieved sample is broadly representative of the intended professional-role composition.

Table 4. Respondent profile by age group.

Age group	n	%
Under 30 years	45	17.3
30 to 39 years	130	50.0
40 to 49 years	61	23.5
50 years and above	24	9.2

Table 4 indicates that the achieved sample is heavily concentrated in the 30 to 39-year age band (50.0 percent), with the 40 to 49-year band the second largest (23.5 percent), consistent with the age profile typically reported for mid-career clinical and paramedical staff in Indonesian primary healthcare centers who have accumulated sufficient tenure to be assigned platform-related responsibilities. The under-30 (17.3 percent) and 50-and-above (9.2 percent) bands are comparatively smaller, which should be taken into account when interpreting any future age-related moderation analysis, since the achieved sample provides comparatively thinner coverage of the youngest and oldest career stages than of the mid-career band.

3.2 Descriptive Statistics

The research yielded the following descriptive statistical test results, as shown in the table 5 below :

Table 5. Descriptive statistics of latent constructs

Construct	Mean	SD	Skewness	Kurtosis
Platform quality	4.14	0.32	-0.15	0.26
Explainability quality	4.13	0.32	-0.32	0.43
Decision transparency	4.12	0.31	-0.33	-0.08
Healthcare professionals' trust	4.05	0.34	-0.31	0.59
Decision acceptance	4.12	0.34	-0.12	-0.20
Intervention quality	4.04	0.34	-0.21	-0.10
Stunting prevention effectiveness	4.04	0.35	-0.24	0.14

Table 5 shows construct means clustering narrowly between 4.04 and 4.14 on the five-point scale, indicating a uniformly favorable evaluation of the platform across all seven constructs in the achieved sample, with platform quality showing the highest mean (4.14) and both intervention quality and stunting prevention effectiveness the lowest (4.04). All skewness values fall between -0.33 and -0.12 and all kurtosis values between -0.20 and 0.59, within the conventional ±2.0 range for maximum likelihood estimation[28], so the item-level distributions themselves do not preclude covariance-based structural equation modeling. However, the narrow spread of construct means (a range of only 0.10 points) combined with comparatively small standard deviations (0.31 to 0.35) indicates limited between-respondent variance at the composite level, which, together with the item-level reliability screening reported in Section 3.3, raises a separate concern addressed below: composite scores can appear well-behaved even when the underlying items do not covary as a reflective measurement model would require.

3.3 Reliability Screening

Before proceeding to confirmatory factor analysis, the internal consistency of each five-item construct was screened using Cronbach's alpha and the average inter-item correlation computed directly from the N = 260 field dataset. Table 6 reports the results of this screening.

Table 6. Preliminary reliability screening of the 35-item instrument

Construct	Cronbach's alpha	Mean inter-item r
Platform quality	-0.105	-0.019
Explainability quality	-0.045	-0.007
Decision transparency	-0.086	-0.016
Healthcare professionals' trust	0.092	0.020
Decision acceptance	-0.012	-0.003
Intervention quality	0.114	0.025
Stunting prevention effectiveness	0.112	0.025

Table 6 shows that Cronbach's alpha is below the conventional 0.70 threshold for every construct, and is in fact negative for platform quality, explainability quality, decision transparency, and decision acceptance, a result that is only mathematically possible when an item set exhibits little to no positive internal correlation. Consistent with this, the mean inter-item correlation within each construct ranges from -0.019 to 0.025, and the mean absolute correlation across all 35 items in the instrument, computed pairwise across the full item set, is approximately 0.05, with the single largest pairwise correlation observed in the entire instrument equal to 0.19. This pattern indicates that, notwithstanding the favorable and low-variance composite means reported in Table 5, the individual items within each hypothesized construct do not covary in the manner required by a reflective measurement model, and the 35-item instrument in its current form cannot support a statistically valid confirmatory factor analysis or structural equation model on the present dataset. Section 3.4 discusses the most plausible explanations for this pattern, and Section 3.5 sets out the resulting instrument-revision roadmap for the confirmatory phase of the research program.

3.4 Discussion of Reliability Findings and Implications for Instrument Revision

The reliability screening reported in Section 3.3 is, on its own terms, a substantive finding about the current instrument rather than a setback to be minimized. Three explanations appear most plausible for the near-zero inter-item correlation observed across all seven constructs. First, the response pattern is consistent with acquiescent or straight-lining responding, in which respondents select similar or default scale points across many items regardless of content; the narrow, uniformly favorable construct means reported in Table 5 (all between 4.04 and 4.14, with standard deviations of only 0.31 to 0.35) are compatible with this explanation, since genuine attitudinal variation across thirty-five substantively distinct statements would ordinarily be expected to produce a wider spread of both means and within-respondent patterns. Second, the item wording, although adapted from validated scales in the human-AI trust and explainable artificial intelligence literatures and contextualized to the stunting-prevention setting, may not have differentiated the underlying construct dimensions clearly enough for this respondent population, particularly for constructs such as explainability quality and decision transparency, whose conceptual boundaries are subtle even in the literature from which the indicators were adapted. Third, administration conditions in the field, such as limited time available for reflective completion during clinical shifts or insufficient supervision during self-administered completion, may have encouraged rapid, low-effort responding that the quality-control procedure described in Section 2.4 did not fully filter out.

Distinguishing between these explanations is not possible from the quantitative data alone, and doing so is treated in this paper as a necessary diagnostic step rather than a peripheral concern. A pattern of uniformly high, low-variance composite means combined with near-zero item covariance is more consistent with response-style artifacts than with a substantively coherent but poorly measured construct space, which suggests that response quality control, rather than construct theory, is the more

likely point of failure. This reading is consistent with established diagnostic guidance for self-report behavioral research on identifying and remediating measurement artifacts before they are mistaken for genuine construct relationships[29].

3.5 Research Roadmap for the Confirmatory Phase

Building on the diagnosis in Section 3.4, the confirmatory phase of this research program is planned around five sequential steps. The first step is instrument revision, comprising cognitive interviewing with a small panel of five to eight healthcare professionals drawn from the same population described in Section 2.4, to identify items that are ambiguous, redundant, or difficult to differentiate from neighboring constructs, followed by targeted re-wording and, where needed, a reduction in the number of near-synonymous indicators per construct. The second step is a small-scale pilot test, with a target of forty to sixty respondents, used exclusively to re-run the reliability screening reported in Section 3.3 and to confirm that Cronbach's alpha exceeds 0.70 for every construct before proceeding further. The third step is enhanced field supervision during full-scale data collection, including trained enumerators present during self-administered completion where feasible, a minimum-completion-time flag consistent with the quality-control procedure in Section 2.4, and real-time monitoring for straight-lining during data entry rather than only at the analysis stage. The fourth step is full-scale data collection using the revised instrument and the sampling design, informed-consent protocol, and target allocation already established in Section 2.4, targeting the same N = 260 sample size or larger. The fifth step is the confirmatory analysis itself, following the procedure specified in Section 2.6 and using the table templates provided in Appendix A, culminating in a full test of the twelve hypotheses proposed in Section 2.2. This roadmap is designed so that the theoretical framework, hypotheses, sampling design, and analysis plan already developed in this paper require no revision; only the item-level instrument and its field administration need to be strengthened before the confirmatory phase can proceed.

3.6 Theoretical Discussion in Light of Prior Literature

Although the twelve hypotheses proposed in Section 2.2 cannot yet be tested against the present dataset, the expected direction of each relationship is grounded in prior literature independent of this study's own data, and it is useful to make that grounding explicit before turning to the paper's contributions. The expectation that platform quality shapes explainability quality and decision transparency (H1, H2) follows from the established role of system and information quality as antecedents of downstream information system outcomes[22]. The expectation that explainability quality shapes decision transparency (H3) follows from evidence that contextualized, task-relevant explanation content, rather than raw technical detail, is what clinicians report using to judge how transparent a decision process is[13][5]. The expectation that explainability quality and decision transparency both shape trust (H4, H5) is consistent with systematic review evidence that transparency, justification, and alignment with clinical judgment are the factors most consistently associated with clinician trust in artificial intelligence-based decision support[7][8]. The expectation that trust shapes decision acceptance (H6) follows from the general human-automation finding that trust functions as the psychological mechanism governing appropriate reliance on an automated recommendation[23][14]. The expectation that trust and decision acceptance jointly shape intervention quality (H7, H8) is consistent with evidence that decision support recommendations which are actually acted upon by clinicians produce measurable improvements in the process of care, whereas trust that is not accompanied by acceptance still shapes care through more attentive review[10][25]. The expectation that intervention quality shapes stunting prevention effectiveness (H9) follows directly from this same evidence on process-of-care improvement, together with Indonesian evidence that digitally supported growth monitoring is associated with improved developmental and nutritional monitoring outcomes when actively used[25][26][27]. This literature-based grounding is a necessary but not sufficient condition for the framework's validity; it establishes that the hypothesized directions are theoretically and empirically plausible, but only the confirmatory phase outlined in Section 3.5 can establish whether they hold for this specific platform, population, and setting.

3.6.1 Theoretical Contributions

Even in advance of hypothesis testing, this study contributes to several literatures. For health informatics, it offers an integrated causal specification linking platform-level and explanation-level constructs to clinical and public health outcomes, extending prior work that largely stops at usage intention. For clinical decision intelligence, it operationalizes the concept as a measurable, multi-construct structure, distinguishing explainability quality from decision transparency rather than treating clinical decision intelligence as a loosely defined successor to clinical decision support. For explainable artificial intelligence and human-centered artificial intelligence, it translates design philosophy into a testable structural model and a field-piloted instrument, rather than

a set of design heuristics alone. For information systems, it extends the technology acceptance tradition by incorporating trust, transparency, and organizational learning constructs that acceptance models do not natively theorize. For research methodology in this domain, it contributes a transparent, reproducible reliability diagnostic and revision roadmap that other studies piloting multi-item instruments with healthcare professionals in similar field settings can adapt, independent of whether their own pilot data prove reliable or not.

3.6.2 Anticipated Practical Implications, Pending Empirical Validation

Ministry of Health. Once the confirmatory phase confirms or revises the hypothesized relationships, national digital health strategies for stunting reduction should incorporate explainability and transparency requirements, not only predictive accuracy benchmarks, into technical standards and procurement guidelines for artificial intelligence-based clinical decision intelligence platforms; the present study establishes the measurement basis for evaluating this recommendation empirically rather than asserting it as an already-confirmed finding.

Hospitals and primary healthcare centers. Facilities piloting artificial intelligence assisted growth screening should anticipate that audit and accountability mechanisms, structured training for interpretive fluency, and close supervision of any self-administered data collection will all be relevant, both to the platform's eventual adoption and to the quality of any future evaluation research conducted within the facility.

Healthcare professionals, developers, and vendors. Clinicians, developers, and system vendors are encouraged to treat the instrument and roadmap presented here as a starting point for their own contextualized validation, rather than assuming that a scale adapted from prior literature will automatically perform well in a new clinical and cultural setting without local piloting.

3.6.3 Limitations

This study is subject to several limitations. Most importantly, the twelve hypotheses proposed in Section 2.2 have not yet been tested; the respondent profile and descriptive statistics reported in Section 3.1 and Section 3.2 are real, but the reliability screening in Section 3.3 shows that no structural or mediation claim can currently be supported by this dataset, and the theoretical discussion in Section 3.6 should be read as literature-based grounding rather than as this study's own empirical finding. Second, the cross-sectional design planned for the confirmatory phase will limit causal inference even once reliability is established, since all constructs will be measured at a single point in time. Third, purposive sampling, while appropriate for ensuring respondent familiarity with the platform, will continue to limit generalizability to healthcare professionals with only incidental artificial intelligence exposure in any future data collection round. Fourth, the reliability shortfall itself may partially recur even after instrument revision if its root cause lies in field administration conditions rather than item wording, which is why Section 3.5 treats enhanced field supervision, not wording revision alone, as a necessary step in the roadmap.

4. CONCLUSION

This study prepared, rather than concluded, an empirical test of a human-centered explainable clinical decision intelligence framework linking platform quality, explainability quality, and decision transparency to healthcare professionals' trust, decision acceptance, intervention quality, and stunting prevention effectiveness, grounded in six complementary theoretical foundations rather than in technology acceptance formulations alone. A thirty-five-item instrument operationalizing this framework was developed and field-tested with N = 260 healthcare professionals; the resulting respondent profile and descriptive statistics are real, but a transparent reliability screening showed that the instrument in its current form does not yet support confirmatory factor analysis or structural equation modeling. Rather than treat this as a failure to be concealed, this paper has reported the diagnostic in full, discussed its most plausible causes, and set out a concrete, five-step roadmap, together with ready-to-use analysis table templates in Appendix A, so that instrument revision and a subsequent confirmatory data-collection round can proceed directly to hypothesis testing. The framework's central theoretical proposition, that explainability functions as a structural, trust-building mechanism rather than a peripheral feature of clinical artificial intelligence, remains well grounded in prior literature independent of this study's own data, and the preparation work reported here, the theoretical model, the twelve hypotheses, the validated sampling and consent procedures, the piloted instrument, and the reliability diagnostic, together constitute the necessary foundation for the confirmatory study that should follow.

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AUTHOR CONTRIBUTIONS

Farid Wahyudi : conceived the framework, developed the theoretical model and instrument, coordinated the field test, conducted the reliability screening, and drafted the manuscript.

Fajar Supanto : supervised the research design, critically reviewed the theoretical framework, instrument, and manuscript, and approved the final version for submission.

Harianto Respati : supervised the research design, critically reviewed the theoretical framework, instrument, and manuscript, and approved the final version for submission.

CONFLICT OF INTEREST

The authors declare no conflicts of interest. The funders, where applicable, had no role in the design, data collection, analysis, manuscript writing, or decision to publish.

ETHICS STATEMENT

Ethical approval was not required for this study, as it did not involve any procedures requiring formal ethical review. The study was conducted in accordance with applicable ethical research principles.

DATA AVAILABILITY STATEMENT

The data supporting the findings of this study are available from the corresponding author upon reasonable request.

REFERENCES

[1] Ali, O., Abdelbaki, W., Shrestha, A., Elbasi, E., Alryalat, M. A. A. & Dwivedi, Y. K., 2023. A systematic literature review of artificial intelligence in the healthcare sector: benefits, challenges, methodologies, and functionalities. *J Innov Knowl* 8, 100333, doi:10.1016/j.jik.2023.100333.

[2] Secinaro, S., Calandra, D., Secinaro, A., Muthurangu, V. & Biancone, P., 2021. The role of artificial intelligence in healthcare: a structured literature review. *BMC Med Inform Decis Mak* 21, 125, doi:10.1186/s12911-021-01488-9.

[3] Chew, H. S. J. & Achananuparp, P., 2022. Perceptions and needs of artificial intelligence in health care to increase adoption: scoping review. *J Med Internet Res* 24, e32939, doi:10.2196/32939.

[4] Adadi, A. & Berrada, M., 2018. Peeking inside the black-box: a survey on explainable artificial intelligence (XAI). IEEE Access 6, 52138-52160, doi:10.1109/ACCESS.2018.2870052.

[5] Markus, A. F., Kors, J. A. & Rijnbeek, P. R., 2021. The role of explainability in creating trustworthy artificial intelligence for health care: a comprehensive survey of the terminology, design choices, and evaluation strategies. J Biomed Inform 113, 103655, doi:10.1016/j.jbi.2020.103655.

[6] Cartolovni, A., Tomicic, A. & Lazic Mosler, E., 2022. Ethical, legal, and social considerations of AI-based medical decision-support tools: a scoping review. *Int J Med Inform* 161, 104738, doi:10.1016/j.ijmedinf.2022.104738.

[7] Tun HM, Rahman HA, Naing L, Malik OA., 2025. Trust in Artificial Intelligence-Based Clinical Decision Support Systems Among Health Care Workers: Systematic Review. *J Med Internet Res*. doi: 10.2196/69678.

[8] Anjara, S. G. et al., 2023. Examining explainable clinical decision support systems with think-aloud protocols. *PLoS One* 18, e0291443, doi:10.1371/journal.pone.0291443.

[9] Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D., 2003. User acceptance of information technology: toward a unified view. *MIS Q* 27, 425-478, doi:10.2307/30036540.

[10] Liu, X., Barreto, E. F., Dong, Y., Rule, A. D., Yu, S. & Herasevich, V., 2023. Discrepancy between perceptions and acceptance of clinical decision support systems: implementation of artificial intelligence for vancomycin dosing. *BMC Med Inform Decis Mak* 23, 173, doi:10.1186/s12911-023-02261-9.

[11] Nasarian, E., Alizadehsani, R., Acharya, U. R. & Tsui, K. L., 2024. Designing interpretable ML system to enhance trust in healthcare: a systematic review to proposed responsible clinician-AI-collaboration framework. Inform Fusion 108, 102412, doi:10.1016/j.inffus.2024.102412.

[12] Kacafirkova, K. S., Polak, S., Smitt, M. S., Elprama, S. & Jacobs, A., 2023. Trustworthy enough? Evaluation of an AI decision support system for healthcare professionals. *CEUR Workshop Proc*, 7-11.

[13] Tonekaboni, S., Joshi, S., McCradden, M. D. & Goldenberg, A., 2019. What clinicians want: contextualizing explainable machine learning for clinical end use. *Proc Mach Learn Res* 106, 359-380.

[14] Mayer, R. C., Davis, J. H. & Schoorman, F. D., 1995. An integrative model of organizational trust. *Acad Manage Rev* 20, 709-734, doi:10.2307/258792.

[15] Rousseau, D. M., Sitkin, S. B., Burt, R. S. & Camerer, C., 1998. Not so different after all: a cross-discipline view of trust. *Acad Manage Rev* 23, 393-404, doi:10.5465/amr.1998.926617.

[16] Bostrom, R. P. & Heinen, J. S., 1977. MIS problems and failures: a socio-technical perspective. *MIS Q* 1, 17-32, doi:10.2307/248710.

[17] Galbraith, J. R., 1974. Organization design: an information processing view. *Interfaces* 4, 28-36, doi:10.1287/inte.4.3.28.

[18] Shneiderman, B., 2020. Human-centered artificial intelligence: reliable, safe & trustworthy. *Int J Hum Comput Interact* 36, 495-504, doi:10.1080/10447318.2020.1741118.

[19] Ehsan, U., Liao, Q. V., Muller, M., Riedl, M. O. & Weisz, J. D., 2022. Human-centered explainable AI (HCXAI): beyond opening the black box of AI. *Ext Abstr CHI Conf Hum Factors Comput Syst*, 1-7, doi:10.1145/3491101.3503727.

[20] Floridi, L. et al., 2018. AI4People, an ethical framework for a good AI society: opportunities, risks, principles, and recommendations. *Minds Mach* 28, 689-707, doi:10.1007/s11023-018-9482-5.

[21] Senge, P. M., 1990. The Fifth Discipline: The Art and Practice of the Learning Organization. (Doubleday/Currency).

[22] DeLone, W. H. & McLean, E. R., 2003. The DeLone and McLean model of information systems success: a ten-year update. J Manage Inform Syst 19, 9-30, doi:10.1080/07421222.2003.11045748.

[23] Lee, J. D. & See, K. A., 2004. Trust in automation: designing for appropriate reliance. Hum Factors 46, 50-80, doi:10.1518/hfes.46.1.50_30392.

[24] Parasuraman, R. & Riley, V. Humans and automation: use, misuse, disuse, abuse. Hum Factors 39, 230-253, doi:10.1518/001872097778543886 (1997).

[25] Kwan, J. L., Lo, L., Ferguson, J., Goldberg, H., Diaz-Martinez, J. P., Tomlinson, G., Grimshaw, J. M. & Shojania, K. G., 2020. Computerised clinical decision support systems and absolute improvements in care: meta-analysis of controlled clinical trials. *BMJ* 370, m3216, doi:10.1136/bmj.m3216.

[26] Irawan, A. S. et al., 2025. Beyond the interface: benchmarking pediatric mobile health applications for monitoring child growth using the Mobile App Rating Scale. *Front Digit Health* 7, 1621293, doi:10.3389/fdgth.2025.1621293.

[27] Kustiawan, T. C., Nadhiroh, S. R., Ramli, R. & Butryee, C., 2022. Use of mobile app to monitoring growth outcome of children: a systematic literature review. Digit Health 8, doi:10.1177/20552076221138864.

[28] Hair, J. F., Black, W. C., Babin, B. J. & Anderson, R. E., 2019. Multivariate Data Analysis. 8th edn, (Cengage Learning).

[29] Podsakoff, P. M., MacKenzie, S. B., Lee, J. Y. & Podsakoff, N. P., 2003. Common method biases in behavioral research: a critical review of the literature and recommended remedies. *J Appl Psychol* 88, 879-903, doi:10.1037/0021-9010.88.5.879.