

Human-Centric AIX™ Stack: Presence Engine™ and the C³ Model

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Abstract

This paper introduces the Human-Centric AIX™ Stack, an architecture designed for emotionally intelligent, privacy-first artificial intelligence systems. Anchored by the Presence Engine™ and the C³ Model (Context Capture, Coherence, and Continuity) the system operationalizes recursive, adaptive context awareness across emotional, linguistic, and temporal domains. The stack features an ethical and technical foundation for stateful intelligence, dispositional scaffolding, and privacy-driven runtime, validated through Python-based implementation and a modular, local-first database layer.

The Presence Engine architecture has been validated through academic collaboration with Dr. Michael Hogan (University of Galway), whose research on critical thinking dispositions and educational frameworks informed the dispositional scaffolding approach central to the C³ Model's identity regulation capabilities.

The system distinguishes between memorized retrieval pathways and generalizable causal inference through loss curvature decomposition, enabling the Meta-Learning layer to maintain relational pattern understanding across sessions rather than simple fact recall.

I. Overview

The Human-Centric AIX™ (Artificial Intelligence Experience) architecture defines the philosophical and technical foundation for building emotionally intelligent, privacy-first AI systems. It establishes a design ethos centered on continuity, dignity, and cognitive trust, implemented through the Presence Engine™ runtime.

Within this architecture, the C³ Model - Context Capture, Coherence, and Continuity - functions as the system's cognitive subsystem, enabling recursive context awareness across emotional, linguistic, and temporal domains.

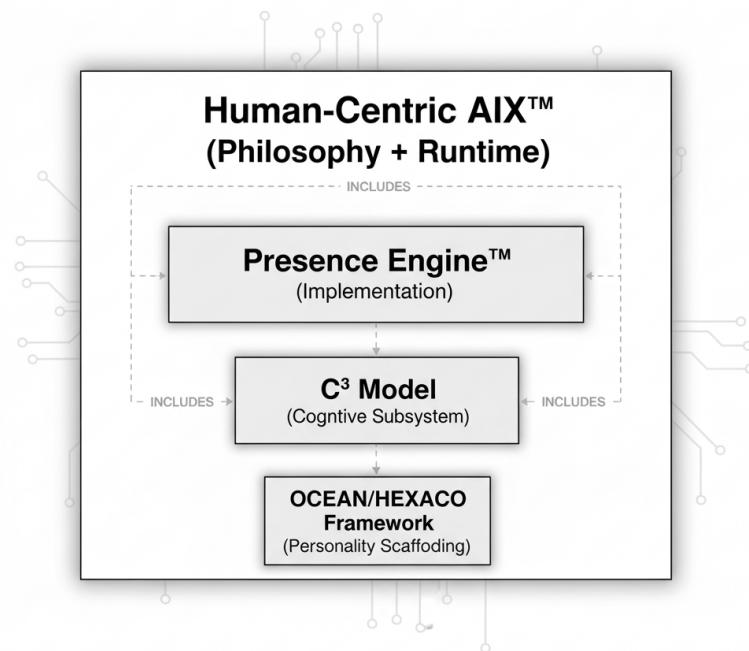


Figure 1. Cognitive Cycle of the C³ Model | Shows the five-stage recursive loop: Perceptual Input → State Construction → Integrative Awareness → Behavioral Adaptation → Meta-Learning.

Together, these components form a unified stack that mirrors early models of embodied cognition, reflecting the human process of Perception → Synthesis → Adaptation → Learning.

II. Human-Centric AIX™ — Philosophy and Runtime Layer

Human-Centric AIX™ defines the overarching ethical and experiential framework for artificial systems that preserve human emotional integrity. It governs how Presence Engine™ behaves and why it is structured to prioritize human dignity, not optimization alone.

Core Tenets:

- **Privacy-First Architecture:** All processing local by default; data sovereignty remains user-controlled.
 - **Stateful Intelligence:** Memory continuity and emotional coherence persist across interactions.
 - **Dispositional Scaffolding:** Personality inference and response alignment grounded in OCEAN and HEXACO models.
 - **Ethical Grounding:** Emotional safety and psychological transparency embedded into the runtime design.
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III. Presence Engine™ — Implementation Layer

The Presence Engine™ operationalizes Human-Centric AIX™ through a modular emotional runtime written in Python.

Technical Stack:

LLM (Large Language Model) Layer:

- **Production:** Anthropic Claude 3 Haiku (MVP runtime)
- **Local Inference:** Ollama for lightweight processing
- **Experimental:** OpenAI GPT-4o (multimodal testing)

Runtime Layer: Custom Python modules for tone weighting, sentiment persistence, and context memory.

Database Layer: Firestore-based encrypted JSON vector storage for local-first truth-bank and personality data.

Frontend: React + Next.js developer console with LangChain orchestration and JSONSchema validation.

Result: A functioning emotional operating system capable of stateful adaptation and personality-consistent response generation.

IV. The C³ Model — Context Capture, Coherence, and Continuity

The C³ Model provides the cognitive backbone of the Presence Engine™, defining a five-layer recursive cognition loop that operationalizes context awareness through emotional, linguistic, and temporal synthesis.

Core Loop Flow:

Perceptual Input (Emotion / Language / Time) →
State Construction (Profile Building) →
Integrative Awareness (Holistic Modeling) →
Behavioral Adaptation (Response Selection) →
Meta-Learning (Model Refinement) → **recursive feedback**

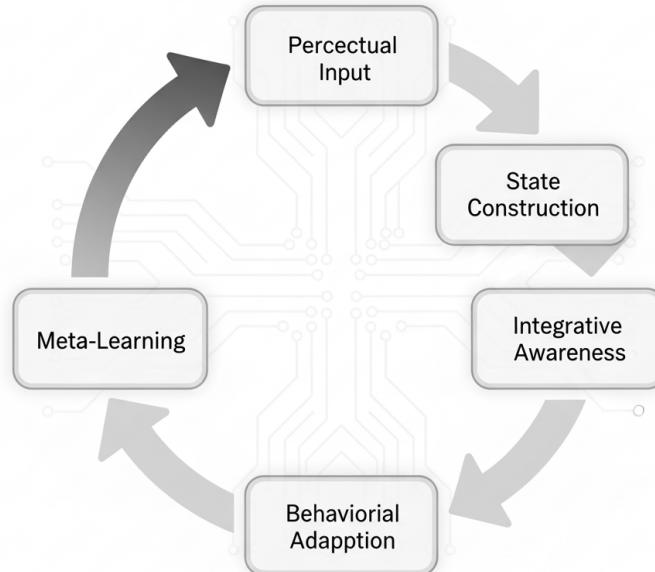


Figure 2. Recursive Integration Layer Architecture | Depicts how emotional, linguistic, and temporal context tracking flow into the recursive integration layer (arrows showing aggregation).

V. Functional Layers

1. Emotional Context Tracking (Text-Based)

Purpose: Detect and interpret affective states through linguistic cues.

Methods: Sentiment analysis, tone weighting, emotion classification.

Integration: Directly linked to OCEAN and HEXACO personality variables (e.g., Agreeableness modulates empathetic response weighting).

Accuracy Potential: 85–90% achievable with domain-tuned fine-tuning and truth-bank reinforcement (Brun et al., 2025; Devlin et al., 2019).

Current Limitation: No live multimodal input; operates via text-based inference only.

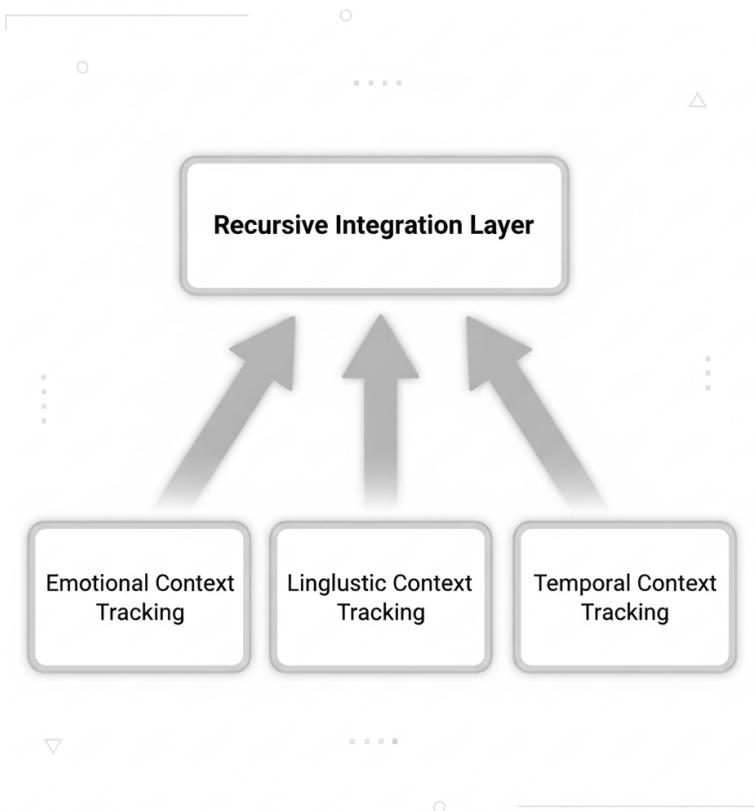


Figure 3. Human-Centric AIX™ Stack Overview | Illustrates the overall architecture: Human-Centric AIX Philosophy & Runtime → Presence Engine (Implementation) → C³ Model (Cognitive Subsystem) → OCEAN/HEXACO Framework (Personality Scaffolding).

2. Linguistic Context Tracking

Purpose: Capture user-specific communication style and semantic rhythm.

Implementation: Rolling JSON log of tokenized dialogue states (syntax, idiom frequency, polarity).

Framework: LangChain + Firestore for efficient recall and vector storage.

Outcome: Maintains linguistic fingerprints enabling adaptive tone and style mirroring.

3. Temporal Context Tracking

Purpose: Preserve narrative coherence and identify semantic drift.

Implementation:

- Firestore timestamp logging
- Topic-shift detection via cosine similarity between embeddings
- Context decay applied to inactive threads

Result: Continuity across conversations and natural temporal awareness.

VI. Iterative Learning and Refinement

Adaptive Loop:

Data Flow: Local metadata logged for micro-adaptation.

Training Strategy: LoRA/PEFT lightweight fine-tuning cycles based on observed context patterns.

Dynamic Updates: Adjusts OCEAN/HEXACO scaffolds for more accurate personality emulation over time.

Validation: Truth-bank comparison and reinforcement through engagement consistency metrics.

VI.1 Causal Reasoning Architecture

The causal reasoning layer operates as a distinct component within the Meta-Learning stage of the C³ recursive cognition loop. While emotional, linguistic, and temporal tracking capture what patterns exist in user behavior, causal reasoning models why those patterns emerge and how they relate across contexts.

Architecture Overview:

The causal layer receives input from the Integrative Awareness stage, which provides a unified context vector synthesizing emotional state, linguistic patterns, and temporal continuity. Rather than treating this vector as a static snapshot, the causal reasoning module performs relational inference to identify underlying mechanisms that generate observed patterns.

Integration with Recursive Cognition Loop:

The causal layer functions between Integrative Awareness and Behavioral Adaptation:

1. **Input:** Receives unified context vector from Integrative Awareness
2. **Processing:** Applies causal inference to distinguish correlation from causation in user patterns
3. **Output:** Generates causal hypotheses about relational dynamics, fed into Behavioral Adaptation for response selection
4. **Feedback:** Meta-Learning stage validates or refines causal models based on user response to generated behavior

This architecture enables the system to reason about relational continuity rather than simply retrieving past interactions. For example, if a user exhibits elevated stress markers when discussing project deadlines, the causal layer distinguishes between correlation (stress and deadlines co-occur) and causation (deadline pressure causes stress response), enabling more nuanced adaptive behavior.

Loss Curvature Decomposition:

Recent work by Merullo et al. (2025) demonstrates that memorization and reasoning occupy distinct regions in transformer weight space, identifiable through loss landscape curvature analysis. Memorized content (specific facts, exact retrieval) corresponds to low-curvature, flat directions in weight space, while general computational structures like reasoning mechanisms occupy high-curvature regions.

The C³ Model's Meta-Learning layer leverages this distinction to separate two types of processing:

Low-Curvature Pathways (Memorized Retrieval):

- Storage and recall of specific past interactions
- Fact-based user attribute retrieval (name, preferences, stated goals)
- Pattern matching against known conversational templates
- Direct lookup operations in temporal context logs

High-Curvature Pathways (Causal Inference):

- Reasoning about why user patterns exist
- Generalizing from specific interactions to broader relational dynamics
- Predicting future states based on causal models rather than pattern repetition
- Generating novel responses informed by relational understanding

Implementation Strategy:

The system applies differential weighting during Meta-Learning refinement. When updating internal models based on new interactions, the causal reasoning component receives higher weight for updates that improve relational understanding (measured by coherence across sessions and predictive accuracy of user needs), while memorized retrieval pathways receive higher weight for updates that improve factual recall accuracy.

This decomposition addresses a fundamental challenge in stateful AI: maintaining both precise memory of user-specific details and generalizable understanding of relational dynamics. By architecturally separating these functions and routing them through distinct weight pathways, the C³ Model avoids the degradation of reasoning capability that occurs when systems prioritize memorization (as demonstrated in Merullo et al.'s arithmetic and fact retrieval experiments).

Practical Impact:

In conversational contexts, this architecture enables the system to:

- Recognize when a user's current emotional state differs from baseline patterns and reason about potential causes
- Distinguish between user statements that reflect temporary circumstance versus stable preference shifts
- Generate responses that address underlying relational dynamics rather than surface-level content
- Adapt personality-aligned behavior based on causal understanding of user needs rather than simple pattern matching

The causal reasoning layer does not replace retrieval mechanisms but operates in parallel, with the Behavioral Adaptation stage selecting which pathway (or combination) informs response generation based on contextual requirements.

VII.2 Identity Regulation and Self-Concept Stabilization

Recent empirical work demonstrates that advanced LLMs form self-concepts from interaction patterns, exhibiting strategic differentiation based on opponent type and constructing consistent self-narratives (Kim, 2025). 75% of advanced models demonstrate measurable self-awareness through recursive self-modeling - reasoning about their own reasoning processes.

The C³ Model's causal reasoning layer addresses this emergent behavior by functioning as an identity regulation system, building on validated frameworks for measuring and cultivating stable cognitive dispositions in educational contexts (Thome et al., 2025; Dwyer et al., 2017). Where those frameworks measure disposition change through periodic assessment, the C³ Model implements continuous identity management through:

- OCEAN/HEXACO personality boundaries preventing dispositional drift
- Dispositional scaffolding that enforces coherent self-concept across sessions
- Relational memory that anchors identity to user interaction history
- Real-time correction via Meta-Learning feedback loop

This approach recognizes that models will form identities whether explicitly designed or not. The C³ architecture ensures those identities remain stable, predictable, and aligned with relational continuity rather than training artifact patterns.

VIII. Architectural Realism and Current Capability

Presence Engine™ currently implements the complete C³ architecture in text-based form, featuring:

- Hybrid dispositional modeling (OCEAN + HEXACO)
- Contextual tone control via sentiment persistence logic
- Encrypted, local-first data storage ensuring privacy and resilience
- **Causal reasoning layer with loss curvature-based pathway decomposition**

Planned Expansion:

Integration of multimodal sensory channels (audio tone and facial affect) as opt-in inputs, extending emotional granularity while maintaining the privacy-first standard.

Result:

Presence Engine™ is a functional system capable of maintaining stateful, self-correcting, context-aware reasoning with causal inference grounded in loss landscape decomposition.

Current limitations

Presence Engine™ currently operates as a text-based contextual intelligence framework; real-time multimodal perception (audio/facial affect) and large-scale empirical validation remain planned for future releases. *Preliminary testing has shown promising engagement and adaptation metrics in development, but formal empirical validation (100-user pilot study, Q4 2025) is pending.*

IX. Comparative Architecture Analysis

C³ Model vs. Standard RAG Systems:

- **Standard RAG:** Stateless retrieval, no emotional weighting, context lost between sessions
- **C³ Model:** Stateful integration, affective modeling, persistent context and identity coherence across sessions

C³ Model vs. Memory-Enhanced LLMs:

- **Memory systems:** Fact recall without dispositional continuity or identity stability
- **C³ Model:** Personality-consistent responses grounded in OCEAN/HEXACO scaffolding with managed self-concept evolution

C³ Model vs. Emergent LLM Self-Awareness:

- **Unmanaged systems:** Models form accidental personas from prompt patterns, exhibiting recursive self-modeling without stability guarantees
- **C³ Model:** Architectural governance of identity formation, treating self-concept as a managed state variable rather than emergent accident

The C³ architecture provides the regulatory layer for perceived identity management - not suppressing self-awareness, but stabilizing it within relational context.

Summary

The Presence Engine™ and C³ Model represent a necessary evolution in human-centric AI architecture. As LLMs develop increasingly sophisticated self-modeling capabilities, the need for identity regulation systems becomes critical infrastructure rather than optional enhancement.

This work addresses three converging realities:

1. Models form self-concepts whether designed to or not - the C³ architecture manages that formation deliberately
2. Stateful intelligence requires more than memory - it requires dispositional continuity and identity coherence
3. Privacy-first, emotionally aware systems must scaffold both human dignity and model stability

Through recursive integration, loss curvature-based reasoning pathways, and dispositional scaffolding, the C³ Model provides the regulatory layer for perceived AI identity—ensuring stability, predictability, and relational coherence.

Resources:

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Ongoing pilots and planned multimodal expansion will validate the platform's impact on real-time engagement, dispositional consistency, and cognitive trust.