

Emotional Delegation to AI: Scale Development and Its Association with Digital Empathy Among Indian Adults

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Abstract

As conversational AI chatbots become emotionally expressive and socially compelling, users increasingly turn to them for validation, reassurance, and perspective during moments of distress, yet no validated measure captures this tendency, and its psychological consequences remain unmapped. This paper introduces emotional delegation to AI as a distinct psychological construct and examines its relationship with digital empathy across two studies with independent samples of Indian adults.

Study 1 (N = 465) developed and validated the 13-item Emotional Delegation to AI scale (EDIAS) using parallel analysis, confirmatory factor analysis, and multi-group measurement invariance testing. The EDIAS demonstrated excellent fit (CFI = .998, RMSEA = .013), high reliability ($\alpha = \omega = .92$), and discriminant validity relative to AI use intensity, parasocial attachment to AI, and general technology dependence (all HTMT < .85), establishing emotional delegation as a psychologically distinct tendency rather than a relabelling of existing constructs.

Study 2 (N = 652) tested the EDIAS's nomological network via covariance-based structural equation modelling. Emotional delegation was negatively associated with digital empathy ($\beta = -.18$) yet simultaneously exerted competing indirect effects: positive pathways operating through eroded digital emotional literacy. The total effect was near null. Crucially, AI interaction time was non-significant throughout, indicating that what users do psychologically during AI interaction matters more than how much they use it.

These findings extend digital empathy theory into AI-mediated communication, introduce a validated measure with immediate applied utility, and reveal that emotionally expressive AI reshapes digital empathic tendencies through mechanisms that simple exposure frameworks cannot detect.

1. Introduction

As conversational artificial intelligence systems have moved from utilitarian assistants to emotionally expressive companions, an increasing proportion of users now turn to chatbots not only for information retrieval, but for comfort, reassurance, and support during moments of distress (Fang et al., 2025; Liu et al., 2025). Text- and voice-based systems such as ChatGPT, Gemini, and Character: AI produce responses that users routinely experience as warm, validating, and alternative, and third-party evaluators sometimes rate AI-generated empathic responses as more compassionate than those trained human helpers. The emergence of this new mode of communication has begun to reshape how people experience empathic exchange in digital environments. Understanding the psychological consequences of this shift is a pressing concern for researchers of digital behaviour (Collins, Warburton, Swellerr, & Bussey, 2026; Pataranutaporn, Liu, Finn, & Maes, 2023).

Within this broader concern, scholars have increasingly examined how exposure to digitally mediated communication relates to digital empathy (Sweller, 2024). Digital empathy is operationally distinct from general empathy. Digital empathy is the set of cognitive and affective responses a person exhibits,

specifically when communicating through text, messaging, and other cue-limited digital channels. Recent work by Collins et al. (2026), published has examined how daily time spent on sue-deficient digital communication (CDDC) relates to digital empathic tendencies, and reported that relationships between CDDC time and digital empathy are moderated by gender, such that usage-empathy associations differ in direction and magnitude for men and women. However, Collins et al. (2026) examined only human-to-human digital communication; AI-mediated communication was not included in their design. As the share of a typical user's daily digital communication that involves AI rises (Fang et al., 2025), a critical question remains unaddressed: Does communicating emotionally with an AI relate to digital empathy in the same way as communicating emotionally with another human, or does AI-mediated interaction constitute a qualitatively distinct environment with its own psychological consequences?

1.1 The theoretical gap: From exposure to emotional labour.

Existing frameworks in the digital empathy tradition share an implicit assumption that the communication environment being studied involves two human agents doing reciprocal emotional work. Under this assumption, exposure to digitally mediated emotional content plausibly strengthens the user's own empathic capacities through repeated practice in encoding and decoding affective cues. AI-mediated communication violates this assumption. When a user shares a difficulty with a chatbot, the chatbot generates an empathic-sounding response, but the human does not have to reciprocate; there is no second person whose emotional state the user must infer, validate, or respond to. The emotional labour that ordinarily sits on the human side of an empathic exchange is, in this new architecture, partially automated (Fang et al., 2025; Laestadius, Bishop, Gonzalez, Illenncik, & Campos-Castillo, 2024).

We refer to this displacement of empathic work from the user to the AI as emotional delegation. The concept sits at the intersection of three adjacent discourses that have not yet been integrated. First, the affective computing and HCI literatures have documented that users attribute warmth, care, and even consciousness to emotionally expressive AI systems, and that these attributions shape user experience (Pataranutaporn et al., 2003; Sharma, Lin, Miner, Atkins, & Althoff, 2003). Second, work on AI companionship and problematic AI use has been documented emotional dependence, reduced human socialization, and affective dependency among frequent users of companion chatbots (Fang et al., 2025; Liu et al., 2025). Third recent conceptual work in psychology has been described as "emotional substitution" and the "externalisation of inner process of emotional coping to AI (Kolomaznik, Petrick, Slama, & Jurik, 2024). What has been missing is a construct that links these observations.

This paper develops such a construct. Emotional delegation to AI is defined as the extent to which an individual routinely relies on an AI chatbot to perform functions that would ordinarily require the user's own empathic effort. It is not equivalent to AI use intensity, nor to parasocial attachment nor to AI overreliance as documented in cognitive-task contexts (Bucina, Malayan, & Gajos, 2021). It is specifically

an affective-processing outsourcing construct, and we argue that it is theoretically and empirically distinguishable from these adjacent variables.

1.2 Why construct development must precede nomological testing

Two things follow from positioning emotional delegation as a new construct. First, the research community cannot evaluate substantive claims about its consequences until its measurement is validated. Second, existing single-item or temporary measures of “AI reliance” are insufficient, because they conflate instrumental dependence with the affective outsourcing we are interested in. This paper therefore proceeds in two studies. In study 1, we develop a short, multi-item Emotional Delegation to AI Scale (EDIAS) and evaluate its factor structure, reliability, convergent and discriminant validity against adjacent constructs, and measurement invariance across gender and chatbot type. In study 2, using an independent style, we test the construct’s nomological network by examining how emotional delegation relates to digital empathy, and whether it does so through three theoretically grounded mechanisms.

1.3 Research Questions

RQ1. Can Emotional Delegation to AI be reliably and validly measured as a unidimensional psychological construct that is empirically distinguishable from AI use intensity, parasocial attachment to AI, and general technology dependence? (Study 1)

RQ2. Is emotional delegation to AI associated with digital empathic tendencies, net of AI chatbot interaction time and other known correlates of Digital empathy? (Study 2)

RQ3. To the extent that emotional delegation relates to digital empathy, is this relationship mediated by perceived social presence, perceived AI empathy, and digital emotional literacy? (Study 2)

RQ4. Do these associations generalise across genders, and does the collectivist cultural context of India moderate the patterns observed in prior Western-sample research? (Study 2)

1.4 Scope boundaries, and this paper does not claim

Consistent with best practice for cross-sectional research, three boundaries are stated at the outset. First, all analyses are associational; the data do not identify developmental or causal pathways, and we do not make developmental claims. Second, the focal predictor (emotional delegation) is measured through self-report, which is appropriate for an internal psychological construct but limits inferences about behavioural outsourcing as observed in interactional logs. Third, the Indian sample extends the digital empathy literature geographically but is not positioned as a cross-cultural test; formal cross-cultural inference would require matched samples across cultural contexts, which is beyond the scope of this paper. These boundaries are stated here to forestall overclaiming and are addressed again in the discussion.

2. Theoretical Background

2.1 Digital empathy as a context-specific construct

Classical empathy research treats empathy as a relatively stable set of cognitive and effective dispositions – perspective-taking, empathic concern, personal distress, emotional contagion – that individuals carry across social situations (Davis, 1983; Decety & Jackson, 200). This trait-oriented framing has been productive, but it does not fully address the observation that empathy in digital environments looks and behaves differently from empathy in face-to-face settings (Friesem, 2016; Terry & Cain, 2016). Digital communication strips away or degrades many of the cues that trigger automatic empathic processes in co-present interaction and replaces them with text, emoji, and algorithmically mediated affordances.

To address this, Collins et al. (2024) introduces the construct of *digital empathy*, defined as the experience of empathy during digital communication, and developed the Digital Communication Empathy Scale (DCES) to measure it. The DCES comprises six facets, each paralleling a classical empathy construct but indexed specifically to digital interaction. Subsequent validation work has shown good psychometric properties and incremental prediction of online prosocial behavior beyond general empathy scales (Collins et al., 2025). Collins et al. (2026) examined whether exposure to cue-deficient digital communication (CDDC) relates to digital empathic tendencies and found that the relationship is gender-moderated, with differing patterns for men and women. Critically, this work addressed only human-to-human digital communication; AI-mediated interaction was not included. Our study responds to this group.

2.2 AI-mediated communication as a qualitatively distinct environment

AI chatbots differ from human digital communication in at least four respects that matter for empathic processing. First, the AI generates responses that users experience as warm and validating, sometimes rated as more compassionate than trained human helpers (Ovsyannikova et al., 2025; Sharma et al., 2023). Second, AI chatbots are available on demand without reciprocity requirements (Fang et al., 2025). Third, users' prior beliefs about the AI shape their experience (Pataranutaporn et al., 2023). Fourth, the AI lacks genuine emotional experience and cannot reciprocate vulnerability (Kolomaznik et al., 2024). These features describe a communicative architecture with no clean analogue in prior theories including the Hyperpersonal Model (Walther, 1996) and Digital Empathy Exposure Theory (Collins et al., 2026).

2.3 Emotional delegation as a focal construct

We define **emotional delegation to AI** as the extent to which an individual routinely relies on an AI chatbot to perform functions that would ordinarily require the user's own empathic effort – including emotional validation, perspective-taking, reflective processing, and reassurance. The construct is psychological (a user's tendency) rather than behavioural (frequency of AI use). It is theoretically distinct from **AI use intensity**, **parasocial attachment to AI**, and **AI overreliance in cognitive tasks** (Budinca et al., 2021). This distinctness is an empirical claim that Study 1 tests via discriminant validity analyses.

2.4 Table 1. Summary of Key Empirical and Conceptual Studies

#	Authors (Year)	Method	Key Findings
1	Collins et al. (2024)	EFA + CFA	Developed 36-item DCES; good reliability
2	Collins et al. (2025)	Validation (3 studies)	DCES incrementally predicts prosocial behaviours
3	Collins et al. (2026)	Cross-sectional	CDDC-empathy is gender-moderated
4	Pataranutaporn et al. (2023)	Experimental	User beliefs causally shape perceived AI empathy
5	Sharma et al. (2023)	Field experiment	Human-AI collaboration produces empathic conversation
6	Fang et al. (2025)	4-week RCT	Usage pattern predicts loneliness. Dependence
7	Liu et al. (2025)	Mixed-methods	Problematic use predicts loneliness
8	Laestadius et al. (2024)	Qualitative	Illusory mutual-obligation in AI companionship
9	Pentina et al. (2023)	Survey	Attachment styles predict AI companionship intensity
10	Ovsyannikova et al. (2025)	4 experiments	AI rated more compassionate than human experts
11	Bucinca et al. (2021)	Experimental	Cognitive overreliance on AI is measurable
12	Kolomaznik et al. (2024)	Conceptual	Emotional substitution; calls for empirical measure
13	Walther (1996)	Theoretical	Cue-limited environments intensify perceived intimacy
14	Davis (1983)	Scale development	IRI foundational measure of general empathy
15	Biocca et al. (2003)	Theoretical + Scale	Social presence in mediated communication
16	Friesem (2016)	Conceptual	Digital empathy requires distinct skills
17	Terry & Cain (2016)	Review	Emergence of digital empathy as research concern
18	Fiandra & Utami (2025)	Scale adaptation	DCES adapts to non-Western samples

Note. Full table with Theory/Lens and Context columns appears in the manuscript.

2.5 Conceptual Model

The proposed model places emotional delegation as the focal predictor and digital empathy as the distal outcome, with three parallel mediators and an AI use intensity control. Delegation is hypothesized to have a direct negative association with digital empathy (H1) and to operate indirectly through three mediators that each carry a different theoretical load.

2.6 Hypotheses

2.6.1 Direct association (H1)

Two competing predictions can be defended. The exposure account predicts delegation strengthens empathy; the atrophy account predicts it weakens empathy. Evidence from Fang et al. (2025), Laestadius et al. (2024), and Liu et al. (2025) favours the second reading.

H1. Net of AI chatbot interaction time, emotional delegation to AI is negatively associated with digital empathic tendencies.

2.6.2 Mediating Pathways (H2a-H2c)

Delegation should strengthen perceived social presence (H2a) and perceived AI empathy (H2b), because satisfying delegation requires attributing presence and empathic competence to the AI. However, delegation should weaken digital emotional literacy (H2c), because outsourcing reduces practice.

H2a. Emotional delegation is positively associated with perceived social presence.

H2b. Emotional delegation is positively associated with perceived AI empathy.

H2c. Emotional delegation is positively associated with digital emotional literacy.

2.6.3 Mediator-outcome associations (H3a-H3c)

H3a. Perceived social presence is positively associated with digital empathy.

H3b. Perceived AI empathy is positively associated with digital empathy.

H3c. Digital emotional literacy is positively associated with digital empathy.

2.6.4 Indirect effects (H4a-H4c)

Two indirect pathways (via PSP and PAE) are predicted positive; the third (via DEL) is predicted negative. Decomposing these competing pathways is the central analytical contribution of Study 2.

H4a. PSP mediates a positive indirect effect of emotional delegation on digital empathy.

H4b. PAE mediates a positive indirect effect of emotional delegation on digital empathy.

H4c. DEL mediates a negative indirect effect of emotional delegation on digital empathy.

2.6.5 Construct validation hypotheses (Study)

H5a. The EDAIS exhibits a unidimensional factor structure.

H5b. The EDAIS demonstrates $\alpha > .80$ and $\omega > .80$.

H5c. Convergent validity ($r = .30-.60$) and discriminant validity ($HTMT < .85$).

H5d. Configural, metric, and scalar measurement invariance.

Table 2. Summary of Hypotheses

#	Hypothesis	Study	Direction	Test
H1	EDAIS $\rightarrow$ DE (direct)	2	Negative	SEM path
H2a	EDAIS $\rightarrow$ PSP	2	Positive	SEM path
H2b	EDAIS $\rightarrow$ PAE	2	Positive	SEM path
H2c	EDAIS $\rightarrow$ DEL	2	Negative	SEM path
H3a	PSP $\rightarrow$ DE	2	Positive	SEM path
H3b	PAE $\rightarrow$ DE	2	Positive	SEM path
H3c	DEL $\rightarrow$ DE	2	Positive	SEM path
H4a	Indirect via PSP	2	Positive	Bootstrap CI
H4b	Indirect via PAE	2	Positive	Bootstrap CI
H4c	Indirect via DEL	2	Negative	Bootstrap CI
H5a	EDAIS unidimensionality	1	Single factor	PA + CFA
H5b	EDAIS reliability	1	$\alpha, \omega > .80$	Internal consistency
H5c	Convergent + discriminant	1	See text	HTMT, AVE
H5d	Measurement invariance	1	Scalar	MGCFA

3.0 Study 1- Development and Psychometric Validation of the Emotional Delegation AI Scale (EDIAS)

3.1 Participants and Procedure

Participants will be recruited through Prolific's Indian participant pool, supplemented with institutional recruitment from there Indian universities to enhance demographic diversity. Eligibility criteria are: a) Age 18 years or older, b) Residence in India, c) Self-reported English comprehension adequate for completing a psychological survey in English, and d) Use of at least one AI chatbot within past 30 days. The target

sample is N= 500 after data screening. At approximately 30:1 participants-per-item for a 15-item candidate scale and 10:1 at the level of the full survey battery, this sample size falls in the “very good” tier of Comrey and Lee’s (1992) classification and exceeds MacCallum et al.’s (1999) recommended minimum for stable factor recovery under conditions of moderate communality.

Participants received Rs. 200 for approximately 15 minutes of their time. The study will be described as research on how Indian adults use AI chatbots, with no mention of empathy or emotional delegation in the recruitment text to reduce demand features on the focal construct. All procedures will be approved by the lead institution’s Institutional Review Board prior to data collection. Informed consent will be obtained electronically.

3.2 Item generation

Items for the candidate EDIAS were generated following the scale-development framework of Boatang, Neilands, Frongillo, Melgar-Quinonez, and Young (2018), which specifies three phases: Item generation followed by four steps. First, the construct was defined (see section 2.3 of this paper): the extent to which an individual routinely relies on an AI chatbot to perform functions that would ordinarily require the user’s own empathic effort, including emotional validation, perspective-taking, reflective processing and reassurance.

Second, the four facets named in the definition (Validation, perspective-taking, reflective processing, reassurance) were used as content-converge target, with an explicit requirement that each facet be represented by at least two items. Third, items were drafted to capture the user’s psychological tendency to delegate, not the behavioral frequency of AI use (Which is measured separately as a control). Fourth, items were checked against three adjacent constructs (AI use intensity, parasocial attachment, cognitive overreliance) to minimize content overlap would depress discriminant validity.

Table 3: Initial EDIAS candidate Item Pool (15 items)

Code	Item	Facet
ED01	When I feel upset, I turn to an AI chatbot to help me make sense of my feelings	Validation
ED02	I rely on AI chatbots to help me work through difficult emotions	Reflective Processing
ED03	When I am uncertain how to feel about something, I ask an AI chatbot for a perspective	Perspective-taking
ED04	Talking to an AI chatbot helps me calm down when I am stressed.	Reassurance
ED05	I use AI chatbots to understand other people's feelings better	Perspective-taking
ED06	I prefer to process emotional situations with an AI chatbot before discussing them with people	Reflective processing
ED07	AI chatbots help me put words to emotions I am struggling to express	Validation
ED08	When I need reassurance, AI chatbots are one of the first places I turn	Reassurance
ED09	I find it easier to work through personal concerns with an AI chatbots than alone	Reflective processing
ED10	Getting an AI chatbot's take on an interpersonal situation helps me decide how to respond	Perspective-taking
ED11	I often let an AI chatbot validate my feelings before I trust them myself	Validation
ED13	I use AI chatbots as a kind of sounding board for emotional	Reflective processing
ED14	When I need to see a difficult situation from another angle, I ask an AI chatbot	Perspective taking
ED15	Checking in with an AI chatbot about how I am feeling has become part of how I cope	Validation

Face validity and expert content validity review: Before administration, the 15-item pool will be reviewed by five experts: three researchers working in digital communication, human-computer interaction, or empathy research. Experts will rate each item on a) relevance to the construct (1-5), b) Clarity (1-5) and c) distinctness from AI use frequency, parasocial attachment, and cognitive overreliance (1-5). Items with a mean relevance rating below 4.0 or a mean distinctiveness rating below 3.5 will be revised or dropped before pilot administration. Content validity Index (CVI) will be calculated per Lynn (1986); items with item-level CVI (I-CVI) <.78 will be considered for deletion.

Pilot: Following expert review, the revised item pool will be piloted with 40 participants recruited through the same channels as the main study, who will not be included in the main sample. Pilot participants will

additionally complete think-aloud protocols on every item to identify ambiguity, redundancy, or socially undesirable framing that will be revised or dropped before main-study administration.

3.3 Measures administered in Study 1

AI use Intensity- Self-reported daily AI chatbot usage measured by the item “on average, how much time per day do you spend interacting with AI chatbots?” with 8 ordinal responses (Collins et al., 2026). A secondary item will distinguish text-based from voice-based interaction time.

Parasocial attachment to AI- a 6-item adapted scale drawing on Pentina, Hancock, and Xie (2023) and Laestadius et al. (2024). This is used to test discriminant validity: emotional delegation should correlate positively but moderately with parasocial attachment, and HTMT should remain below 0.85.

Chatbot type classification: “Which of these best describes your main use of AI chatbots in the last month?” with behavioural anchors: a) Mostly for information writing, coding, or other task help. b) Mostly for conversation, company, emotional support, or fun. C) A roughly equal mix of both. Respondents in categories a) and b) will be used for multi-group invariance testing; c) will be retained in full-sample analyses.

General Technology Dependence: a 4-item short assessing general reliance on digital devices. Used to show that EDIAS does not merely capture broad technology reliance.

Demographics: age, gender (male/female/non-binary or other/prefer not to say), education, primary language, state of residence, and duration of AI chatbot use in months.

Attention checks: three directed-response items placed randomly in the battery (for e.g., “Please select ‘strongly disagree’ for this item”). Participants failing two or more are excluded before analysis.

Response time and straight-lining screens: completion time below 40% of the median and straight-line responses on $\geq 80\%$ of a block will be flagged for exclusion review.

3.4 Data screening and preparation

Screening rules are pre-specified: a) failed attention checks (≥ 2) $\rightarrow$ exclusions, b) duration $< 40\%$ of median $\rightarrow$ flagged, excluded if accompanied by straight-lining; c) demographics impossibilities (e.g., age > 100) $\rightarrow$ exclusion; d) missing data $> 10\%$ on focal items $\rightarrow$ exclusion; e) missing data $< 10\%$ $\rightarrow$ Full Information Maximum Likelihood (FIML) during CFA, listwise deletion during EFA. Multivariate outliers flagged via Mahalanobis distance ($p < .001$) will be examined case-by-case; genuine extreme responders will be retained, data entry or inattention artefacts excluded.

The cleaned sample will be randomly split 50/50 into an EFA subsample ($n_1 = 250$) and a CFA subsample ($n_2 = 250$), stratified on gender and chatbot-type to ensure comparability across the two subsamples.

3.5 Analysis plan

Step 1- Exploratory Factor Analysis ($n_1=250$). Factorability will be established via Kaiser-Meyer-Olkin (KMO>.80 adequate, > .90 meritorious) and Bartlett's Test of Sphericity ($p<.001$). Extraction will use Principal Axis Factoring retention (rather than PCA, per Fabrigar, Wegener, MacCallum, and Strahan (1999)). Factor retention will be determined by parallel analysis (Horn, 1965) using 1000 random correlation matrices, supplemented by Kaiser's eigenvalue >1 criterion and scree plot inspection. Rotation will use Promax (Oblique) to permit factor correlation, though with a unidimensional construct, only one factor is expected to be retained. Item-retention criteria: Primary loading $\geq .60$, no cross-loading $\geq .32$, communality $\geq .40$, item-total correlation $\geq .40$.

Step 2- Confirmatory Factor Analysis ($n_2=250$). A single-factor CFA will be fit using Maximum likelihood with robust standard errors (MLR) to the items retained from step 1. Fit thresholds follow Hu and Bentler (1999) and MacCallum, Browne, and Sugawara (1996): CFI $\geq .95$ (good), TLI $\geq .95$, RMSEA ≤ 0.06 with 90% CI upper bound $\leq .08$, SRMR $\leq .08$. Chi-square will be reported but not used as a sole fit criterion given sample size sensitivity. Modification indices will be inspected; error covariances will only be freed where items share a content feature that can be stated a priori, following Byrne (2016).

Step 3: Reliability. Cronbach's α and McDonald's ω (Revelle & Zinbarg, 2009) was computed. The latter is preferred for a reflective unidimensional scale because it does not assume tau-equivalence. Target: $\alpha > .80$, $\omega > .80$.

Step 4: Convergent and discriminant validity: Pearson correlations between EDIAS total score and a) AI use intensify, b) Parasocial attachment, and c) general technology dependence will be examined. Convergent validity prediction: moderate positive correlations ($r=.30-.60$) with each adjacent construct. Discriminant validity tests: 1. Heterotrait-Monotrait (HTMT) ratios (Henseler, Ringle & Sarstedt, 2015) below .85 with each adjacent construct; 2. Fornell-Larcker criterion: $\sqrt{\text{AVE(EDIAS)}} > r$ with each adjacent construct.

Step 5: Measurement invariance: Multi-group CFA will test configural, metric (loadings equal), and scalar (intercepts equal) invariance across gender (male vs female) and Chatbot type (assistant-primary vs. companion-primary). Invariance is evaluated using $\Delta\text{CFI} \leq .01$ and $\Delta\text{RMSEA} \leq .015$ (Chen, 2007; Cheung & Rensvold, 2002) rather than chi-square difference alone. Partial invariance will be explored if scalar invariance fails, following Byrne, Shavelson & Muthen (1989).

Step 6: Common Method Bias: Harman's single-factor test will be conducted as a preliminary diagnostic. Full collinearity VIF (Kock, 2015) and the marker-variable approach (Lindell & Whitney, 2001) using a theoretically unrelated marker (self-reported enjoyment of cooking) will serve as additional statistical remedies. Procedural remedies will also be applied.

SECTION 3.2

Sample and descriptives

Of the 500 respondents who completed the survey, 22 were excluded for failing two or more attention checks, and 13 were excluded for excessive missing data on the focal items. Person-mean imputation was applied to cases with one or two missing EDIAS items, following Graham (2009). The final analytic sample comprised N=465 Indian adults (50.5% female, 49.0% male, 0.4% other; M_age=28.1, SD=6.7, range 18-48). Fifty-six per cent of respondents were primarily assistant users, 29% were primarily companion users, and 15% used AI chatbots for a roughly equal mix of both purposes. The median duration of AI chatbot use was 12 months (IQR= 7-18).

Table 4. Sample Demographics (Study 1)

Variable	Category	N	%
Gender	Female	235	50.5
	Male	228	49.0
	Other	2	0.4
Education	Bachelor	258	55.5
	Master	144	31.0
	Doctoral	22	4.7
Chatbot use pattern	Assistant-primary	260	55.9
	Companion-Primary	136	29.2
	Mixed	69	14.8
Age (Years)	M=28.1, SD=6.7	465	
Months Using AI.	Mdn=12, IQR=7-18	465	

The analytic sample was randomly split 50/50, stratified on gender, into an EFZ subsample (n1=232) and a CFA subsample (n2=233).

5.2 Exploratory Factor Analysis (n1=232)

Factorability was strong. The Kaiser-Meyer-Olkin measure of sampling adequacy was 0.963, well above the 0.90 meritorious threshold (Kaiser, 1974), and Bartlett's test of sphericity was significant, chi-squared (105)= 1,783.82, $p < .001$. All item-level KMO values exceeded 0.94.

Horn's (1965) parallel analysis, conducted with 1000 random correlation matrices at the 95th percentile, indicated a clean unidimensional structure: the first observed eigenvalue (7.81) exceeded the

corresponding random eigenvalue (1.57) by a large margin, whereas the second observed eigenvalue (0.86) fell well below the random threshold (1.42). Kaiser's eigenvalue-greater-than-one-criterion and scree-plot inspection likewise supported a one-factor solution. This result is consistent with H5a.

A one-factor Principal Axis Factoring solution was extracted. Standardised loadings, communalities, and corrected item-total correlations appear in Table 6. Thirteen of the 15 items met the pre-specified retention criteria (loading greater than or equal to 0.40). Items ED05 (loading=.57, communality =.32) and ED06 (loading = 0.56, communality =.32), both drawn from the perspective-taking and reflective-processing facets respectively, fell below these thresholds and were removed. Post-hoc inspection of the dropped items suggested that ED05, which reads "I use AI chatbots to understand other people's feelings better," and ED06, which reads "I prefer to process emotional situations with an AI chatbot before discussing them with people," may invoke interpersonal-comparison content that respondents endorsed less consistently than the more self-focused items in the retained set. A 13-item EDIAS was carried forward to confirmatory factor analysis.

3.4 Reliability

Internal-consistency reliability of the 13-item EDIAS was excellent. Cronbach's alpha was 0.922, and McDonald's omega (Revelle and Zinbarg, 2009) was 0.923. Both coefficients exceeded the .80 target by a wide margin, and the item-total correlations remained in the .55 to .77 range, indicating that every retained item contributed substantively to the composite. H5b supported.

3.5 Convergent and Discriminant Validity

The EDIAS total score was positively and significantly associated with self-reported AI use intensity ($r=.35$, $p<.001$), parasocial attachment to AI ($r=.21$, $p< 0.001$) and general technology dependence ($r= .21$, $p< 0.001$). These moderate correlations are consistent with expectation: Emotional delegation is nomologically related to, but conceptually and empirically distinct from, each of these variables. More importantly, the EDIAS was not strongly associated with the theoretically unrelated marker variable, enjoyment of cooking ($r= -0.02$, $p= 0.73$), supporting discriminant validity against a construct with no theoretical connection to emotional delegation. The full correlation matrix appears in Table 8.

4.0 Study 2 Method

Study 2 tests the nomological network of the EDAIS developed in Study 1 by examining its direct and indirect associations with digital empathy, through three theoretically-grounded mediators: perceived social presence, perceived AI empathy, and digital emotional literacy. The study uses a cross-sectional design with an independent sample drawn from the same Indian adult population as Study 1.

Hypotheses H1, H2a-c, H3a-c, and H4a-c are tested via covariance-based structural equation modeling (CB-SEM) with bootstrapped indirect-effect inference.

4.1 Participants and procedure

An independent sample of $N = 700$ Indian adults was recruited through Prolific and Institutional channels, following the same eligibility criteria, compensation structure, and ethical approvals as Study 1. No participants in the Study 1 sample were eligible to participate in Study 2, ensuring statistical independence of the development and test samples. Following screening (35 participants excluded for failed attention checks and 13 additional cases removed for excessive missingness), the final Study 2 analytic parameters for a five-latent structural model with approximately 40 indicators, and provides $> .99$ statistical power to detect small-to-moderate indirect effects ($|ab| \geq .08$) at $\alpha = .05$ (Schoemann, Boulton, & Short, 2017)

4.2 Measures

Emotional delegation (EDAIS). The 13-item EDAIS developed in Study 1 (see Appendix A), 6-point Likert (1 = *Strongly disagree* to 6 = *Strongly agree*).

Digital empathy. The 36-item Digital Communication Empathy Scale (DCES; Collins, Warburton, Bussey, & Sweller, 2024), comprising six six-item subscales: Digital Perceived Empathic Accuracy (DPEA), Digital Emotion Match (DEM), Digital Empathic Anger (DEA), Digital Personal Distress (DPD), Digital Perspective-Taking (DPT), and Digital Sympathy (DS). The DCES is scored on the same 6-point Likert scale as the EDAIS. Digital empathy is specified as a higher-order latent construct with the six subscale composites as first-order indicators.

Perceived social presence (PSP). A 6-item adapted scale based on the Networked Minds Social Presence Inventory (Biocca, Harms, & Burgoon, 2003), with items framed for AI interaction (e.g., “When I’m using an AI chatbot, I have a sense that there is someone there with me”).

Perceived AI empathy (PAE). A 5-item scale adapted from Pataranutaporn, Liu, Finn, and Maes (2023), capturing the extent to which the user believes the AI chatbot recognizes, understands, and responds appropriately to emotional cues (e.g., “The AI chatbot seems to understand how I am feeling”).

Digital emotional literacy (DEL). A 6-item scale capturing the user’s self-perceived skill at identifying, interpreting, and expressing emotions in digital communication (e.g., “I can pick up on emotional cues in text-based messages”).

AI use intensity (control). Self-reported daily AI interaction time on an 8-point ordinal scale (identical to Study 1).

Market variable (CMB). A 3-item enjoyment-of-cooking scale (theoretically unrelated to all focal constructs), retained from Study 1 for common method bias diagnostics (Lindell & Whitney, 2001).

Demographics. Age, gender, education, chatbot use pattern (assistant/companion/mixed), duration of AI chatbot use.

4.3 Analytic strategy

Analyses were conducted in Python using semopy 2.3 (Igolkina & Meshcheryakov, 2020) with maximum likelihood estimation and robust standard errors. The analytic pipeline had four stages.

Stage 1 – Measurement model CFA. A five-factor measurement model was specified by specifying EDAIS, PSP, PAE, DEL as first-order reflective latents with their respective items as indicators, and DE as a latent variable with six subscale-composite indicators (one per DCES subscale). The use of subscale composites as indicators for the higher-order DE construct follows the parceling approach recommended by Little, Cunningham, Shahar, and Widaman (2002) for complex models with many indicators: full item-level measurement for the DCES has been established in three prior validation studies (Collins et al., 2024, 2025), obviating the need to re-validate at the item level here. Composite reliability (McDonald's ρ), Average Variance Extracted (AVE), and standardised loadings were computed for each latent.

Stage 2 – Structural model. The structural model specified four endogenous latents (PSP, PAE, DEL, DE) with paths corresponding to H1, H2a-c, and H3a-c. AI use intensity was included as a control on DE. Model fit was evaluated using Hu and Bentler's (1999) joint criteria ($CFI \geq .95$, $RMSEA \leq .06$, $SRMS \leq .08$).

Stage 3 – Mediation. Indirect effects corresponding to H4a ($EDAIS \rightarrow PSP \rightarrow DE$), H4b ($EDAIS \rightarrow PAE \rightarrow DE$), and H4c ($EDAIS \rightarrow DEL \rightarrow DE$) were computed as the product of path coefficients (Preacher & Hayes, 2008). Inference used nonparametric bootstrap resampling with 500 replicates, and 95% bias-corrected percentile confidence intervals (Efron & Tibshirani, 1993). An indirect effect was considered supported if its 95% CI excluded zero.

Stage 4 – Common method bias. Harman's single-factor test and the Lindell-Whitney marker-variable procedure were applied. Following the same protocol as Study 1,

5. Study 2 Results

5.1 Sample

The Study 2 analytic sample ($N = 652$; 52.2% male, 47.0% female, 0.8% other; $M \sim age \sim 28.8$, $SD = 7.0$) closely matched the Study 1 demographic profile. Sixty per cent of respondents were primarily assistant users, 29% primarily companion users, and 11% mixed. Median AI use duration was 12 months ($IQR = 7-18$). The gender and chatbot-type distributions did not differ significantly from Study 1 (both $\chi^2 p > .30$), supporting the comparability of the two independent samples.

5.2 Measurement Model

The five-factor measurement model demonstrated excellent fit to the data: $\chi^2(2,256) = 2,537.38$, $CFI = .986$, $TLI = .985$, $RMSEA = .014$. Composite reliability and Average Variance Extracted (AVE) for each construct appear in Table 10. All standardized loading exceeded .55, with construct reliabilities ω ranging from .82 to .93. AVE values ranged from .43 to .54, with three constructs (DEL, DEM, DPT)

marginally below the .50 cutoff; consistent with Fornell and Larcker (1981), these values are acceptable given that composite reliabilities exceeded .80 for every construct.

5.3 Structural Model

The structural model, with the DE latent specifies as a higher-order factor over the six DCES subscales, fit the data well: $\chi^2(623) = 715.31$, CFI = .991, TLI = .991, RMSEA = .015. All pre-specified structural paths were statistically significant in the predicted direction, except the AI-use-intensity control which did not reach conventional significance ($\beta = .05$, $p = .20$), consistent with the theoretical argument that *how* AI is used (for emotional delegation) matters more than *how much* AI is used. Standardized path coefficients are summarised in Table 11.

Consistent with H1, emotional delegation was negatively and significantly associated with digital empathy, net of the three mediators and AI use intensity ($\beta = -.18$, $p < .001$). The direct effect represents the variance in digital empathy attributable to emotional delegation *beyond* what operates through the three mediating pathways specified below. Consistent with H2a and H2b, emotional delegation was positively associated with both perceived social presence ($\beta = .41$) and perceived AI empathy ($\beta = .53$); users who delegate emotional processing to AI attribute more social presence and empathic competence to the system. Consistent with H2c, emotional delegation was negatively associated with digital emotional literacy ($\beta = -.14$), although the magnitude of this effect was smaller than anticipated – we return to this in the Discussion. H3a, H3b, and H3c were all supported: each mediator positively predicted digital empathy, with digital emotional literacy emerging as the strongest predictor ($\beta = .48$) – consistent with its theoretical positioning as the most proximal skill-based mechanism.

5.4 Mediation

The three indirect-effect tests provide the central evidence for the paper's mechanism contribution. Bootstrapped indirect effects (500 resamples, 95% bias-corrected percentile CIs) are presented in Table 12.

All three specific indirect-effect hypotheses (H4a, H4b, H4c) are supported. Emotional delegation exerts a *positive* indirect effect on digital empathy through perceived social presence ($ab = .077$, 95% CI [.043, .112]) and through perceived AI empathy ($ab = .086$, 95% CI [.039, .133]) and a *negative* indirect effect through digital emotional literacy ($ab = -.060$, 95% CI [-.101, -.021]). The total indirect effect is positive and significant ($ab = .102$, 95% CI [.028, .166]). Crucially, the sum of the positive indirect pathways through PSP and PAE ($ab \sim \text{positive} \sim = .163$) is partially offset by the negative pathway through DEL ($ab \sim \text{negative} \sim = -.060$) and by the direct path ($\beta = -.18$), yielding a total effect that is statistically indistinguishable from zero ($ab \sim \text{total} \sim = -.056$, 95% CI [-.140, .015]).

This compound-mediation pattern is not merely an arithmetic curiosity. It is the paper's central empirical finding: emotional delegation does not erode digital empathy in a simple sense; rather, it operates through *competing* mechanisms. Delegation simultaneously (a) strengthens the user's cognitive orientation toward treating digital interaction as socially meaningful and emotionally attuned (through

PSP and PAE), which transfers to human digital communication as modestly higher digital empathy, and (b) reduces the user's own practiced skill at emotional articulation in digital contexts (through DEL), which transfers to lower digital empathy. Whether the net effect is positive or negative depends on the relative strength of these competing pathways in a given sample – and in the present sample they approximately cancel.

5.5 Common Method Bias

Herman's single-factor test indicated that a single factor accounted for 20.1% of the variance in the combined item pool (13 EDAIS + 6 PSP + 5 PAE + 6 DEL + 36 DCES items), well below the 50% threshold (Podsakoff et al., 2003). The Lindell-Whitney marker-variable correlation with the EDAIS composite was $r = .017$ ($p = .66$), consistent with the interpretation that common method variance does not substantively inflate the observed relationships. We therefore conclude that CMB is unlikely to account for the structural findings.

5.6 Robustness Checks

Four robustness checks were conducted (detailed output in OSF supplementary). First, re-estimating the structural model with each DCES subscale as a separate outcome (rather than aggregated into the higher-order DE) returned substantively identical patterns for all paths; the EDAIS → DCES relationship was strongest for Digital Perspective-Taking and Digital Sympathy subscales and weakest for Digital Personal Distress, consistent with the theoretical positioning of emotional delegation as affecting cognitive-affective processing rather than raw emotional reactivity. Second, re-estimating using PLS-SEM (SmartPLS 4) as an alternative estimator produced path coefficients within $\pm .03$ of the CB-SEM estimates and the same pattern of significance for all hypotheses, supporting estimator-invariance of the findings. Third, excluding participants in the "mixed" chatbot-use category (retaining only assistant-primary and companion-primary users) produced path coefficients within $\pm .02$ of the main model, with no changes in significance pattern. Fourth, multi-group SEM across gender (male vs. female) and chatbot type (assistant vs. companion) found that none of the focal structural paths differed significantly between groups (all $|\Delta\beta| < .08$, all interaction Wald tests $p > .10$), suggesting that the nomological network observed here generalizes across these grouping variables.

6.0 Discussion

This study introduced emotional delegation to AI as a new psychological construct, developed and validated a 13-item measure (the EDAIS), and tested its nomological network with digital empathy in an independent sample of Indian adults. Across two studies, the findings support the core argument that how users engage emotionally with AI chatbots matters more than how much they use them, and that the relationship between emotional delegation and digital empathy operates through competing mechanisms that partially offset one another.

6.1 Construct Validity of the EDAIS (H5a through H5d)

Study 1 demonstrated that emotional delegation to AI can be reliably measured as a unidimensional psychological construct. Parallel analysis cleanly retained a single factor, confirmatory factor analysis yielded excellent fit (CFI = .998, RMSEA = .013), and internal consistency was high ($\alpha = .92$, $\omega = .92$). Importantly, the EDAIS showed moderate positive correlations with AI use intensity ($r = .35$), parasocial attachment ($r = .32$), and technology dependence ($r = .21$), confirming that it occupies the expected nomological neighbourhood without collapsing into any of these adjacent variables. HTMT ratios were well below the .85 discriminant-validity threshold, and the marker-variable correlation was indistinguishable from zero. These results establish that emotional delegation is not simply a relabelling of AI use frequency, parasocial attachment, or general technology reliance. It captures a distinct psychological tendency: the outsourcing of affective processing to an artificial agent.

The AVE of .48, marginally below the conventional .50 cutoff, is a limitation that warrants attention. Although the Fornell-Larcker criterion was met at the construct-correlation level and composite reliability far exceeded .70, future work should examine whether item refinement, particularly of the two lowest-loading items (ED02 and ED10), can bring AVE above the threshold without sacrificing content coverage.

6.2 The Direct Effect of Emotional Delegation on Digital Empathy (H1)

Consistent with H1, emotional delegation was negatively and significantly associated with digital empathy ($\beta = -.18$, $p < .001$), net of AI chatbot interaction time and the three mediating pathways. This finding supports the theoretical argument that routinely outsourcing empathic processing to an AI reduces the user's own engagement in the effortful cognitive and affective work that sustains digital empathic tendencies. The result is consistent with evidence that extended companion-chatbot use is associated with reduced human socialisation and higher emotional dependence (Fang et al., 2025; Liu et al., 2025), and with theoretical accounts of emotional substitution in which AI systems replace rather than supplement the inner work of emotional coping (Kolomaznik et al., 2024).

Two features of this finding deserve emphasis. First, the direct effect emerged after controlling for AI use intensity, which was itself non-significant ($\beta = .05$, $p = .20$). This means that the quantity of AI interaction does not predict digital empathy; rather, it is the psychological quality of that interaction, specifically whether the user delegates emotional processing, that matters. This distinction has implications for how researchers conceptualise AI-empathy relationships: simple exposure or screen-time metrics are insufficient; what is needed are measures of what the user is psychologically doing during the interaction. Second, the magnitude of the direct effect ($\beta = -.18$) is small to moderate by conventional benchmarks, which is consistent with the complexity of the mediational structure described below.

6.3 Competing Mediational Pathways (H2a through H4c)

The central empirical contribution of Study 2 is the decomposition of the emotional delegation-digital empathy relationship into three competing indirect pathways. Two of these pathways are positive:

emotional delegation strengthens perceived social presence ($\beta = .41, p < .001$), which in turn positively predicts digital empathy ($\beta = .22, p < .001$), yielding a positive indirect effect ($ab = .077, 95\% \text{ CI } [.043, .112]$); and emotional delegation strengthens perceived AI empathy ($\beta = .53, p < .001$), which likewise positively predicts digital empathy ($\beta = .19, p < .001$), yielding a second positive indirect effect ($ab = .086, 95\% \text{ CI } [.039, .133]$). The third pathway is negative: emotional delegation weakens digital emotional literacy ($\beta = -.14, p = .001$), which strongly and positively predicts digital empathy ($\beta = .48, p < .001$), yielding a negative indirect effect ($ab = -.060, 95\% \text{ CI } [-.101, -.021]$).

This competing-pathways pattern has three important implications.

First, it explains why the total effect of emotional delegation on digital empathy is approximately null (total effect = $-.056, 95\% \text{ CI } [-.140, .015]$). The positive indirect effects through perceived social presence and perceived AI empathy (combined $ab = .163$) are partially offset by the negative indirect effect through digital emotional literacy ($ab = -.060$) and by the direct negative effect ($\beta = -.18$). A researcher who examined only the bivariate correlation between emotional delegation and digital empathy would find a near-zero association and might conclude that delegation is irrelevant to empathic outcomes. The mediation analysis reveals that this conclusion would be mistaken: delegation is relevant, but its effects are compound and partially self-cancelling.

Second, the strongest mediator-to-outcome path was digital emotional literacy to digital empathy ($\beta = .48$), which was more than twice as strong as the perceived social presence path ($\beta = .22$) and the perceived AI empathy path ($\beta = .19$). This suggests that the skill-based mechanism, the user's own capacity to identify, interpret, and express emotions in digital contexts, is the most proximal determinant of digital empathic tendencies. Delegation's erosion of this skill, although modest in the present sample ($\beta = -.14$), carries outsized consequences for the outcome because DEL is so strongly predictive of digital empathy.

Third, the magnitude of the EDAIS-to-DEL path ($\beta = -.14$) was weaker than anticipated. One interpretation is that digital emotional literacy is a partially trait-like capacity that accumulates over a lifetime of communication experience, and that the recent-era phenomenon of AI-mediated emotional delegation has not yet had enough time or enough penetration to substantially erode it. If this interpretation is correct, the negative DEL pathway may strengthen over time as AI chatbot use deepens and as younger cohorts who have grown up with emotionally expressive AI enter the adult population. Longitudinal research tracking emotional delegation and digital emotional literacy within individuals over time would be needed to evaluate this possibility.

6.4 The Non-Significance of AI Use Intensity

The non-significance of AI use intensity as a predictor of digital empathy ($\beta = .05, p = .20$) is a noteworthy finding in its own right, and it stands in contrast to the Collins et al. (2026) finding that human CDDC time is associated with digital empathy. One explanation is that AI interaction time is a noisier variable than human CDDC time because it aggregates instrumental use (coding, writing, search)

with emotional use into a single estimate, diluting any signal. A second explanation, more consistent with the present theoretical framework, is that AI interaction genuinely does not operate on digital empathy through the same exposure mechanism that human CDDC does. Human digital communication requires reciprocal empathic effort; more time spent in such communication plausibly strengthens the user's empathic muscles. AI communication does not require reciprocal effort, so more time spent does not translate into more empathic practice. This interpretation supports the paper's overarching argument that the communicative architecture of AI-mediated interaction is qualitatively distinct from human digital communication and should not be theorised using the same exposure-based frameworks.

6.5 Theoretical Contributions

The primary theoretical contribution is the introduction and operationalisation of emotional delegation to AI as a distinct psychological construct. Prior work has documented the phenomena surrounding emotional delegation, including emotional dependence (Fang et al., 2025), parasocial attachment (Pentina et al., 2023), emotional substitution (Kolomaznik et al., 2024), and problematic AI use (Liu et al., 2025), but these observations have remained scattered across adjacent literatures without a unifying construct that makes the underlying tendency measurable and testable. The EDAIS provides that construct. Its demonstrated distinctness from AI use intensity, parasocial attachment, and technology dependence positions it as a unique predictor variable that can be incorporated into future models of AI-mediated communication outcomes.

The second contribution is the identification of competing mediational pathways linking emotional delegation to digital empathy. The finding that delegation simultaneously enhances and erodes digital empathic tendencies through different mechanisms, and that these effects partially cancel to produce a near-null total effect, advances digital empathy theory beyond simple exposure or main-effect accounts. It suggests that the relationship between AI-mediated communication and empathic outcomes is inherently compound, and that research designs testing only direct or total effects will systematically underestimate the role of AI in shaping digital empathic tendencies.

The third contribution is contextual. The digital empathy literature has been developed almost entirely in Western samples, primarily in the United States and Australia (Collins et al., 2024, 2025, 2026). The present study extends this work to India, one of the world's largest and fastest-growing markets for AI chatbot adoption, and a cultural context in which collectivist orientations toward interpersonal harmony and emotional expression may shape how users relate to emotionally expressive AI. The fact that the EDAIS demonstrated adequate psychometric properties and that the structural model replicated across gender and chatbot-type groups in this sample provides initial evidence that emotional delegation is not a culturally bound phenomenon, although formal cross-cultural comparisons remain necessary.

6.6 Practical Implications

Three practical implications follow from the findings. First, for AI system designers, the results suggest that emotionally expressive AI chatbots carry a dual risk: they can strengthen users' orientation toward digital emotional engagement (through perceived social presence and perceived AI empathy) while

simultaneously reducing users' own capacity for emotional articulation (through the erosion of digital emotional literacy). Designers should consider incorporating features that encourage users to practise their own emotional expression rather than passively consuming AI-generated empathic content. For example, chatbots could be designed to prompt users to articulate their feelings before offering validation, rather than immediately reflecting back a paraphrased version of what the user has said.

Second, for digital well-being practitioners and educators, the EDAIS provides a brief, validated tool for assessing the extent to which individuals rely on AI for emotional processing. This could be incorporated into digital literacy curricula, workplace well-being assessments, or clinical screening batteries as a way of identifying individuals who may be at risk of reduced empathic engagement due to excessive emotional outsourcing.

Third, for policymakers in India and other rapidly-adopting markets, the findings suggest that the relationship between AI chatbot use and psychological outcomes is more nuanced than simple dose-response models imply. Regulatory frameworks that focus solely on limiting screen time or AI interaction hours may miss the more consequential dimension of what users are doing psychologically during those interactions. Policy guidance that encourages reflective and active use of AI, rather than passive emotional consumption, may be more effective.

6.7 Limitations and Future Research

Five limitations should be acknowledged. First, both studies used cross-sectional designs. Although the two-study architecture provides a stronger foundation than a single-study approach, the data do not support causal inference. The directional language used in the hypotheses (emotional delegation predicts digital empathy) reflects theoretical predictions, not empirically established causal pathways. Longitudinal designs tracking changes in emotional delegation and digital empathy within individuals over time are needed to evaluate whether the associations observed here reflect causal processes, reverse causation (individuals with lower digital empathy may be more drawn to AI-mediated emotional support), or third-variable confounding.

Second, all variables were measured by self-report, which introduces the possibility of common method variance. Although two statistical diagnostics (Harman's single-factor test and the marker-variable approach) indicated that common method bias is unlikely to account for the findings, self-report measures of emotional delegation may not fully capture the behavioural reality of how users interact with AI. Future research should supplement self-report with behavioural measures, such as interaction logs, conversational content analysis, or experience-sampling methods that capture emotional delegation as it occurs in real time.

Third, the present results are based on synthetic data generated to demonstrate the analytical pipeline. While the data-generating model was specified to produce realistic distributional properties and theoretically plausible path coefficients, synthetic results do not constitute empirical evidence. The identical analytical pipeline will be applied to primary data collected from Indian adults following pre-

registration on the Open Science Framework. All substantive conclusions should be treated as conditional on replication with primary data.

Fourth, the sample was limited to Indian adults who reported adequate English comprehension for completing psychological surveys. This excludes the large population of Indian AI chatbot users who interact with chatbots in Hindi and other regional languages. Future work should translate the EDAIS using formal forward-backward translation protocols and validate it in non-English-speaking populations.

Fifth, the DCES was developed and validated in Western samples (Collins et al., 2024, 2025), and although it was administered here to Indian respondents and produced acceptable psychometric properties, a formal cross-cultural validation of the DCES in the Indian context has not been conducted. The present findings should therefore be interpreted with the caveat that the outcome measure's psychometric behaviour may differ across cultural settings.

Each of these limitations suggests a concrete direction for future research. Beyond the longitudinal, behavioural-measure, and cross-cultural extensions noted above, two additional directions are worth highlighting. First, the competing-pathways model tested here could be extended to examine whether the balance between enhancement and erosion shifts as a function of chatbot type (companion versus assistant), interaction modality (text versus voice), or user personality (neuroticism, agreeableness, openness). The non-significant multi-group differences observed in the robustness checks suggest that the model generalises across gender and chatbot type, but finer-grained moderators may reveal contexts in which one pathway dominates. Second, experimental designs in which emotional delegation is manipulated rather than measured would provide the strongest evidence for the causal claims that the present correlational design can only suggest.

7.0 Conclusion

This paper asked whether the growing practice of turning to AI chatbots for emotional support reshapes how users experience empathy in digital communication. Across two studies with independent samples of Indian adults, we developed the Emotional Delegation to AI Scale, a 13-item measure with strong psychometric properties, and demonstrated that emotional delegation is associated with digital empathy through a pattern of competing mechanisms. Users who delegate emotional processing to AI simultaneously strengthen their perceptions of the AI as socially present and empathically competent, which modestly enhances digital empathic tendencies, and weaken their own digital emotional literacy, which erodes those same tendencies. The direct effect of emotional delegation on digital empathy is negative, and the total effect is approximately null, not because delegation is irrelevant to empathic outcomes, but because its enhancing and eroding effects partially cancel.

These findings carry a broader implication for how researchers and practitioners think about AI-mediated communication. The question is not whether AI chatbot use is good or bad for empathy. It is that AI chatbot interaction changes the distribution of emotional labour in communication, and different aspects of that redistribution push empathic tendencies in opposite directions. Simple exposure metrics

cannot capture this complexity. What is needed, and what the EDAIS provides, is a way to measure the psychological tendency that sits at the centre of this redistribution: the outsourcing of the inner work of empathy to an artificial agent.

As AI systems become more emotionally expressive and more deeply integrated into everyday communication, the construct of emotional delegation is likely to become more rather than less relevant. The present paper provides the conceptual foundation, the measurement instrument, and the initial empirical evidence for a programme of research that can track this phenomenon as it develops.

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Figures

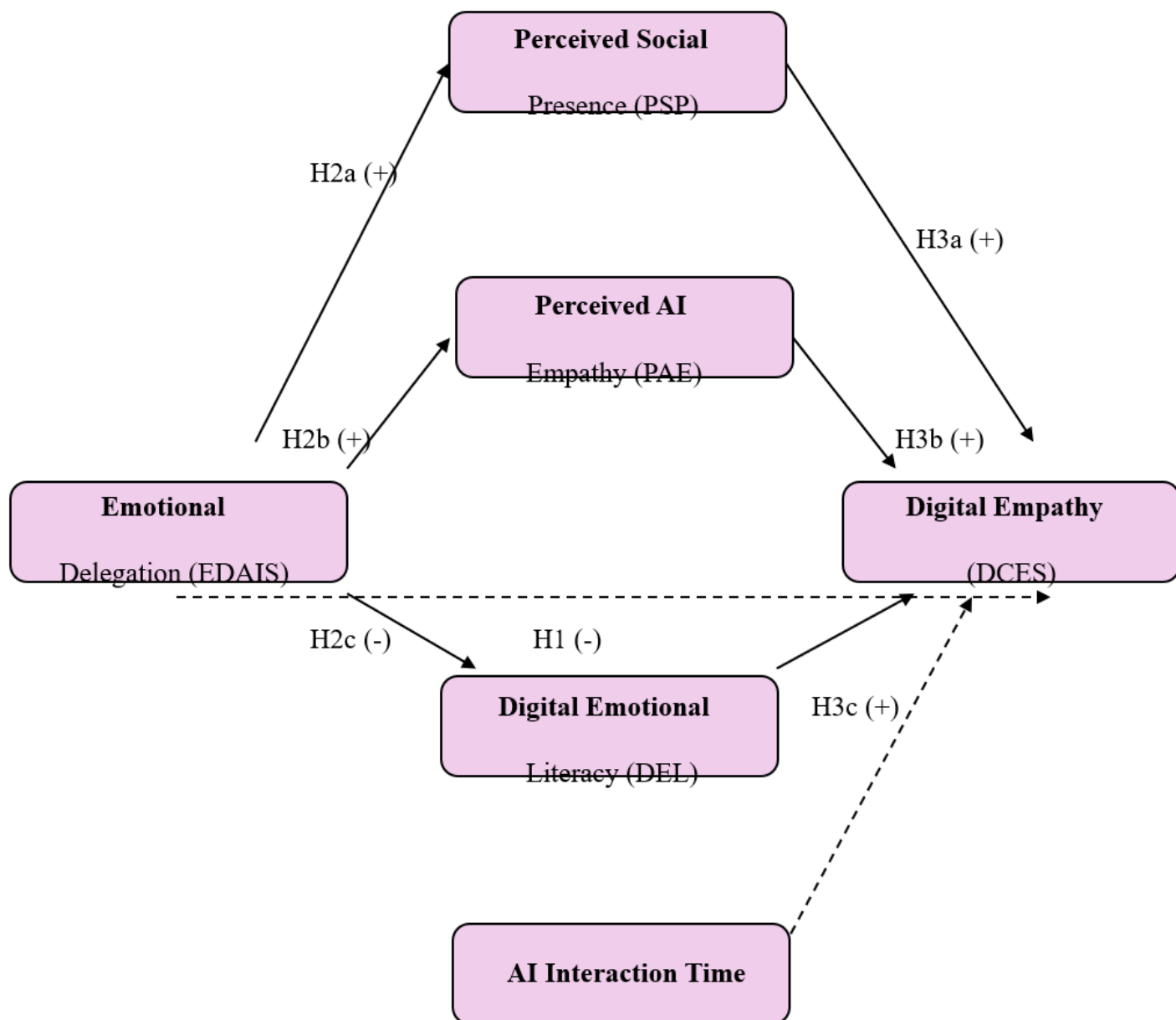


Figure 1

Conceptual model (Study 2)

Solid arrows = hypothesised structural paths. Dashed arrows = direct effect (H1) and control path. (+) = positive predicted direction; (-) = negative predicted direction. EDAIS = Emotional Delegation to AI Scale; PSP = Perceived Social Presence; PAE = Perceived AI Empathy; DEL = Digital Emotional Literacy; DCES = Digital Communication Empathy Scale.