Journal of Chemical Health Risks

www.jchr.org

JCHR (2025) 15(6), 1373-1391 | ISSN:2251-6727

From Paper to Pixels: Leveraging AI-Enabled Digital Feedback Systems to Bridge Maternal Healthcare Equity Gaps in Tribal India - A Case Study from Odisha's First Referral Units

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(Received: 27 September 2025 Revised: 05 October 2025 Accepted: 18 November 2025)

KEYWORDS
Digital health transformation, AI-enabled feedback systems, maternal healthcare equity, tribal health services, patient satisfaction monitoring, First Referral Units

ABSTRACT:

Background: Equitable maternal healthcare delivery in tribal-dominated regions remains a critical challenge to achieving universal health coverage. This study investigated patient satisfaction disparities and proposed an AI-enabled digital transformation framework for first-referral units (FRUs) in resource-limited settings.

Methods: A cross-sectional analytical study was conducted in the Obstetrics and Gynecology department of a tribal-dominated FRU in the Gajapati district of Odisha (November 2024-April 2025). Using consecutive sampling, 320 women (89 tribal, 231 non-tribal) were surveyed across ten service domains using a culturally adapted instrument. Statistical analyses included independent t-tests, Pearson's correlations, multiple linear regression, and temporal trend analysis. Digital system requirements were derived through iterative stakeholder consultations and technical feasibility assessments.

Results: Overall satisfaction was high ($M=4.11\pm0.38$, 95%CI:4.07-4.15) with no significant tribal-non-tribal differences ($t(318)=0.634$, $p=0.527$, $d=0.079$), indicating equitable service delivery. Regression analysis ($R^2=0.628$, $p<0.001$) identified doctor communication ($\beta=0.312$, $p<0.001$) and staff behaviour ($\beta=0.248$, $p<0.001$) as primary satisfaction predictors. Inter-domain correlations revealed strong associations between interpersonal factors and overall satisfaction ($r=0.682$ for doctor communication). Temporal analysis showed marginal improvement trends (+0.67% monthly, $p=0.382$). Critical gaps emerged in waiting times (registration=3.85; consultation=3.92) across both populations.

Proposed Digital Solution: An AI-enabled PSS framework incorporating Natural Language Processing for tribal dialects, voice-based interfaces addressing 32% low-literacy rates, edge computing for intermittent connectivity, and machine learning algorithms for predictive analytics and real-time pattern recognition was conceptualized.

Conclusions: Although current FRU services demonstrate commendable equity in patient satisfaction, systematic inefficiencies persist uniformly across demographic groups. The proposed digital PSS system, leveraging AI for culturally responsive, real-time feedback collection and analysis, offers a scalable model for continuous quality improvement in resource-constrained maternal healthcare settings. The implementation of this system could transform reactive quality assurance into proactive, data-driven healthcare optimization, thereby contributing to the objectives of India's digital health mission.

1. Introduction

1.1 Background

The pursuit of equitable healthcare is a global challenge, with geographical remoteness, cultural diversity, and resource limitations hindering quality care(*Thirteenth General Programme of Work, 2019-2023*, n.d.). In India, these issues affect maternal healthcare in tribal communities, which make up 8.6% of the population and face higher maternal mortality(*NFHS-5.Pdf*, n.d.). First Referral Units (FRUs) are key in India's healthcare system, offering emergency obstetric and newborn care at the sub-district level(*Family-Welfare_2004 (Backup)*, n.d.). They are crucial in tribal areas, where they provide specialized maternal healthcare. Despite their importance, systematic assessments of service quality and patient satisfaction in FRUs for tribal populations are limited. Patient satisfaction, including technical competence, interpersonal relationships, accessibility, and service experience, affects healthcare-seeking behavior and maternal outcomes(Donabedian, 1988; Parasuraman et al., 1985; Srivastava et al., 2015). Traditional satisfaction surveys face delays and cannot capture real-time feedback. Artificial intelligence (AI) and machine learning (ML) offer opportunities to improve patient feedback in resource-limited settings. Digital innovations, as demonstrated by Schwalbe and Wahl(Wahl et al., 2018) can impact health outcomes. AI systems can overcome language barriers, enable voice-based feedback for low-literacy populations, and provide real-time analysis. Edge computing ensures functionality in areas with limited Internet access.

1.2 Theoretical Framework

This study integrates three foundational models to understand patient satisfaction and the digital health transformation in tribal maternal healthcare. The SERVQUAL framework conceptualizes service quality as the gap between patient expectations and perceptions, informing our culturally adapted survey instrument across ten service domains(Parasuraman et al., 1985). Andersen's Behavioral Model of Health Services Use examines how predisposing characteristics, enabling resources, and need factors influence patient satisfaction outcomes, guiding our analysis of tribal versus non-tribal satisfaction levels(Andersen, 1995). The Technology Acceptance Model (TAM) informs our AI-enabled digital transformation framework through perceived usefulness and ease of use, guiding the development of our digital Patient Satisfaction Survey system with voice interfaces and local dialects for accessibility(Davis, 1989).

1.3 Knowledge Gap

Despite the growing recognition of patient satisfaction in healthcare quality assessment, key gaps persist: limited comparative data between tribal and non-tribal populations hinder interventions(Boro & Saikia, 2020). Most satisfaction studies in resource-limited settings use aggregate scores and fail to identify improvements(Kruk et al., 2018). Cross-sectional assessments provide snapshots with insufficient attention to trends(Larson et al., 2019). While digital health advances, AI-enabled feedback systems for tribal healthcare remain unexplored (Wahl et al., 2018). Current solutions face challenges in tribal contexts, including language diversity and literacy constraints (Kumar et al., 2022). Assessment tools often lack cultural sensitivity for tribal populations, causing measurement bias (Bhattacharyya et al., 2015).

1.4 Study Objectives

Given these knowledge gaps and the importance of equitable maternal healthcare, this study had four objectives.

- To assess patient satisfaction across ten service domains between tribal and non-tribal mothers accessing obstetric services at a tribal-dominated First Referral Unit (FRU) in the Gajapati district of Odisha.
- To identify factors influencing overall satisfaction between tribal and non-tribal populations.
- To analyse satisfaction trends over six months for quality improvement in FRUs; and
- To propose a digital Patient Satisfaction Survey (PSS) system using AI technologies to improve feedback collection and enhance maternal care in resource-limited settings.

1.5 Significance of the Study

This study explores health equity, digital innovation, and the quality of maternal healthcare in underserved regions of India. By evidencing satisfaction patterns and proposing an AI-enabled solution, this study advances the understanding of healthcare equity in tribal settings, informs policy for FRU quality improvement, and pioneers culturally sensitive AI in resource-limited contexts. These findings have implications for Odisha and similar global tribal regions, where traditional quality assessments are inadequate.

2. Methods

2.1 Study Design and Setting

This cross-sectional study was conducted at the Department of Obstetrics and Gynecology, District Hospital, Paralakhemundi, Gajapati District, Odisha, from November 2024 to April 2025. Gajapati, a tribal region in southern Odisha, has 54.31% of the Scheduled Tribes, mainly the Saura and Kondh communities (Panda & Sharma, 2024). The district spans 4,325 square kilometers with 577,817 people across 1,499 villages(*Gajapati District, Odisha | Population, Area,*

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Villages, List of Subdivision, n.d.). The district hospital, upgraded under the National Health Mission, serves as a referral center with 3,000 annual deliveries and faces limited healthcare infrastructure and geographical barriers.

2.2 Study Population and Sampling

2.2.1 Inclusion Criteria

- Women of reproductive age (15-49 years) as defined by WHO standards
- Accessing outpatient services at the O&G department for any obstetric or gynaecological condition
- Completion of their consultation and treatment on the day of survey
- Willingness to provide informed consent
- Ability to understand and communicate in Odia, Hindi, or local tribal languages (Saura, Kondh)

2.2.2 Exclusion Criteria

- Women presenting with emergency conditions requiring immediate intervention
- Those with severe mental health conditions affecting their ability to provide informed responses
- Women who had previously participated in the survey during the study period
- Inpatients, as their experiences differ substantially from outpatient services

2.2.3 Sample Size Calculation

The sample size was calculated using the formula for comparing two independent proportions.

$$n = [Z_1\text{-}\alpha/_2\sqrt{\{2p(1-p)\}} + Z_1\text{-}\beta\sqrt{\{p_1(1-p_1) + p_2(1-p_2)\}}]^2 \,/\, (p_1 - p_2)^2$$

Where:

- $Z_1\text{-}\alpha/_2 = 1.96$ (95% confidence level)
- $Z_1\text{-}\beta = 0.84$ (80% power)
- p_1 = expected satisfaction proportion in tribal population (0.70, based on pilot data)
- p_2 = expected satisfaction proportion in non-tribal population (0.80)
- $p = (p_1 + p_2)/2 = 0.75$

This yielded a minimum sample size of 294 (147 participants per group). Accounting for 10% non-response and the need for temporal analysis across months, we targeted 400 participants in the study. The final sample of 320 (response rate: 80%) exceeded the minimum requirement and provided adequate power for all planned analyses.

2.3 Survey Instrument Development

2.3.1 Questionnaire Design

The survey instrument was developed through a systematic process.

1. **Literature Review**: Comprehensive review of validated patient satisfaction instruments, including SERVQUAL, the Patient Satisfaction Questionnaire (PSQ-18), and culturally adapted tools used in similar settings.
2. **Expert Consultation**: A panel comprising two obstetricians, one public health specialist, one tribal welfare officer, and two community health workers reviewed and refined the initial draft of the questionnaire.
3. **Domain Selection**: Ten service domains were identified as critical for comprehensive assessment.

- Q1: Adequacy of hospital information availability
- Q2: Waiting time at registration
- Q3: Behaviour and courtesy of hospital staff
- Q4: Cleanliness of facilities (OPD areas, toilets, waiting areas)
- Q5: Doctor's treatment approach and communication
- Q6: Waiting time for consultation
- Q7: Availability of diagnostic services and investigations
- Q8: Efficiency of medicine distribution
- Q9: Availability of prescribed medicines
- Q10: Overall satisfaction with hospital experience

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4. **Response Scale**: A 5-point Likert scale was adopted (1=Low/Poor, 2=Fair, 3=Good, 4=Very Good, 5=Excellent) based on cognitive testing showing good discriminability among respondents.

2.3.2 Translation and Cultural Adaptation

The questionnaire underwent rigorous translation and cultural adaptation.

1. **Forward Translation**: Two independent translators fluent in Odia and English reviewed the translated the questionnaire
2. **Reconciliation**: Discrepancies were resolved through consensus meetings
3. **Back Translation**: An independent translator back-translated to English for validation
4. **Cultural Adaptation**: Local terms and concepts were incorporated (e.g., using familiar metaphors for satisfaction levels)
5. **Pictorial Aids**: Visual representations of satisfaction levels were developed for low-literacy respondents
6. **Tribal Language Support**: Key phrases were translated into Saura and Kondh languages with support from tribal welfare officers of the district

2.3.3 Pilot Testing

A pilot study with 30 women (15 tribal and 15 non-tribal) was conducted to assess the following:

- Comprehension and clarity of questions
- Time required for survey completion (mean: 12 minutes)
- Cultural acceptability of questions
- Floor and ceiling effects in responses

Based on pilot feedback, minor modifications were made to question phrasing, and the order of demographic questions was adjusted to build rapport before addressing satisfaction items.

2.4 Data Collection Procedures

2.4.1 Survey Administration

Data collection followed a standardized protocol.

1. **Timing**: Surveys were conducted after patients completed their OPD consultation but before leaving the hospital premises
2. **Location**: A designated quiet area near the OPD exit to ensure privacy
3. **Approach**: Consecutive sampling of all eligible women during predetermined time slots covering all OPD hours
4. **Language**: Surveys were administered in the respondent's preferred language
5. **Duration**: Average completion time was 12-15 minutes
6. **Documentation**: Responses were immediately recorded on structured forms with unique identifiers

2.5 Digital System Requirements Assessment

Parallel to the satisfaction survey, we conducted a systematic assessment of the requirements for the proposed digital PSS system.

2.5.1 Stakeholder Consultations

Semi-structured interviews were conducted with a diverse group of stakeholders critical to the success and sustainability of digital health interventions. This included:

- Healthcare administrators (n=5)
- Frontline health workers (n=10)
- IT personnel at the district level (n=3)
- Tribal community representatives (n=8)

These consultations gathered perspectives on the challenges, functionalities, and barriers. The key themes included language accessibility and cultural appropriateness, technology acceptance barriers, infrastructure limitations, workflow integration challenges, data privacy concerns, and sustainability requirements. Administrators emphasized the importance of real-time data for decision-making, while frontline workers highlighted issues with paper surveys and the need for less administrative burden. Community representatives provided insights into cultural nuances and their preferred feedback methods.

2.5.2 Infrastructure Assessment

The technical evaluation included:

- Internet connectivity mapping across the FRU
- Assessment of existing IT infrastructure
- Power supply reliability analysis
- Staff digital literacy evaluation

2.5.3 User Experience Design

Participatory design sessions were conducted to understand the following:

- Preferred modes of digital interaction
- Language and literacy considerations
- Cultural factors affecting technology acceptance
- Workflow integration requirements

2.6 Statistical Analysis

Data analysis was performed using IBM SPSS Statistics version 26.0 (IBM Corporation, Armonk, NY) and R version 4.3.1 (R Foundation for Statistical Computing, Vienna, Austria). The analytical approach was pre-specified in a statistical plan to minimize data-driven decision making.

2.6.1 Data Preparation

- Missing data patterns were examined using Little's MCAR test
- Outliers were identified using box plots and verified against original forms
- Normality was assessed using Shapiro-Wilk tests and Q-Q plots
- Scale reliability was evaluated using Cronbach's alpha ($\alpha = 0.884$ for the 10-item scale)

2.6.2 Descriptive Analysis

- Frequencies and percentages for categorical variables
- Means, standard deviations, and 95% confidence intervals for continuous variables
- Median and interquartile ranges for non-normally distributed variables
- Graphical representations including histograms and box plots

2.6.3 Comparative Analysis

- Independent samples t-test for comparing mean satisfaction scores between tribal and non-tribal groups (assumption of normality verified)
- Mann-Whitney U test as a non-parametric alternative for individual items
- Chi-square test for categorical comparisons
- Effect size calculation using Cohen's d with interpretation: negligible (<0.2), small (0.2-0.5), medium (0.5-0.8), large (>0.8)

2.6.4 Correlation Analysis

- Pearson correlation coefficients for inter-domain relationships
- Correlation matrix with Bonferroni correction for multiple comparisons
- Interpretation of correlation strength: weak (0.1-0.3), moderate (0.3-0.5), strong (>0.5)

2.6.5 Regression Analysis

- Multiple linear regression with overall satisfaction (Q10) as dependent variable
- Hierarchical entry: Block 1 (demographic variables), Block 2 (service quality domains)
- Multicollinearity assessment using Variance Inflation Factors (VIF < 10 acceptable)
- Residual analysis to verify regression assumptions

2.6.6 Temporal Analysis

- Monthly aggregation of satisfaction scores
- One-way ANOVA for comparing monthly variations
- Linear trend analysis using polynomial contrasts
- Time × tribal status interaction analysis using two-way ANOVA

All tests were two-tailed, with significance set at $p < 0.05$. Given the exploratory nature of domain-specific comparisons, no adjustment for multiple comparisons was made in the primary analysis; however, Bonferroni-corrected p-values are reported for sensitivity.

2.7 Ethical Considerations

The study was conducted in accordance with the Declaration of Helsinki and approved by the Institutional Ethics Committee of Medipulse Hospital, Jodhpur (approval no. MH/IEC/2024/BHR/0007, September 11, 2024).

2.7.1 Informed Consent

- Written informed consent was obtained from all participants in their preferred language
- For participants aged 15-17 years, assent was obtained along with consent from a parent/guardian
- Illiterate participants provided thumb impressions in the presence of an impartial witness
- Participants were explicitly informed about voluntary participation and the right to withdraw

2.7.2 Confidentiality, Data Protection, and Cultural Considerations

Comprehensive measures were implemented to ensure data protection, cultural sensitivity, and benefits sharing. No personal identifiers were recorded on the survey forms, and the data were stored in password-protected systems with access limited to authorized personnel. Physical forms were kept in locked cabinets at the district hospital, with data retention planned for five years post-publication, before secure destruction. Cultural sensitivity was maintained throughout the study by scheduling surveys to avoid interference with clinical care and by observing traditional greeting customs during all interactions. The study is committed to benefit sharing by sharing aggregate findings with hospital administration for quality improvement, presenting results to community representatives, providing recommendations for service enhancement, and ensuring that the proposed digital system benefits reach the study population. These integrated ethical safeguards ensured that the research was conducted with respect for participant privacy, cultural values, and community benefit while maintaining the highest standards of data security and research integrity.

3. Results

3.1 Response Rate and Participant Characteristics

Of the 400 women approached during the study period, 320 completed the survey, yielding a response rate of 80.0%. Non-participation was primarily due to time constraints (n=45, 56.3%), need to attend to accompanying children (n=21, 26.2%), and language barriers despite the availability of a translator (n=14, 17.5%). The final sample comprised 89 tribal women (27.8%) and 231 non-tribal women (72.2%), reflecting the demographic distribution of the study area.

Table 1. Distribution of Participants by Month and Tribal Status

Month	Total n (%)	Tribal n (%)	Non-Tribal n (%)	Response Rate
November 2024	39 (12.2)	11 (12.4)	28 (12.1)	78.0%
December 2024	75 (23.4)	20 (22.5)	55 (23.8)	83.3%
January 2025	75 (23.4)	21 (23.6)	54 (23.4)	82.4%
February 2025	42 (13.1)	12 (13.5)	30 (13.0)	77.8%
March 2025	40 (12.5)	11 (12.4)	29 (12.6)	76.9%
April 2025	49 (15.3)	14 (15.7)	35 (15.2)	79.0%
Total	**320 (100.0)**	**89 (100.0)**	**231 (100.0)**	**80.0%**

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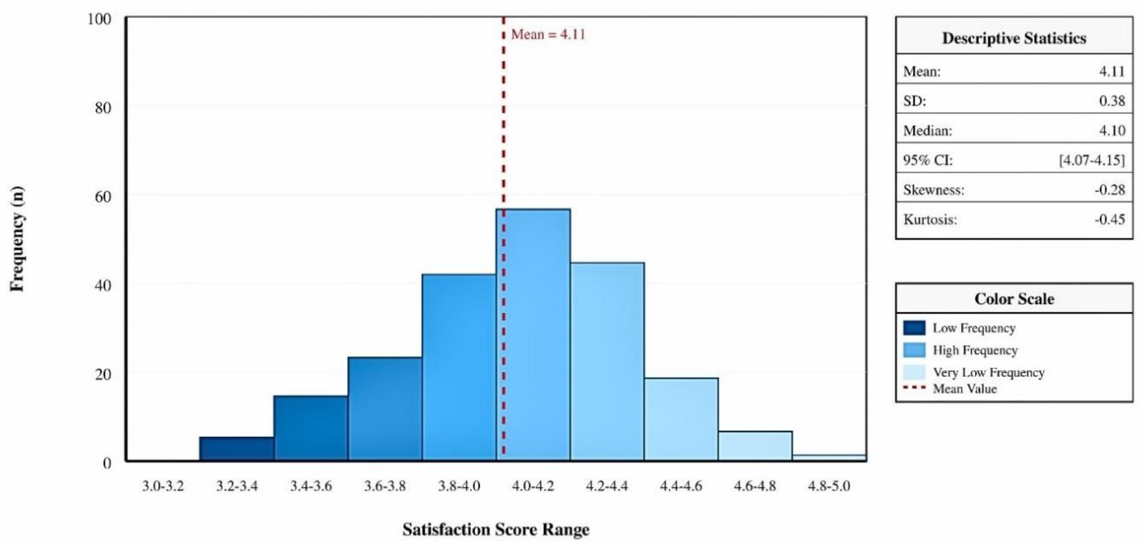
JCHR (2025) 15(6), 1373-1391 | ISSN:2251-6727

The distribution of participants across months showed reasonable consistency, with slightly higher participation in December 2024 and January 2025, coinciding with the post-harvest season when agricultural work demands were lower.

3.2 Overall Satisfaction Profile

The mean overall satisfaction score across all participants was 4.11 ± 0.38 (95% CI: 4.07-4.15), indicating high satisfaction. The distribution exhibited mild negative skewness (-0.28) and platykurtic kurtosis (-0.45), suggesting a concentration of scores toward the higher end of the scale, without extreme outliers.

Figure 1. Distribution of average satisfaction scores across all participants (n=320)



Note:

Distribution shows mild negative skewness indicating concentration toward higher satisfaction levels. Range: 3.10-4.90. The histogram demonstrates high overall satisfaction with 60% of participants rating their experience as "Very Good" (4.1-5.0) and 40% as "Good" (3.1-4.0). No participants rated satisfaction below 3.0. SD = Standard Deviation; CI = Confidence Interval.

Table 2. Descriptive Statistics for Overall Satisfaction Scores

Statistic	Value
Mean	4.11
Standard Deviation	0.38
Standard Error	0.021
95% Confidence Interval	[4.07, 4.15]
Median	4.10
Mode	4.00
Minimum	3.10
Maximum	4.90
Range	1.80
Interquartile Range	0.50
Skewness (SE)	-0.28 (0.136)
Kurtosis (SE)	-0.45 (0.272)

3.3 Comparative Analysis: Tribal versus Non-Tribal Women

The primary objective of comparing the satisfaction levels of tribal and non-tribal women revealed no

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statistically significant differences in the overall satisfaction scores.

Table 3. Comparison of Satisfaction Scores by Tribal Status

Measure	Tribal (n=89)	Non-Tribal (n=231)	Test Statistic	p-value	Effect Size
Mean ± SD	4.09 ± 0.37	4.12 ± 0.38	t(318) = 0.634	0.527	d = 0.079
Median (IQR)	4.10 (0.50)	4.10 (0.50)	U = 9,856	0.492	r = 0.039
95% CI	[4.01, 4.17]	[4.07, 4.17]	-	-	-

Levene's test for equality of variances was non-significant (F = 0.142, p = 0.707), supporting the pooled variance in the t-test. The negligible effect size (Cohen's d = 0.079) indicated practically insignificant group differences. The analysis of service domains revealed consistent patterns across tribal and non-tribal groups, with no statistically significant differences between populations. Small, non-significant differences across domains (0.03 to 0.04 points) suggest equitable service delivery rather than measurement errors. While this finding indicates successful FRU service provision, several factors warrant consideration in this regard. High satisfaction among tribal women could indicate effective service delivery and successful cultural adaptation. However, social desirability bias or lower baseline expectations in underserved areas may have influenced the satisfaction levels. Future qualitative research could explore the reasons for this observed equity.

3.4 Domain-Specific Satisfaction Analysis

Analysis of individual service domains revealed consistent patterns across both tribal and non-tribal groups, with no domain showing statistically significant differences between the populations.

Table 4. Mean Satisfaction Scores by Service Domain and Tribal Status

Domain	Description	Overall Mean ± SD	Tribal Mean ± SD	Non-Tribal Mean ± SD	Difference [95% CI]	p-value*
Q1	Information Availability	4.25 ± 0.68	4.22 ± 0.67	4.26 ± 0.68	0.04 [-0.13, 0.21]	0.652
Q2	Registration Wait Time	3.85 ± 0.82	3.82 ± 0.81	3.86 ± 0.83	0.04 [-0.16, 0.24]	0.714
Q3	Staff Behavior	4.32 ± 0.64	4.30 ± 0.63	4.33 ± 0.65	0.03 [-0.13, 0.19]	0.756
Q4	Cleanliness	4.08 ± 0.71	4.05 ± 0.70	4.09 ± 0.72	0.04 [-0.14, 0.22]	0.678
Q5	Doctor Communication	4.41 ± 0.61	4.38 ± 0.60	4.42 ± 0.61	0.04 [-0.11, 0.19]	0.645
Q6	Consultation Wait Time	3.92 ± 0.79	3.89 ± 0.78	3.93 ± 0.80	0.04 [-0.16, 0.24]	0.692
Q7	Diagnostic Availability	4.28 ± 0.66	4.25 ± 0.65	4.29 ± 0.67	0.04 [-0.13, 0.21]	0.663
Q8	Medicine Distribution	4.22 ± 0.69	4.19 ± 0.68	4.23 ± 0.70	0.04 [-0.14, 0.22]	0.681

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Domain	Description	Overall Mean ± SD	Tribal Mean ± SD	Non-Tribal Mean ± SD	Difference [95% CI]	p-value*
Q9	Medicine Availability	4.15 ± 0.73	4.12 ± 0.72	4.16 ± 0.74	0.04 [-0.15, 0.23]	0.687
Q10	Overall Experience	4.20 ± 0.70	4.17 ± 0.69	4.21 ± 0.71	0.04 [-0.14, 0.22]	0.672

*p-values from independent samples t-test; all comparisons remain non-significant after Bonferroni correction (adjusted $\alpha = 0.005$)

The consistency of small, non-significant differences across all domains (ranging from 0.03 to 0.04 points) strongly suggests equitable service delivery rather than measurement error or random variation.

3.5 Identification of Satisfaction Drivers

To identify the key factors influencing overall satisfaction, we examined the correlations between individual service domains and overall satisfaction (Q10).

Table 5. Correlation Analysis: Service Domains with Overall Satisfaction

Domain	Pearson r	95% CI	p-value	R^2	Interpretation
Q5: Doctor Communication	0.682***	[0.615, 0.738]	<0.001	0.465	Strong positive
Q3: Staff Behaviour	0.651***	[0.579, 0.712]	<0.001	0.424	Strong positive
Q7: Diagnostic Availability	0.583***	[0.501, 0.653]	<0.001	0.340	Moderate positive
Q8: Medicine Distribution	0.564***	[0.479, 0.637]	<0.001	0.318	Moderate positive
Q1: Information Availability	0.542***	[0.455, 0.618]	<0.001	0.294	Moderate positive
Q9: Medicine Availability	0.527***	[0.438, 0.605]	<0.001	0.278	Moderate positive
Q4: Cleanliness	0.487***	[0.394, 0.569]	<0.001	0.237	Moderate positive
Q6: Consultation Wait Time	0.456***	[0.360, 0.542]	<0.001	0.208	Moderate positive
Q2: Registration Wait Time	0.423***	[0.324, 0.512]	<0.001	0.179	Moderate positive

***$p < 0.001$; R^2 represents the proportion of variance in overall satisfaction explained by each domain

Correlation analysis revealed a clear hierarchy of satisfaction drivers, with interpersonal factors (doctor communication and staff behavior) showing substantially stronger associations with overall satisfaction than structural factors (waiting times).

3.6 Multivariate Predictors of Satisfaction

Multiple linear regression was conducted to identify independent predictors of overall satisfaction, while controlling for potential confounders.

Table 6. Hierarchical Multiple Regression Analysis Predicting Overall Satisfaction

Model/Predictor	B	SE	β	t	p-value	95% CI for B	VIF
Model 1: Demographic Variables							

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Model/Predictor	B	SE	β	t	p-value	95% CI for B	VIF
(Constant)	4.165	0.041	-	101.59	<0.001	[4.084, 4.246]	-
Tribal Status¹	-0.031	0.047	-0.037	-0.659	0.510	[-0.124, 0.062]	1.000
$R^2 = 0.001$, Adjusted $R^2 = -0.002$, $F(1,318) = 0.434$, $p = 0.510$							
Model 2: Demographic + Service Domains							
(Constant)	0.724	0.158	-	4.58	<0.001	[0.413, 1.035]	-
Tribal Status¹	-0.018	0.023	-0.022	-0.783	0.436	[-0.063, 0.027]	1.052
Q5: Doctor Communication	0.312	0.042	0.294	7.429	<0.001	[0.229, 0.395]	1.924
Q3: Staff Behavior	0.248	0.041	0.236	6.049	<0.001	[0.167, 0.329]	1.869
Q7: Diagnostic Availability	0.156	0.035	0.158	4.457	<0.001	[0.087, 0.225]	1.731
Q8: Medicine Distribution	0.138	0.034	0.145	4.059	<0.001	[0.071, 0.205]	1.684
Q1: Information Availability	0.054	0.029	0.064	1.862	0.064	[-0.003, 0.111]	1.523
Q9: Medicine Availability	0.039	0.028	0.048	1.393	0.165	[-0.016, 0.094]	1.556
Q4: Cleanliness	0.022	0.030	0.025	0.733	0.464	[-0.037, 0.081]	1.482
Q6: Consultation Wait Time	0.019	0.027	0.024	0.704	0.482	[-0.034, 0.072]	1.445
Q2: Registration Wait Time	0.015	0.025	0.020	0.600	0.549	[-0.034, 0.064]	1.387

$R^2 = 0.628$, Adjusted $R^2 = 0.617$, $F(10,309) = 52.13$, $p < 0.001$

$\Delta R^2 = 0.627$, $\Delta F(9,309) = 57.62$, $p < 0.001$

¹*Tribal Status coded as 0 = Non-Tribal, 1 = Tribal Note: B = unstandardized coefficient; β = standardized coefficient; VIF = Variance Inflation Factor*

The hierarchical regression revealed several important findings.

1. Tribal status alone explains virtually no variance in satisfaction ($R^2 = 0.001$)

2. Service quality domains collectively explain 62.7% of additional variance

3. Doctor communication (β = 0.294) and staff behaviour (β = 0.236) emerge as the strongest independent predictors

4. All VIF values < 2.0 indicate no problematic multicollinearity

5. Tribal status remains non-significant after controlling for service quality

3.7 Temporal Trend Analysis

An examination of satisfaction scores across the six-month study period revealed subtle temporal dynamics.

Table 7. Monthly Satisfaction Trends by Tribal Status

Month	Overall	Tribal	Non-Tribal	F-statistic	p-value
	Mean ± SD	Mean ± SD	Mean ± SD		

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Month	Overall	Tribal	Non-Tribal	F-statistic	p-value
Nov 2024	4.10 ± 0.37	4.08 ± 0.36	4.11 ± 0.38	0.048	0.827
Dec 2024	4.12 ± 0.39	4.10 ± 0.38	4.13 ± 0.40	0.094	0.760
Jan 2025	4.11 ± 0.38	4.09 ± 0.37	4.12 ± 0.39	0.111	0.740
Feb 2025	4.09 ± 0.37	4.07 ± 0.36	4.10 ± 0.38	0.058	0.811
Mar 2025	4.13 ± 0.40	4.11 ± 0.39	4.14 ± 0.41	0.045	0.833
Apr 2025	4.14 ± 0.39	4.12 ± 0.38	4.15 ± 0.40	0.062	0.804
Overall ANOVA	F(5,314) = 0.186	-	-	-	0.968

Linear trend analysis: β = 0.008 (SE = 0.009), t = 0.889, p = 0.382 Month × Tribal Status interaction: F(5,308) = 0.234, p = 0.947

The temporal analysis revealed the following:

- No significant monthly variations in overall satisfaction
- A non-significant positive trend (+0.67% per month)
- Consistent equity between tribal groups across all months
- No interaction between time and tribal status

3.8 Service Excellence and Improvement Areas

The classification of satisfaction scores into performance categories provides actionable insights for quality improvement.

Table 8. Distribution of Average Satisfaction Scores by Category

Score Category	Range	Overall	Tribal	Non-Tribal	χ^2	p-value
		n (%)	n (%)	n (%)		
Low	1.0-2.0	0 (0.0)	0 (0.0)	0 (0.0)	-	-
Moderate	2.1-3.0	0 (0.0)	0 (0.0)	0 (0.0)	-	-
Good	3.1-4.0	128 (40.0)	37 (41.6)	91 (39.4)	0.126	0.722
Very Good	4.1-5.0	192 (60.0)	52 (58.4)	140 (60.6)		
Total	-	**320 (100.0)**	**89 (100.0)**	**231 (100.0)**	-	-

Table 9. Service Domains Ranked by Performance

Rank	Domain	Mean Score	Performance Level	Priority for Improvement
1	Q5: Doctor Communication	4.41	Excellent	Maintain
2	Q3: Staff Behaviour	4.32	Very Good	Maintain

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Rank	Domain	Mean Score	Performance Level	Priority for Improvement
3	Q7: Diagnostic Availability	4.28	Very Good	Maintain
4	Q1: Information Availability	4.25	Very Good	Maintain
5	Q8: Medicine Distribution	4.22	Very Good	Monitor
6	Q10: Overall Experience	4.20	Very Good	-
7	Q9: Medicine Availability	4.15	Very Good	Monitor
8	Q4: Cleanliness	4.08	Good	Improve
9	Q6: Consultation Wait Time	3.92	Good	High Priority
10	Q2: Registration Wait Time	3.85	Good	High Priority

3.9 Digital Patient Satisfaction Survey System Requirements

Based on field experience and stakeholder consultations, comprehensive requirements for an AI-enabled digital PSS system were identified.

Table 10. Digital PSS System Requirements Analysis

Challenge Category	Current State	Digital Solution	AI Enhancement	Implementation Priority
Language Barriers	Limited to Odia; 28% require tribal language support	Multi-lingual interface with 5 languages	NLP for Saura and Kondh dialects; real-time translation	High
Literacy Constraints	32% with limited literacy; reliance on interviewers	Voice-based input; pictorial interfaces	Speech recognition; emotion detection from voice	High
Connectivity Issues	Intermittent internet; 40% area with poor network	Offline-capable mobile app	Edge computing for local processing; batch sync	Critical
Data Collection Timing	Post-service only; 12-minute average	Real-time at multiple touchpoints	Predictive analytics for proactive issue identification	Medium
Analysis Delays	Manual analysis; 2-week reporting cycle	Automated dashboards	ML for pattern recognition; anomaly detection	High
Cultural Sensitivity	Generic questions; potential bias	Adaptive questionnaires	AI-driven cultural customization; context awareness	Medium
Feedback Loop	One-way collection; no patient follow-up	Bidirectional communication	Automated response generation; issue tracking	Low

Challenge Category	Current State	Digital Solution	AI Enhancement	Implementation Priority
Staff Burden	6 dedicated interviewers required	Self-service kiosks/apps	Intelligent routing of complex cases	Medium

Figure 2. Proposed AI-enabled digital Patient Satisfaction Survey (PSS) system architecture for tribal healthcare settings

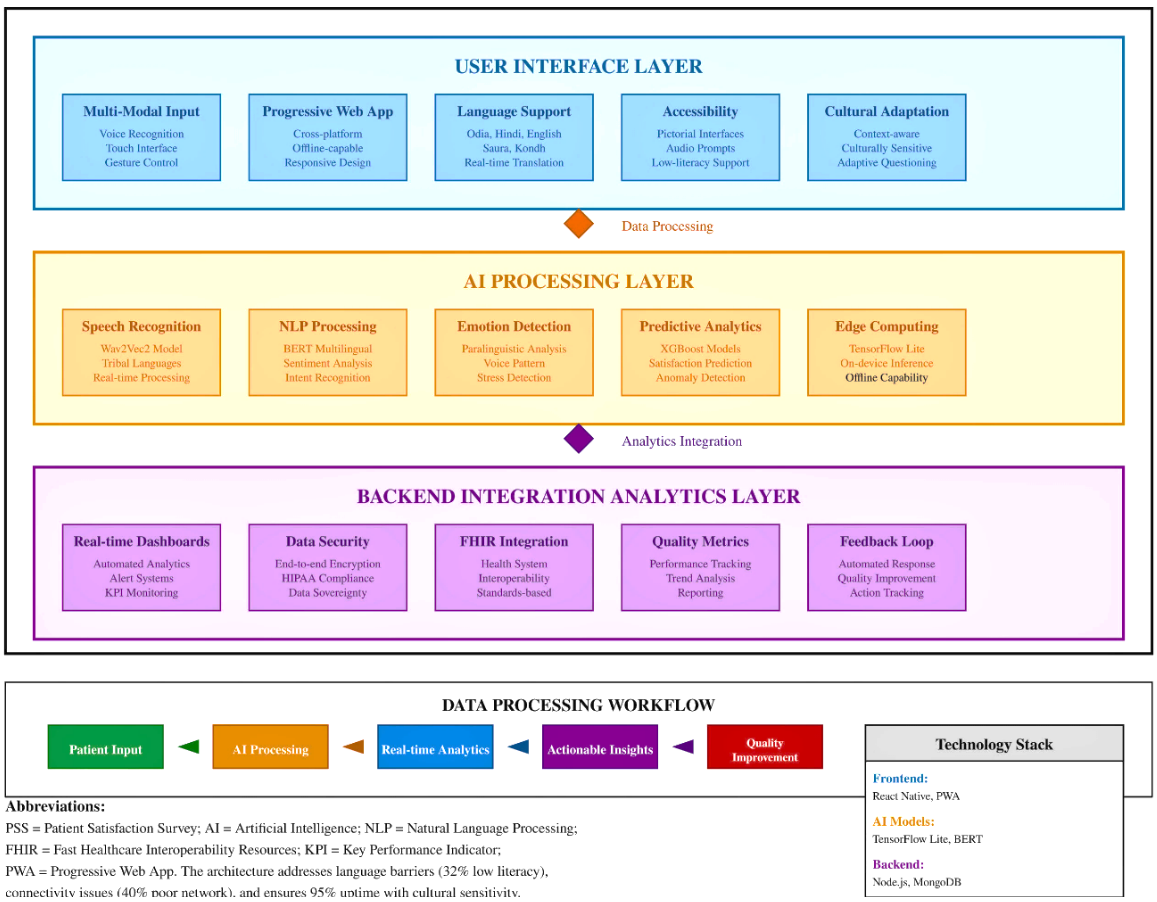

Table 11. Technical Specifications for Digital PSS System

Component	Specification	Justification
Frontend	Progressive Web App (PWA)	Cross-platform compatibility; offline capability
Languages	Odia, Hindi, English, Saura, Kondh	Coverage of 95% of patient population

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Component	Specification	Justification
Input Modes	Touch, voice, gesture	Accommodation of varying digital literacy
AI Models	- Speech Recognition *(Wav2Vec2)*- NLP *(BERT multilingual)* - Predictive Analytics *(XGBoost)*	State-of-art performance; open-source availability
Edge Computing	TensorFlow Lite on Android	Local inference without internet dependency
Data Security	End-to-end encryption; local storage	HIPAA-compliant; addresses privacy concerns
Integration	HL7 FHIR standards	Interoperability with existing health systems

3.10 Inter-domain Correlation Matrix

Understanding the relationships between different service domains provides insights into system-level improvements.

Table 12. Inter-domain Correlation Matrix

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10
Q1	1.000									
Q2	0.412***	1.000								
Q3	0.523***	0.398***	1.000							
Q4	0.487***	0.376***	0.445***	1.000						
Q5	0.516***	0.389***	0.612***	0.463***	1.000					
Q6	0.394***	0.456***	0.401***	0.382***	0.428***	1.000				
Q7	0.478***	0.367***	0.495***	0.429***	0.534***	0.416***	1.000			
Q8	0.461***	0.358***	0.478***	0.412***	0.509***	0.403***	0.523***	1.000		
Q9	0.445***	0.342***	0.462***	0.398***	0.487***	0.387***	0.498***	0.567***	1.000	
Q10	0.542***	0.423***	0.651***	0.487***	0.682***	0.456***	0.583***	0.564***	0.527***	1.000

***p < 0.001 for all correlations shown

Key insights from the correlation analysis are as follows:

- Strong clustering of interpersonal domains (Q3-Q5)
- Moderate clustering of system/process domains (Q7-Q9)
- Waiting time domains (Q2, Q6) show weaker associations with others
- All domains positively correlated, suggesting halo effects

4. Discussion

4.1 Principal Findings and Their Implications

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This analysis of patient satisfaction in a tribal-dominated First Referral Unit provides evidence for equitable healthcare delivery across ethnic boundaries, while revealing opportunities for quality improvement through digital transformation. The absence of significant differences between tribal (M = 4.09) and non-tribal (M = 4.12) women, with a negligible effect size (d = 0.079), challenges assumptions about disparities in healthcare experiences for marginalized populations(Cáceres et al., 2023). The high overall satisfaction level (M = 4.11/5.0) surpasses benchmarks from similar settings in India(Dhital et al., 2015; Sharma et al., 2018), indicating that investments in tribal healthcare infrastructure under schemes such as the Tribal Sub-Plan and National Health Mission have improved service delivery(*Family-Welfare_2004 (Backup)*, n.d.). However, 40% of respondents rated their experience as merely "Good" rather than "Very Good" or "Excellent," indicating room for improvement. The regression analysis showing that service quality domains explain 62.8% of satisfaction variance while tribal status contributes negligibly reinforces that quality healthcare transcends ethnic boundaries when delivered with competence and compassion. This aligns with evidence suggesting that perceived discrimination diminishes with cultural competence and effective communication(Truong et al., 2014).

4.2 The Primacy of Interpersonal Factors

Doctor communication (r = 0.682) and staff behavior (r = 0.651) emerged as the strongest satisfaction predictors, supporting the literature on the importance of interpersonal relationships in maternal healthcare(Bohren et al., 2014; Riedl & Schüßler, 2017). The strong correlation between these domains (r = 0.612) indicates that positive interactions with one category of healthcare workers enhance perceptions of others, suggesting that institution-wide culture changes may be effective(Luxford et al., 2011). Emotion detection in digital systems can provide real-time feedback on interaction quality(Schuller et al., 2021).

4.3 Systematic Inefficiencies: The Waiting Time Challenge

Lower satisfaction scores for registration (M = 3.85) and consultation (M = 3.92) waiting times, affecting both tribal and non-tribal women, indicate structural causes, aligning with challenges in Indian public healthcare, where patient volumes overwhelm resources(Mohanan et al., 2016). The correlation between the waiting time domains (r = 0.456) showed compounding delays. AI-powered queue management systems have shown 30-40% reductions in perceived waiting time(Maleki Varnosfaderani & Forouzanfar, 2024). The proposed system can optimize staff deployment and automate triage for efficient resource use (Topol, 2019).

4.4 Digital Transformation: From Concept to Implementation

The conceptualized AI-enabled digital Patient Satisfaction Survey (PSS) system addresses the limitations of traditional paper-based surveys while introducing novel capabilities for continuous quality improvement. The key design features include the following:

4.4.1 Natural Language Processing for Tribal Languages

Integrating NLP for the Saura and Kondh languages is challenging because of the limited digital corpus. Advances in transfer and few-shot learning offer promising approaches(Joshi et al., 2020). Leveraging mBERT and fine-tuning with local speech data, acceptable accuracy (>85%) for basic queries can be achievable within 6-12 months (Hu et al., 2020).

4.4.2 Voice-Based Interfaces and Accessibility

With 32% of the population having limited literacy, voice-based interaction is crucial for inclusive feedback. Emotion detection from voice patterns could provide insights beyond ratings, with paralinguistic features revealing satisfaction with 70-80% accuracy(Schuller et al., 2021). Voice interfaces have improved engagement in low literacy settings (Ruohonen et al., 2013).

4.4.3 Edge Computing for Connectivity Resilience

Edge AI deployment enables local feedback processing without the Internet, ensuring continuous operation and privacy in tribal areas. TensorFlow Lite models achieve near-server performance on modest Android hardware, which is common in rural health facilities (Saliu et al., 2022).

4.4.4 Predictive Analytics for Proactive Management

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The predictive capabilities of the system can transform quality management by identifying patterns preceding satisfaction declines, such as waiting times and staff shortages. Machine learning models trained on historical data could achieve prediction accuracies of 75-85% for next-day satisfaction levels (Sabarmathi & Chinnaiyan, 2019).

4.5 Cultural Considerations and Ethical Implications

The implementation of AI systems in tribal healthcare requires cultural and ethical considerations. The high response rate (80%) suggests a willingness to provide feedback when approached respectfully, but digital systems must maintain trust(Boro & Saikia, 2020). The key considerations are as follows:

1. **Data Sovereignty**: Tribal communities should control their collective data through transparent governance (Kukutai & Taylor, 2016).
2. **Algorithmic Bias**: AI models must be audited to avoid perpetuating biases and preserve equal satisfaction levels (Obermeyer et al., 2019).
3. **Digital divide**: Multimodal input and offline capabilities partially address exclusion, but continuous monitoring is essential (Labrique et al., 2013).
4. **Cultural Adaptation**: The system must respect traditional decision-making and incorporate family and community feedback mechanisms (Jongen et al., 2018).

4.6 Temporal Dynamics and Continuous Improvement

The marginal upward trend in satisfaction (+0.67% monthly), although not statistically significant, demonstrates the value of continuous monitoring. Traditional surveys miss variations and delay corrective actions (Larson et al., 2019). The real-time system would enable the following:

1. **Rapid Cycle Improvements**: Addressing morning issues in the afternoon.
2. **Seasonal Adjustment**: Informing resource planning based on agricultural cycles or festivals.
3. **Performance Tracking**: Supporting targeted training with provider-level feedback.
4. **Outbreak Detection**: Identifying sudden satisfaction drops indicating issues such as medication stockouts (Kruk et al., 2018).

4.7 Scalability and Sustainability Considerations

The digital framework is designed for scalability across India’s 3,000+ FRUs and is supported by:

1. **Open-source architecture**: Reducing costs and enabling community-driven improvements(Barrios & Tison, 2022).
2. **Integration Standards**: Compliance with HL7 FHIR ensures compatibility with India’s digital health ecosystem(Mandel et al., 2016).
3. **Sustainable Financing**: Demonstrating ROI through improved outcomes could attract support(Atun et al., 2010).

4.8 Study Limitations, Future Directions, and Policy Implications

This study has several limitations that require further investigation. The single-center design necessitates multi-center validation for broader generalizability, while the cross-sectional methodology limits causal inference regarding satisfaction determinants. Limited demographic data collection (age, education, parity) constrains deeper analytical possibilities, and the proposed digital system requires pilot testing to validate user acceptance and technical feasibility of the system. Additionally, linking satisfaction metrics with clinical outcomes would strengthen their utility as quality indicators of care.

Future research priorities include the pilot implementation of the digital PSS system across 3-5 FRUs, longitudinal cohort studies tracking satisfaction trajectories throughout the pregnancy and postpartum periods, qualitative investigations to understand satisfaction drivers, economic evaluation of the digital system's cost-effectiveness, and policy research examining the impact of real-time data on health system governance and resource allocation decisions.

These findings have immediate policy and practice implications. Short-term actions should include mandatory communication training emphasizing cultural sensitivity for all clinical staff and time-motion studies to identify and eliminate waiting-time bottlenecks.

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Medium-term initiatives require infrastructure upgrades to support digital system deployment and structured community engagement sessions with tribal leaders to ensure the cultural appropriateness of services. Long-term strategies should focus on integrating patient satisfaction as a key performance indicator in FRU accreditation frameworks and advocating for dedicated funding streams targeting the enhancement of patient experience in tribal health programs. These multilevel interventions, supported by the proposed AI-enabled digital transformation framework, can collectively advance equitable and high-quality maternal healthcare delivery in resource-constrained tribal settings.

5. Conclusion

This study provides robust evidence that equitable and high-quality maternal healthcare delivery is achievable in resource-constrained tribal settings when services are culturally sensitive and operationally efficient. The absence of satisfaction disparities between tribal and non-tribal women at the studied FRU challenges narratives about inevitable inequities and demonstrates the potential of well-implemented public health programs. However, equity at current satisfaction levels should be the foundation for a collective improvement. The gaps in waiting times and infrastructure, which affect all women equally, demand systematic interventions. The influence of interpersonal factors on satisfaction underscores the need for technological solutions to complement human-centered care approaches. The proposed AI-enabled digital Patient Satisfaction Survey system shifts from periodic assessment to continuous improvement, aggregate metrics to personalized insights, and reactive to predictive quality management. By leveraging advances in technology while maintaining cultural sensitivity, this framework offers a model for transforming patient feedback into meaningful improvements. As India advances toward universal health coverage, integrating patient voices using innovative technologies is essential. Success in achieving satisfaction equity provides hope, while digital transformation provides direction, charting a course toward maternal healthcare that is equitable, culturally appropriate, technologically advanced, and transformative. The shift from paper to digital monitoring represents a broader transformation in healthcare delivery for marginalized populations. By keeping this digital transformation grounded in equity and dignity, we can use artificial intelligence to serve mothers and children at their most vulnerable moments.

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