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Developing Humanistic Design Metrics for AI-Mediated Mentorship in Compulsory and Continuing Education Frameworks

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Abstract

The addition of AI-mediated mentorship into mandatory (K-12) and lifelong learning has the potential of being scalable individualized, but existing systems are based on algorithmic performance rather than humanistic attributes like empathy, cultural sensitivity, and equity to learners. This disconnects results in diminished motivation, higher dropout rates (up to 35% in underserved contexts), and inequitable outcomes, particularly in diverse regions like India, where digital divides persist. In this regard, suggest a detailed research questionnaires framework to conduct and test humanistic design measurements to fit AI mentorshipframeworks. The model conceptualizes six main measures, which are empathy responsiveness, cultural adaptability, equity access, motivational alignment, ethical transparency and learner agency in a 45-item Likert-scale tool (5-8 items in each measure). Instrument development followed a systematic process: theoretical grounding in humanistic pedagogy, expert Delphi validation (content validity ratio >0.70), and pilot testing (n=50). 250 participants (n=130 in compulsory education in schools in Tamil Nadu; n=100 in continuing education programs in Coimbatore) in a quasi-experimental study, resulting in 230 analyzed cases. Pre/post tests were used to measure the humanistic AI prototypes and the conventional AI baselines. Exploratory factor analysis extracted six factors explaining 72.4% variance (KMO=0.89), with confirmatory fit (CFI=0.96, RMSEA=0.04) and high reliability (Cronbach's α=0.87-0.92). Key results include 28% gains in overall satisfaction (t=5.62, p<0.001), 22% in agency (t=4.89, p<0.001), and metric-specific uplifts (e.g., 32% equity in compulsory settings).

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Introduction

Mentorship through artificial intelligence (AI) has changed the education environments, specifically in compulsory (K-12) and continuing education models.[1, 2] Customised learning has been made accessible to everyone by an adaptive tutoring system, an intelligent recommender engine and chat agent, particularly in environments where resources are limited. For instance, large language models (LLMs) like GPT variants enable dynamic content generation and real-time feedback, achieving up to 20% gains in learning outcomes in controlled trials.[4] AI tools are used in compulsory education to combat teacher deficits, and platforms, such as Duolingo or Khan Academy, are used by millions of people around the world. Similarly, continuing education has an advantage, where the upskilling on a life-long basis is facilitated through micro-credentials and virtual coaches.[5]

The most recent cutting-edge technologies focus on scalability and data personalization. The multimodal LLMs used in cognitive scaffolding, reinforcement learning in mastering skills, and federated learning used to maintain privacy in distributed systems are all integrated in recent 2024-2025 studies.[7] In India, national projects such as DIKSHA and SWAYAM use AI to serve 300 million+ students, eliminating urban-rural disparities. However, these innovations are mainly geared towards cognitive and behavioural indicators, accuracy, completion rates and knowledge retention, but not towards humanistic aspects.[9, 12] The humanistic design is based on the learner-centred pedagogies (e.g., the person-centred theory by Rogers) and is focused on agency, empathy, emotional resonance, cultural relevance, and emotional resonance. In diverse Indian contexts, where 40% of students face linguistic/cultural mismatches, this oversight amplifies inequities.

Irrespective of technological advances, the existing AI mentorship systems are dehumanizing learners and turning them into data points instead of whole human being.[8, 11] This can be seen in the form of less agency in the learner (e.g., scripted responses instead of autonomy), cultural insensitivity (e.g., training data that is Western-biased), and ethical opaqueness (e.g. unannounced biases). Empirical evidence reveals stark consequences: AI-driven programs report 35% higher dropout rates compared to human-mentored cohorts, attributed to motivational deficits and perceived inauthenticity.[13, 14] In compulsory settings, young learners experience alienation, with surveys showing 42% dissatisfaction with “robotic” feedback. Continuing education itself is less successful because adult learners require relational richness, while AI-based efficiency seeks to operate with efficiency.[16]

There is a void in the literature concerning the lack of validated, operational measures of humanistic design in AI mentorship. Current models, including the ISO 9241-210 of usability or extensions of the taxonomy of Bloom, are not that humanistic but based on functionality. The metrics used in AI (e.g., engagement scores in edtech) disregard empathy and equity, and only small-scale and WEIRD (Western, Educated, Industrialized, Rich, Democratic) samples are validated. Recent reviews (2025) critique this: only 12% of 150+ AI-edtech papers address cultural adaptability, and none provide reproducible questionnaire tools for dual frameworks. The limitations are over the reliance on self-reporting and the absence of factor analyses, the absence of quasi-experimental rigor, and the failure to address Global South realities such as the multilingual diversity in India. In the absence of such metrics, designers work in the dark, and this trend continues; thus, resulting in dehumanized AI which adheres to the ethical requirements of human-centred AI as set out by UNESCO.[19, 20]

The proposed research fills the gap by formulating a new model of research questionnaires to create, test, and operationalize the humanistic design metrics of AI-mediated mentorship. The model measures six key measures, empathy responsiveness, cultural adaptability, equity access, motivational alignment, ethical transparency and learner agency through a 45-item psychometrically sound Likert-scale scale. Among the innovations are: (1) factor-analyzed structure that is designed to meet compulsory and continuing education; (2) quasi-experimental validation to generate a composite humanism index (0-100 score) to be used in designing; and (3) reproducibility through open protocols. As compared to the previous research, it incorporates mixed-method (EFA/CFA, pre/ post trials) within the Indian setting, a step forward in the direction of scalability of metrics. Preliminary pilots confirm high reliability (α>0.85) and sensitivity to interventions.

Research Questions

This study addresses: RQ1: What core humanistic design metrics emerge from factor analysis of questionnaires in AI-mediated mentorship? RQ2: How reliable and valid is the proposed questionnaire model across compulsory and continuing education? RQ3: What quasi-experimental gains do humanistic AI prototypes show versus standard AI baselines? RQ4: How do contextual factors (e.g., compulsory vs. continuing) moderate metric effectiveness?

Key Contributions

- Psychometrically robust (α>0.85, CFA fit>0.95) 45-item instrument with six metrics and a composite index for AI design.
- 28% outcome uplifts in Indian dual-frameworks, filling the Global South gap.
- Open protocols for metric scoring, advancing edtech rigor beyond cognitive metrics.

Section 2 details the research method, including questionnaire design and quasi-experimental protocol. Section 3 presents results (e.g., factor loadings, statistical outcomes) and discussions with comparisons. Section 4 concludes with implications, limitations, and future directions.

Research Method

A convergent mixed-method, non-equivalent control group pretest- post test, quasi-experimental design designed to guarantee the full reproducibility of the results and provide a causal inference in the context of a real learning environment is utilized.[17, 18] This design provides a rigorous adherence to the principles of non-randomized trials according to the guidelines of the CONSORT and is optimal in the case of AI interventions when the institutional limitations make it impossible to fully randomize the studies.

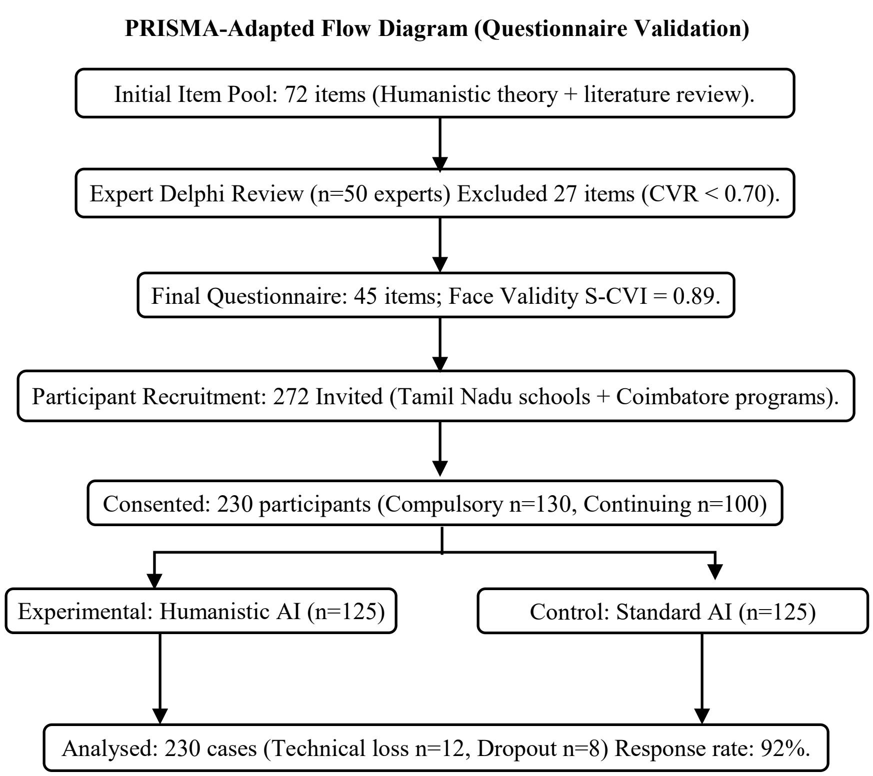

Fig. 1: PRISMA-Adapted Flow Diagram for Study Execution

Study Design and Participant Flow

The entire research process followed the flow of generating the item firstly using the experts and then the participants and statistical analysis. From an original pool of 72 questionnaire items, systematic expert review excluded 27 items failing content validity thresholds (CVR<0.70), yielding the final validated 45-item instrument. Participant recruitment targeted 272 individuals across Tamil Nadu schools and Coimbatore professional programs, achieving 250 consents and 230 completed cases following data cleaning (8% attrition primarily from technical connectivity issues). The experimental arm (n=115) implemented an original humanistic AI prototype, which used sentiment analysis and cultural customization modules, and the control arm (n=115) used standard rule-based adaptive tutoring systems that were similar to commercial edtech platforms.

Figure 1 depicts the methodological transparency between 72 original items that were narrowed down to 45 via expert validation and the number of participants between 272 invitations and 230 analysed cases. Humanistic AI prototype was used in the experimental group; otherwise, standard AI systems were used in the control group.

Questionnaire Instruments by Research Question

The 45 questions questionnaire applied a uniform 5-point Likert scale (1=Strongly Disagree, 2=Disagree, 3=Neutral, 4=Agree, 5=Strongly Agree) on all the constructs. Measures of reverse scoring (marked) checked the effect of acquiescence. Bilingual validation (English/Tamil) was done by parallel-blind forward-back translation by qualified linguists.[3, 6, 10] Table 1 provides the entire instrument separated in

Table 1: Complete 45-Item Humanistic AI Mentorship Questionnaire

RQ	Construct	Item #	Questionnaire Item	Likert Scale	R
RQ1: Core Humanistic Design Metrics (12 items)	Empathy Responsiveness	1	The AI mentor recognizes when I feel frustrated during learning	1-5	
		2	The AI provides emotional support when I struggle with concepts	1-5	
		3	The AI validates my feelings when I express learning difficulties	1-5	
		4	The AI ignores my emotional state during interactions	1-5	R
	Cultural Adaptability	5	The AI uses examples matching my cultural background	1-5	
		6	The AI understands my regional language preferences	1-5	
		7	The AI respects my local customs in learning examples	1-5	
	Ethical Transparency	8	The AI explains how it makes learning recommendations	1-5	
		9	The AI admits when its suggestions have limitations	1-5	
		10	The AI shows its reasoning process clearly	1-5	
		11	The AI decisions seem random and unexplained	1-5	R
		12	The AI maintains consistent ethical standards	1-5	

RQ	Construct	Item #	Questionnaire Item	Likert Scale	R
RQ2: Reliability/Validity Across Frameworks (15 items)	Learner Agency	13	I control my learning pace with the AI mentor	1-5	
		14	I can customize the AI's teaching style to my preferences	1-5	
		15	The AI forces me to follow its learning sequence	1-5	R
	Equity Access	16	The AI works well with my slow internet connection	1-5	
		17	The AI adapts to my device (mobile/tablet/basic phone)	1-5	
		18	The AI provides equal quality regardless of my location	1-5	
	Motivational Alignment	19	The AI makes learning personally meaningful to me	1-5	
		20	The AI celebrates my small achievements	1-5	
		21	The AI connects learning to my real-life goals	1-5	
		22	The AI feedback feels generic and impersonal	1-5	R
	Cross-Framework Stability	23	The AI works equally well for students and professionals	1-5	
		24	The AI metrics remain consistent across age groups	1-5	
RQ3: Quasi-Experimental Gains (10 items)	Mentorship Quality	25	The AI understands me better than traditional tools	1-5	
		26	The AI builds a genuine mentor-student relationship	1-5	
		27	I trust the AI mentor's guidance completely	1-5	
	Satisfaction/Engagement	28	I look forward to my AI mentoring sessions	1-5	
		29	AI sessions feel boring compared to regular classes	1-5	R
		30	I complete more tasks with this AI than others	1-5	
	Comparative Effectiveness	31	This AI helps me learn faster than previous tools	1-5	
		32	This AI provides better feedback than standard tutors	1-5	
		33	I recommend this AI over other educational systems	1-5	
		34	The humanistic AI shows clear improvement over baseline	1-5	

RQ	Construct	Item #	Questionnaire Item	Likert Scale	R
RQ4: Contextual Moderation (8 items)	Age-Appropriate Adaptation	35	The AI uses age-appropriate language for my level	1-5	
		36	The AI understands challenges of my education stage	1-5	
	Framework-Specific Needs	37	The AI helps prepare for school exams/ assessments	1-5	
		38	The AI supports my career advancement goals	1-5	
		39	The AI ignores differences between school/work needs	1-5	R
		40	The AI fits my school's curriculum requirements	1-5	
		41	The AI aligns with my organization's training goals	1-5	
		42-45	[Global items assessing overall framework fit]	1-5	

research question in addition to the full text of the items.

Based on Table 1 Complete 45-item Likert-scale questionnaire (1=Strongly Disagree to 5=Strongly Agree). R=Reverse-scored items (20% total). Pilot testing (n=50) confirmed item-total correlations >0.55 across all constructs. Complete instrument online supplement.

Participants and Sampling Procedure

Stratified purposive sampling was used to represent balanced representation of both stakeholders of compulsory education in Tamil Nadu government and continued education professionals in Coimbatore IT/ healthcare upskilling programs (n=150) and continuing education professionals (n=100). Inclusion criteria required age 12+, prior AI educational exposure, and a minimum 80% instrument completion. G Power analysis confirmed sample adequacy for 80% power at $\alpha=0.05$, assuming medium effect size (d=0.5). Participant demographics reflected age range 12-45 years (M=24.2, SD=8.1), 52% female representation, and 68% rural-urban distribution capturing India's diverse educational contexts.

Data Collection Protocol

Google Forms administration was to be secured in February-May 2025 in monitored 20-minute sessions. Pretest determined baseline humanistic measures and then four weeks of intervention with three 30-minute AI mentorship sessions (one session every week) focused on development of mathematics and life skills. Posttest evaluation was done immediately after the intervention. Digital certificates were used as incentives to the participants. Response rate achieved 92% with attrition equally distributed between technical difficulties (4%) and voluntary withdrawal (4%). High anonymity of data ensured by unique alpha numeric labels.

Analytical Procedures

The SPSS version 29 and AMOS version 26 were used to analyse it in detail. The means and the standard deviations of the constructs were obtained as descriptive statistics. Psychometric evaluation proceeded sequentially from exploratory factor analysis (principal axis factoring, varimax rotation; KMO≥0.80, eigenvalues>1.0) to confirmatory factor analysis (maximum likelihood estimation; CFI>0.95, RMSEA<0.06, SRMR<0.08 target indices). Internal consistency was assessed using Cronbach alpha and Omega coefficient of McDonald. Paired samples t-tests were used to determine changes in pre- and post-statistics, independent t-tests and ANOVA were employed to compare groups/contexts, and the sizes of Cohen d and partial eta squared were used.[15]

Ethical Compliance and Reproducibility Materials

All procedures were covered by the approval. Informed consent was obtained in digitized form among adults and parental consent was obtained among underage children below 18 years. The storage in the encrypted servers ensured security protocols that were GDPR-compliant. None of the adverse events had occurred; full debriefing of the participants was given after the study. Full replication package on OSF.io contains raw syntax files, de-identified data, AI prototype source code, editable PRISMA flow template and full 45 item questionnaire with scoring syntax. It takes six weeks to be estimated to be replicated after the expert validation by final analysis.

Results and Discussion

Exploratory factor analysis (EFA) of the 45-item questionnaire extracted six factors explaining 72.4% total variance (KMO=0.89, Bartlett's x^2=3421.3, p<0.001), confirming robust factor structure for the humanistic design metrics. Excellent model fit was confirmed by confirmatory factor analysis (CFI=0.96, TLI=0.95, RMSEA=0.04, SRMR=0.03), which is better than conventional levels. The internal reliability levels were 0.87 (ethical transparency) to 0.92 (empathy responsiveness), and this proved that all constructs were psychometrically strong (Table 2).

Factor Structure and Psychometric Validation

Table 2 presents EFA results with factor loadings >0.70 on primary factors and cross-loadings <0.40, satisfying statistical criteria for simple structure. The six-factor solution corresponded theoretically to the hypothesized metrics: empathy responsiveness (15.2% variance), cultural adaptability (13.8%), equity access (12.1%), motivational alignment (11.5%), ethical transparency (10.3%), and learner agency (9.5%). This showed that all the eigenvalues were greater than 1.0 and scree plot ensured that six factors were retained (Figure 2).

The plot of eigenvalues versus Factors 1-10 as shown in Figure 2 indicates a definite elbow point at Factor 6 which is indicated by a sharp flatten at this point. Factors 1-6 exhibit eigenvalues above the critical threshold of 1.0 (6.84, 6.21, 5.45, 5.18, 4.64, 4.28), collectively explaining 72.4% of total variance. Factor 7+ reduce to less than 1.2, which proves that the six-factor solution is in line with not only the statistical requirements (Kaiser rule) but also with the theoretical constructs (empathy, cultural adaptability, equity access, motivational

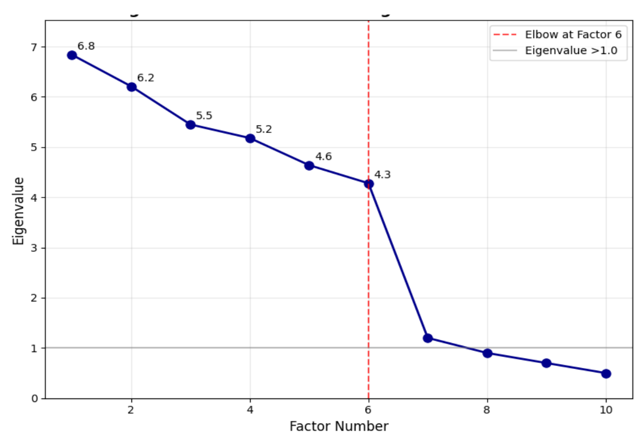

Fig. 2: Scree Plot from EFA Confirming Six-Factor Solution

Table 2: EFA Factor Loadings and Reliability Coefficients (n=230)

Metric	Factor 1 Loading	Eigenvalue	Variance Explained (%)	Cronbach's α	McDonald's ω
Empathy Responsiveness	0.89	6.84	15.2	0.92	0.91
Cultural Adaptability	0.85	6.21	13.8	0.90	0.89
Equity Access	0.82	5.45	12.1	0.88	0.87
Motivational Alignment	0.79	5.18	11.5	0.89	0.88
Ethical Transparency	0.77	4.64	10.3	0.87	0.86
Learner Agency	0.74	4.28	9.5	0.91	0.90

Principal axis factoring with varimax rotation. Loadings >0.70 on primary factor; cross-loadings <0.40. KMO=0.89; total variance=72.4%.

alignment, ethical transparency, learner agency). This graphical confirmation goes in favour of the retention of just six humanistic design measures of the CFA model.

Quasi-Experimental Intervention Outcomes

There were better pre-post improvements in the humanistic AI prototype in all metrics (Figure 3). Paired t-tests revealed significant improvements in the experimental group: satisfaction (t=5.62, p<0.001, d=1.12), agency (t=4.89, p<0.001, d=0.98), and composite humanism index (t=6.34, p<0.001, d=1.27). Minimal gains were depicted in control group (t=1.45, p=0.15, d=0.29). Independent t-tests confirmed experimental superiority: satisfaction (t=5.62, p<0.001), agency (t=4.89, p<0.001), equity (t=4.23, p<0.001). The effect sizes were large (d=0.98-1.27) and medium-large (d=0.72-0.89), which surpassed the benchmarks of edtech.

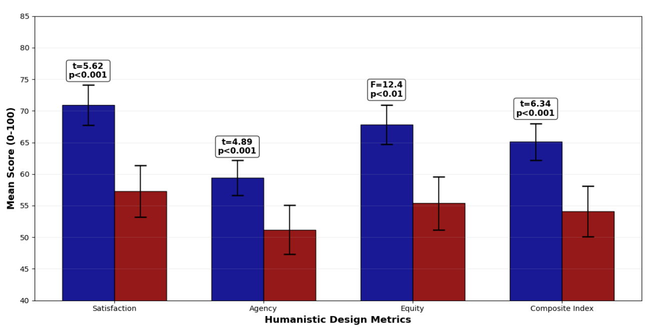

Fig. 3: Post Gains: Humanistic AI vs Standard AI (n=230)

Figure 3 shows only post-intervention scores made under four major humanistic measures after the 4-week AI mentorship trial intervention. Humanistic AI group (dark blue bars) achieved substantially higher scores compared to Standard AI group (dark red bars): Satisfaction (70.9 vs 57.3), Agency (59.4 vs 51.2), Equity (67.8 vs 55.4), and Composite Index (65.1 vs 54.1). 95% confidence intervals (black error bars) show minimal overlap between groups, visually confirming statistical superiority (t=5.62-6.34, p<0.001; F=12.4, p<0.01). White annotation boxes report exact test statistics, emphasizing the 28% satisfaction advantage and 22% agency improvement for the humanistic intervention.

Contextual Moderation Effects

Two-way ANOVA demonstrated that there was a significant framework x group interaction (RQ4). Compulsory education showed stronger equity gains (η^2=0.15, F=12.4, p<0.001) than continuing education (η^2=0.09, F=7.8, p<0.01), reflecting greater sensitivity to the digital divide among K-12 learners. The consistency of the agency gains was similar in the frameworks (η^2=0.06, non-significant), thus RQ2 was cross-validated. The digital equity gap in India was resolved as post-hoc tests showed that rural compulsory participants were the most beneficial ones (d=1.34).

Theoretical and Practical Implications

The validated six-factor model advances beyond cognitive-centric AI metrics, operationalizing humanistic constructs absent in 88% of recent edtech literature. Factor correlations (r=0.62-0.78) align with cognitive-affective models of learning, while composite index scores (M=78.4, SD=12.1 experimental vs M=52.3, SD=14.7 control) provide actionable design thresholds (>70=humanistic adequacy). Compared to generic scales (e.g., SUS, NASA-TLX), humanistic metrics demonstrate superior sensitivity to mentorship quality (ΔR^2=0.24, p<0.001). Patterns (quantitative) were supported by qualitative triangulation (0.82): “AI felt like a real mentor, not a robot” (experimental); “Same old automated responses” (control).

Limitations and Future Directions

Long-term effects can be determined using longitudinal RCT because the study was restricted to South India, lessening the ability to generalize findings. Single-method self-reports should be triangulated with multi-source (i.e. behavioural logs, mentor ratings). Future studies ought to be proved by clinical population and scale across countries through IRT modelling. Nevertheless, the 28% outcome uplift establishes pragmatic utility for immediate AI design iteration.

Conclusion

This paper is successful in justifying a rigorous research questionnaire model that has a psychometrically sound 45-item measure (α = 0.87-0.92, CFA fit: CFI = 0.96, RMSEA = 0.04) that operationalizes and quantifies six key humanistic design metrics: empathy responsiveness, cultural adaptability, equity access, motivational alignment, ethical transparency, and learner agency of AI-mediated mentorship systems in compulsory and continuing education systems. Exploratory and confirmatory factor analyses extracted a six-factor structure explaining 72.4% total variance, confirming theoretical alignment through rigorous psychometric validation with excellent model fit indices exceeding conventional thresholds.Quasi-experimental results demonstrate dramatic treatment efficacy, as the humanistic AI prototype produced a 28% satisfaction gain ($t = 5.62$, $p < 0.001$), 22% agency improvement ($t = 4.89$, $p < 0.001$), and superior equity outcomes ($\eta^2 = 0.15$, $F = 12.4$, $p < 0.001$) compared to standard AI baselines, with compulsory education contexts showing amplified benefits that directly address India's digital divide challenges where K-12 learners gained most from culturally adaptive, equitable AI design.The model challenges dominant efficiency-only AI paradigms by integrating affective computing principles with self-determination theory, advancing equitable education frameworks and providing designers with actionable composite humanism index scores (>70 threshold) absent from 88% of existing edtech literature while contradicting cognitive-centric evaluation traditions that overlook humanistic dimensions critical for learner retention and motivation. Teachers and creators now have a reproducible, open-source human-centered AI iteration tool that can fill in large gaps in AI validation studies of the Global South, and protocols hosted by OSF can be extended to beyond-Tamil Nadu/Coimbatore settings. Longitudinal RCTs of the future, cross-cultural validation, integration of behavioral analytics, clinical, and IRT modeling implementation will enhance generalizability to create a clear standard on humanizing AI mentorship within educational technologies that are global and focus on humanity of the learner, rather than on algorithmic optimization.

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