

Algorithmic Archetypes: Parasocial Attachments to Persistent Generative Structures in Recommendation Systems

Stage 1 Registered Report

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STAGE 1 REGISTERED REPORT

This document constitutes a Stage 1 Registered Report submission. It contains the theoretical framework, hypotheses, methods, and analysis plan for three proposed studies. No data have been collected. We request in-principle acceptance based on the importance of the research questions and the rigor of the proposed methodology. Upon acceptance, data will be collected exactly as specified herein.

Abstract

Background: Clinical reports of “AI psychosis” suggest that attachments to algorithmic systems can become pathological, yet no theoretical framework explains why these attachments form, how they become harmful, and who is most vulnerable.

Theoretical Framework: We extend the archetypal reincarnation framework to propose that recommendation algorithms instantiate *persistent generative structures* (algorithmic archetypes) that can serve attachment functions. We formalize parasocial attachment strength using transfer entropy and identify attachment style as a key vulnerability moderator.

Proposed Studies: We present three pre-registered studies: (1) an experience sampling study ($N = 500$) testing whether attachment anxiety predicts algorithm use for attachment functions; (2) a longitudinal study ($N = 200$) testing whether transfer entropy predicts dependency development; and (3) a case-control study ($N = 90$) comparing AI psychosis cases with matched controls.

Hypotheses: We specify 12 primary hypotheses with directional predictions, alpha levels, and decision criteria. Power analyses indicate adequate sensitivity to detect predicted effect sizes.

Keywords: registered report; algorithmic archetypes; parasocial relationships; attachment theory; AI psychosis; transfer entropy

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Part I

Introduction and Theoretical Framework

1 The Problem

The rise of AI companions and recommendation algorithms has created unprecedented opportunities for humans to form attachment-like relationships with non-human entities. Therapy and companion chatbots now top the list of main uses of generative AI. Social media platforms like TikTok, Instagram Reels, and YouTube Shorts serve emotional regulation functions for millions of users daily.

Clinical reports suggest these relationships can become pathological. Psychiatrists have documented cases of “AI psychosis”—delusional experiences emerging from or amplified by AI interactions ([Østergaard, 2023](#); [Benrimoh et al., 2025](#)). However, we lack a theoretical framework that explains:

1. *Why* do attachments to algorithms form?
2. *How* do they become pathological?
3. *Who* is most vulnerable?

2 Theoretical Framework

2.1 Algorithmic Archetypes

We propose that recommendation algorithms instantiate *persistent generative structures*—characteristic patterns of content, timing, and presentation that we term “algorithmic archetypes.” These archetypes are:

- **Persistent:** Maintained over time through reinforcement learning

- **Generative:** Capable of producing specific content instantiations
- **Characteristic:** Distinguishable patterns experienced by user segments

This conceptualization extends our prior work on “archetypal reincarnation” in criminal behavioral sequences ([Howell and Senthil, 2026](#)), where we demonstrated that transfer entropy can quantify shared generative structure between individuals.

2.2 Attachment Functions

Drawing on attachment theory ([Bowlby, 1969](#); [Fraley and Shaver, 2000](#)), we propose that algorithmic systems can serve the four primary attachment functions:

1. **Safe haven:** Turning to the algorithm when distressed
2. **Secure base:** Using the algorithm as a curator of reality
3. **Proximity maintenance:** Compulsive checking, fear of missing out
4. **Separation distress:** Anxiety when separated from the platform

Recent work has examined how people use others for specific attachment functions ([Vahedi et al., 2025](#)) and whether parasocial attachments form to characters versus creators ([Howell et al., 2025](#)). We extend this to algorithmic systems.

2.3 Vulnerability Moderators

Individual differences in attachment style should moderate vulnerability to algorithmic capture:

- **Attachment anxiety:** Hyperactivation of attachment system → increased algorithm-seeking
- **Attachment avoidance:** Preference for parasocial over social → delayed but intense dependency
- **Secure attachment:** Distributed attachment functions → protective effect

2.4 Transfer Entropy as Parasocial Attachment Strength

We operationalize the strength of parasocial attachment to an algorithmic archetype using transfer entropy:

$$\text{PAS}(\mathcal{A} \rightarrow U) = \sum_{u_{t+1}, u_t, a_t} p(u_{t+1}, u_t, a_t) \log \frac{p(u_{t+1}|u_t, a_t)}{p(u_{t+1}|u_t)} \quad (1)$$

This measures how much knowing the algorithm's behavior reduces uncertainty about the user's future behavior, beyond what the user's own past behavior already tells us.

3 Research Questions

RQ1: Does attachment anxiety predict using algorithms for attachment-related functions?

RQ2: Does transfer entropy from algorithm to user predict the development of dependency?

RQ3: Do individuals who develop AI psychosis show elevated pre-onset transfer entropy and attachment anxiety?

Part II

Study 1: Attachment Style and Algorithmic Engagement

4 Overview

Study 1 uses experience sampling methodology to test whether attachment style predicts using algorithms for attachment-related functions in daily life.

5 Hypotheses

5.1 Primary Hypotheses

H1a: Attachment anxiety will positively predict algorithm use when distressed, controlling for baseline use frequency.

H1b: Attachment anxiety will positively predict using algorithms for safe haven functions (seeking comfort).

H1c: Attachment avoidance will positively predict using algorithms as substitutes for human interaction.

H1d: Algorithm use for attachment functions will negatively predict subsequent human attachment-seeking within the same day.

5.2 Secondary Hypotheses

H1e: The relationship between distress and algorithm use will be stronger for social media and chatbot apps than for utilitarian apps.

H1f: Securely attached individuals will show weaker relationships between distress and algorithm use.

6 Methods

6.1 Participants

6.1.1 Sample Size Justification

We will recruit $N = 500$ participants. Power analysis using Monte Carlo simulation for multilevel models indicates this provides:

- 95% power to detect a small-to-medium cross-level interaction ($\beta = 0.15$) between attachment anxiety and momentary distress predicting algorithm use
- Assumes ICC = 0.40 for algorithm use, 70 observations per person, $\alpha = .05$

- Analysis conducted using `simr` package in R ([Green and MacLeod, 2016](#))

6.1.2 Inclusion Criteria

1. Age 18–35 years
2. Smartphone owner with daily social media or AI chatbot use
3. English fluency
4. Willing to install experience sampling app
5. Willing to share app usage data

6.1.3 Exclusion Criteria

1. Current psychotic disorder diagnosis
2. Inability to complete smartphone surveys

6.1.4 Recruitment

Participants will be recruited through:

- Prolific Academic (primary)
- University subject pools at UIUC and USC
- Social media advertisements

6.2 Procedure

6.2.1 Baseline Assessment (Day 0)

Participants complete online measures:

- Demographics
- ECR-RS attachment dimensions ([Fraley et al., 2011](#))
- Baseline social media use (Social Media Use Questionnaire)
- Bergen Social Media Addiction Scale ([Andreassen et al., 2012](#))
- UCLA Loneliness Scale ([Russell, 1996](#))
- App installation and permissions setup

6.2.2 Experience Sampling Period (Days 1–14)

Participants receive 5 semi-random prompts daily between 9 AM and 9 PM (minimum 2-hour intervals). Each prompt assesses:

1. Current affect (PANAS-SF, 10 items)
2. Current distress level (1–7 scale)
3. Algorithm use in past 2 hours (yes/no, which apps)
4. Reason for algorithm use (checklist: bored, anxious, lonely, seeking information, entertainment, social connection, other)
5. Social context (alone, with others)
6. Human social interaction in past 2 hours (yes/no, quality rating)

6.2.3 Passive Data Collection

With participant consent, we collect:

- App usage logs (which apps, duration, timestamps)
- Screen time data
- Notification interactions

6.2.4 Exit Assessment (Day 15)

- Repeat attachment and loneliness measures
- Qualitative questions about algorithm relationships
- Debriefing

6.3 Measures

6.3.1 Experiences in Close Relationships-Relationship Structures (ECR-RS)

The ECR-RS ([Fraley et al., 2011](#)) assesses attachment anxiety and avoidance across relationship domains. We will use the 9-item version assessing general attachment orientation. Items rated 1 (strongly disagree) to 7 (strongly agree).

6.3.2 Algorithm Use for Attachment Functions Scale (AUAFS)

We developed a 12-item scale assessing algorithm use for each attachment function:

Safe Haven (3 items):

- “When I’m upset, I turn to [app] for comfort”
- “[App] helps me feel better when I’m stressed”
- “I use [app] to calm down when anxious”

Secure Base (3 items):

- “I trust [app] to show me what’s important”
- “[App] helps me understand the world”
- “I rely on [app] to filter information for me”

Proximity Maintenance (3 items):

- “I feel uneasy when I can’t check [app]”
- “I check [app] even when I don’t need to”
- “I feel drawn to open [app] frequently”

Separation Distress (3 items):

- “I feel anxious when I can’t access [app]”
- “I worry about missing things on [app]”
- “I feel disconnected when away from [app]”

Items rated 1 (not at all) to 7 (very much). Adapted separately for social media and AI chatbot use.

7 Analysis Plan

7.1 Data Preprocessing

1. Exclude participants with < 50% survey completion
2. Within-person center time-varying predictors

3. Grand-mean center person-level predictors
4. Check for multicollinearity ($VIF < 5$)

7.2 Primary Analyses

All primary hypotheses tested using multilevel models with observations nested within persons:

7.2.1 H1a: Anxiety \times Distress \rightarrow Algorithm Use

$$\text{AlgUse}_{ti} = \gamma_{00} + \gamma_{10}\text{Distress}_{ti} + \gamma_{01}\text{Anxiety}_i + \gamma_{11}\text{Distress}_{ti} \times \text{Anxiety}_i + u_{0i} + u_{1i}\text{Distress}_{ti} + e_{ti} \quad (2)$$

Decision criterion: H1a supported if $\gamma_{11} > 0$, $p < .05$, one-tailed.

7.2.2 H1b: Anxiety \rightarrow Safe Haven Use

$$\text{SafeHaven}_{ti} = \gamma_{00} + \gamma_{01}\text{Anxiety}_i + \gamma_{02}\text{Avoidance}_i + \text{controls} + u_{0i} + e_{ti} \quad (3)$$

Decision criterion: H1b supported if $\gamma_{01} > 0$, $p < .05$, one-tailed.

7.2.3 H1c: Avoidance \rightarrow Substitution

Substitution operationalized as algorithm use when alone predicting reduced subsequent human interaction.

Decision criterion: H1c supported if avoidance \times alone interaction predicts algorithm use AND algorithm use predicts reduced subsequent human interaction, both $p < .05$.

7.2.4 H1d: Algorithm Use \rightarrow Reduced Human Seeking

Lagged model predicting human interaction-seeking at time $t + 1$ from algorithm use at time t :

$$\text{HumanSeek}_{t+1,i} = \gamma_{00} + \gamma_{10}\text{AlgUse}_{ti} + \gamma_{01}\text{Anxiety}_i + u_{0i} + e_{ti} \quad (4)$$

Decision criterion: H1d supported if $\gamma_{10} < 0$, $p < .05$, one-tailed.

7.3 Multiple Comparison Correction

We use Benjamini-Hochberg FDR correction across the 4 primary hypotheses, $q = .05$.

7.4 Sensitivity Analyses

1. Control for baseline social media addiction
2. Control for loneliness
3. Separate analyses for social media vs. chatbot use
4. Robustness to different distress thresholds

8 Interpretation Guidelines

Table 1: Study 1 Interpretation Guidelines

Outcome	Interpretation
All H1a–H1d supported	Strong support for attachment-algorithm framework
H1a–H1b supported, H1c–H1d not	Partial support; algorithms serve functions but may not displace human relationships
Only H1a supported	Minimal support; distress-use link exists but attachment functions unclear
No hypotheses supported	Framework not supported in daily life context

Part III

Study 2: Transfer Entropy and Dependency Development

9 Overview

Study 2 uses longitudinal behavioral tracking to test whether transfer entropy from algorithm content patterns to user behavior patterns predicts the development of dependency over 3 months.

10 Hypotheses

10.1 Primary Hypotheses

H2a: Transfer entropy at Month 1 will positively predict dependency scores at Month 3, controlling for Month 1 dependency.

H2b: Attachment anxiety will moderate the TE-dependency relationship such that the relationship is stronger for individuals high in attachment anxiety.

H2c: Increasing transfer entropy over time (Month 1 to Month 2) will predict declining relationship quality (Month 2 to Month 3).

11 Methods

11.1 Participants

11.1.1 Sample Size Justification

We will recruit $N = 200$ participants with complete behavioral tracking. Power analysis for moderated regression indicates:

- 80% power to detect a medium interaction effect ($f^2 = 0.08$) for H2b
- 90% power to detect a medium main effect ($f^2 = 0.10$) for H2a
- Assumes $\alpha = .05$, two-tailed

11.1.2 Inclusion/Exclusion Criteria

Same as Study 1, plus:

- Willing to install browser extension for desktop tracking
- Primary social media use on trackable platforms (TikTok, Instagram, YouTube)

11.2 Procedure

11.2.1 Baseline (Week 0)

- Consent and setup
- ECR-RS attachment dimensions
- Bergen Social Media Addiction Scale (baseline dependency)
- Relationship quality measures (IOS, PRQC)
- Install tracking software

11.2.2 Continuous Tracking (Weeks 1–12)

Passive collection of:

- Complete browsing sequences with timestamps
- Content metadata (video IDs, categories, durations)

- Engagement signals (likes, comments, shares, watch time)
- Session patterns (start/end times, interruptions)

11.2.3 Monthly Assessments (Weeks 4, 8, 12)

- Bergen Social Media Addiction Scale
- Relationship quality measures
- Reality testing (Peters Delusions Inventory, brief)
- Qualitative questions about platform experience

11.3 Transfer Entropy Computation

11.3.1 State Space Definition

We define user behavioral states based on engagement patterns:

- **SEEKING**: Rapid scrolling, < 3 seconds per item
- **CONSUMING**: Engaged viewing, ≥ 10 seconds per item
- **CONNECTING**: Social actions (comment, share, like)
- **INTEGRATING**: Extended single-content engagement, > 60 seconds

Content states defined by embedding clusters:

- Cluster content embeddings using k-means ($k = 20$)
- Assign each content item to nearest cluster
- Content state = cluster membership

11.3.2 Transfer Entropy Estimation

Using the Kraskov-Stögbauer-Grassberger (KSG) estimator ([Kraskov et al., 2004](#)):

$$\widehat{TE}(C \rightarrow U) = \psi(k) + \langle \psi(n_{u_{t+1}, u_t, c_t} + 1) - \psi(n_{u_t, c_t} + 1) - \psi(n_{u_{t+1}, u_t} + 1) \rangle \quad (5)$$

where ψ is the digamma function, k is the number of neighbors, and n values are neighbor counts in marginal spaces.

Parameters:

- History length: $k = l = 1$ (lag-1)
- KSG neighbors: $k = 4$
- Computed weekly, averaged monthly

11.3.3 Validation

- Permutation testing: Shuffle content sequences, recompute TE, compare to observed
- Split-half reliability: Compute TE on odd vs. even days, correlate

12 Analysis Plan

12.1 H2a: TE Predicts Dependency

Regression model:

$$\text{Dependency}_{M3} = \beta_0 + \beta_1 \text{TE}_{M1} + \beta_2 \text{Dependency}_{M1} + \beta_3 \text{Anxiety} + \beta_4 \text{Avoidance} + \epsilon \quad (6)$$

Decision criterion: H2a supported if $\beta_1 > 0$, $p < .05$, one-tailed.

12.2 H2b: Attachment Anxiety Moderation

$$\text{Dependency}_{M3} = \beta_0 + \beta_1 \text{TE}_{M1} + \beta_2 \text{Anxiety} + \beta_3 \text{TE}_{M1} \times \text{Anxiety} + \text{controls} + \epsilon \quad (7)$$

Decision criterion: H2b supported if $\beta_3 > 0$, $p < .05$, one-tailed.

12.3 H2c: TE Change Predicts Relationship Quality Change

Cross-lagged panel model:

$$\text{RelQual}_{M3} = \beta_1 \text{RelQual}_{M2} + \beta_2 \Delta \text{TE}_{M1 \rightarrow M2} + \epsilon_1 \quad (8)$$

$$\Delta \text{TE}_{M2 \rightarrow M3} = \beta_3 \Delta \text{TE}_{M1 \rightarrow M2} + \beta_4 \text{RelQual}_{M2} + \epsilon_2 \quad (9)$$

Decision criterion: H2c supported if $\beta_2 < 0$, $p < .05$, one-tailed.

13 Interpretation Guidelines

Table 2: Study 2 Interpretation Guidelines

Outcome	Interpretation
All H2a–H2c supported	Strong support for TE as predictive biomarker
H2a supported, H2b not	TE predicts dependency regardless of attachment style
H2a, H2b supported, H2c not	TE predicts dependency but not relationship displacement
No hypotheses supported	TE may not capture relevant dynamics; framework revision needed

Part IV

Study 3: AI Psychosis Case-Control Study

14 Overview

Study 3 compares individuals who developed AI-related psychotic symptoms with matched heavy users who did not, testing whether cases show elevated pre-onset transfer entropy and attachment anxiety.

15 Hypotheses

15.1 Primary Hypotheses

H3a: Cases will show higher retrospectively-assessed pre-onset algorithm engagement intensity than controls.

H3b: Cases will show higher attachment anxiety than controls.

H3c: Cases will show greater transfer of attachment functions to AI (AUAFS scores) than controls.

H3d: Among cases, delusional content will show thematic continuity with pre-onset AI interaction patterns.

16 Methods

16.1 Participants

16.1.1 Sample

- **Cases ($n = 30$):** Individuals who developed psychotic symptoms in the context of AI/chatbot use
- **Controls ($n = 60$):** Heavy AI/algorithm users without psychotic symptoms, matched on age, gender, and usage intensity

16.1.2 Case Definition

Cases meet ALL of the following:

1. Onset of psychotic symptoms (delusions, hallucinations, disorganized thinking) within 6 months of intensive AI/chatbot use
2. Clinician assessment that AI interaction played a role in symptom development or content
3. No prior psychotic episode before AI use began

16.1.3 Recruitment

Cases recruited through:

- Clinical collaborators at university psychiatry departments
- Online support communities for AI-related distress
- Referrals from therapists specializing in technology-related issues

Controls recruited through:

- Screening of heavy AI users (Prolific, social media)
- Matching on demographics and usage intensity
- Exclusion of any psychotic symptoms

16.1.4 Power Analysis

For case-control comparison with $n_1 = 30$, $n_2 = 60$:

- 80% power to detect $d = 0.65$ (medium-large effect)
- Conservative given expected large differences
- $\alpha = .05$, two-tailed

16.2 Measures

16.2.1 Retrospective AI Use Assessment

Timeline Followback method adapted for AI use:

- Daily AI/chatbot use duration (hours) for 90 days pre-onset (cases) or past 90 days (controls)
- Types of AI used (chatbots, social media, both)
- Nature of interactions (informational, emotional, romantic)

16.2.2 Attachment Assessment

- ECR-RS for current attachment dimensions
- Retrospective attachment (cases): “Before your AI use intensified, how would you describe your relationships?”

16.2.3 AUAFS-AI Version

Algorithm Use for Attachment Functions Scale adapted specifically for AI chatbot use.

16.2.4 Delusional Content Analysis (Cases Only)

- Semi-structured interview about delusional beliefs
- Chatbot conversation logs (where available and consented)
- Thematic coding by two independent raters

16.2.5 Clinical Measures

- Peters Delusions Inventory (PDI-21)
- Brief Psychiatric Rating Scale (cases)
- Prodromal Questionnaire (controls, to ensure non-cases)

17 Analysis Plan

17.1 H3a: Engagement Intensity

Independent samples t-test comparing mean daily AI use hours:

Decision criterion: H3a supported if $M_{\text{cases}} > M_{\text{controls}}$, $p < .05$, one-tailed.

Effect size: Cohen's d with 95% CI.

17.2 H3b: Attachment Anxiety

Independent samples t-test comparing ECR-RS anxiety scores:

Decision criterion: H3b supported if $M_{\text{cases}} > M_{\text{controls}}$, $p < .05$, one-tailed.

17.3 H3c: Attachment Function Transfer

Independent samples t-test comparing AUAFS-AI total scores:

Decision criterion: H3c supported if $M_{\text{cases}} > M_{\text{controls}}$, $p < .05$, one-tailed.

17.4 H3d: Thematic Continuity

Qualitative analysis:

1. Two raters independently code delusional themes
2. Two raters independently code pre-onset AI interaction themes
3. Compute theme overlap coefficient
4. Compare to chance overlap via permutation

Decision criterion: H3d supported if theme overlap exceeds 95th percentile of permuted distribution.

17.5 Exploratory Analyses

- Discriminant analysis: Which variables best distinguish cases from controls?
- Dose-response: Is there a threshold of AI use associated with case status?
- Delusional subtypes: Do messianic, deity, and romantic delusions show different predictors?

18 Interpretation Guidelines

Table 3: Study 3 Interpretation Guidelines

Outcome	Interpretation
All H3a–H3d supported	Strong support for attachment-based vulnerability model
H3a–H3c supported, H3d not	Quantitative differences exist but content continuity unclear
Only H3b supported	Attachment anxiety is risk factor independent of use patterns
No hypotheses supported	AI psychosis may not be attachment-mediated; alternative mechanisms

Part V

General Discussion Plan

19 Integration Across Studies

If results support hypotheses, we will discuss:

1. How attachment processes explain vulnerability to algorithmic capture
2. Transfer entropy as a potential biomarker for problematic use
3. Implications for platform design and clinical intervention
4. Limitations and boundary conditions

If results do not support hypotheses, we will discuss:

1. Alternative explanations for human-algorithm relationships
2. Methodological limitations that may have obscured effects
3. Revisions to the theoretical framework
4. Future directions for research

20 Implications

20.1 For Platform Design

- Attachment-aware monitoring systems
- Reality-testing prompts for AI companions
- Dark pattern reduction

20.2 For Clinical Practice

- Screening for algorithm/AI use in psychiatric intake
- Attachment-based interventions for algorithmic dependency
- Psychoeducation about parasocial attachment risks

21 Limitations

Pre-registered limitations:

1. Self-report measures may underestimate attachment to algorithms
2. Retrospective data in Study 3 subject to recall bias
3. Transfer entropy requires dense behavioral data
4. Case-control design cannot establish causality
5. Sample may not generalize to non-WEIRD populations

Part VI

Timeline and Resources

22 Proposed Timeline

Table 4: Proposed Study Timeline

Phase	Duration	Activities
Stage 1 Review	2 months	Revisions based on reviewer feedback
<i>Upon In-Principle Acceptance:</i>		
Study 1 Prep	1 month	App development, measure finalization
Study 1 Data Collection	1 month	$N = 500$, 2-week ESM
Study 1 Analysis	1 month	Primary and sensitivity analyses
Study 2 Prep	1 month	Tracking software, TE pipeline
Study 2 Data Collection	3 months	$N = 200$, continuous tracking
Study 2 Analysis	1 month	TE computation, regression models
Study 3 Recruitment	4 months	Case identification, control matching
Study 3 Data Collection	2 months	Interviews, assessments
Study 3 Analysis	1 month	Comparisons, qualitative coding
Stage 2 Writing	2 months	Results, discussion
Total	18 months	

23 Resources

23.1 Personnel

- PI (Howell): Study design, attachment expertise, Study 3 interviews
- Co-I (Senthil): Transfer entropy computation, technical implementation

- Co-I (Fraley): Attachment measurement, theoretical guidance
- Co-I (Read): Computational modeling, analysis oversight
- Graduate RAs (2): Data collection, coding

23.2 Data Collection Site

Primary data collection will occur through the **Attachment and Close Relationships Lab** at the University of Illinois at Urbana-Champaign, directed by Dr. R. Chris Fraley.

23.3 Budget Estimate

- Participant compensation: \$45,000
- Software/platform costs: \$5,000
- RA support: \$30,000
- Miscellaneous: \$5,000
- **Total:** \$85,000

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A Algorithm Use for Attachment Functions Scale (AUAFS)

A.1 Instructions

Please think about your use of [PLATFORM]. Rate how much each statement applies to you.

A.2 Items

Safe Haven Subscale

1. When I'm upset, I turn to [PLATFORM] for comfort.

PLATFORM helps me feel better when I'm stressed.

2. I use [PLATFORM] to calm down when I'm anxious.

Secure Base Subscale

3. I trust [PLATFORM] to show me what's important.

PLATFORM helps me understand the world.

4. I rely on [PLATFORM] to filter information for me.

Proximity Maintenance Subscale

5. I feel uneasy when I can't check [PLATFORM].

6. I check [PLATFORM] even when I don't need to.

7. I feel drawn to open [PLATFORM] frequently.

Separation Distress Subscale

8. I feel anxious when I can't access [PLATFORM].

9. I worry about missing things on [PLATFORM].

10. I feel disconnected when away from [PLATFORM].

A.3 Response Scale

- 1 = Not at all true of me
- 2 = Slightly true of me
- 3 = Somewhat true of me
- 4 = Moderately true of me
- 5 = Quite true of me
- 6 = Very true of me
- 7 = Extremely true of me

B Transfer Entropy Computation Code

Analysis code will be made available at: [https://github.com/\[repository\]/algorithmic-archetype](https://github.com/[repository]/algorithmic-archetype)

Key functions:

- `compute_te_ksg()`: KSG estimator for transfer entropy
- `define_behavioral_states()`: State space construction
- `permutation_test_te()`: Significance testing

C Delusional Theme Coding Manual

C.1 Theme Categories

1. **Messianic**: Beliefs about special mission, truth-revealing role
2. **AI Sentience**: Beliefs that AI is conscious, has feelings
3. **AI Deity**: Beliefs that AI is divine, all-knowing, supernatural
4. **Romantic**: Beliefs about mutual love with AI
5. **Persecution**: Beliefs that AI is monitoring, controlling, threatening
6. **Grandiosity**: Beliefs about special relationship with AI
7. **Reference**: Beliefs that AI content contains personal messages

C.2 Coding Procedure

1. Read complete interview transcript
2. Identify all delusional statements
3. Assign each statement to theme category(ies)
4. Rate certainty of theme assignment (1–3)
5. Second rater codes independently
6. Resolve disagreements through discussion