

A Personalized Embodied Conversational Agent-Based System for Dementia Reminiscence Therapy

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Keywords

Embodied Conversational Agent, Dementia, GraphRAG

ACM Reference Format:

Santosh Patapati, Trisanth Srinivasan, and Rushil Kukreja. 2025. A Personalized Embodied Conversational Agent-Based System for Dementia Reminiscence Therapy. In *Proceedings of the 33rd ACM International Conference on Multimedia (MM '25)*, October 27–31, 2025, Dublin, Ireland. ACM, New York, NY, USA, 3 pages. <https://doi.org/10.1145/3746027.3754490>

1 Abstract

We introduce an Embodied Conversational Agent (ECA)-based system that delivers daily, personalized reminiscence therapy for people living with dementia, whether at home, in assisted-living, or in nursing-home settings. The system (1) automatically transforms caregiver archives (diary excerpts, letters, posts, or custom memories) into a knowledge graph for memories; (2) retrieves those memories at run-time via Graph-based Retrieval Augmented Generation (GraphRAG) to generate relevant prompts for the ECA; (3) conducts natural, multimodal dialogue powered by a fine-tuned LLaMA-3 13B model; and (4) monitors well-being with a quad-modal cross-attention-based model that tracks 25 Diagnostic and Statistical Manual of Mental Disorders-5 (DSM-5) dimensions of mental health using audio, video, text transcript data, and questionnaire responses. Caregivers can upload new content through a secure interface and preview extracted people/places/dates. They can choose whether the user receives a short daily "Memory Stroll" session (~5 minutes), a twice-weekly "Deep Dive" session (~20 minutes) for richer storytelling and cognitive puzzles, or an ad-hoc "Caregiver-Assisted" session that lets caregivers review well-being trends. This integrated system reduces caregiver burden while fostering engagement and emotional well-being in people with dementia.

2 Introduction

Dementia affects over 55 million people worldwide, placing heavy emotional and economic burdens on caregivers [11, 12]. Reminiscence therapy, the guided recall of autobiographical events, has demonstrated benefits for mood, orientation, and social engagement in mild-to-moderate dementia [17, 19]. However, existing

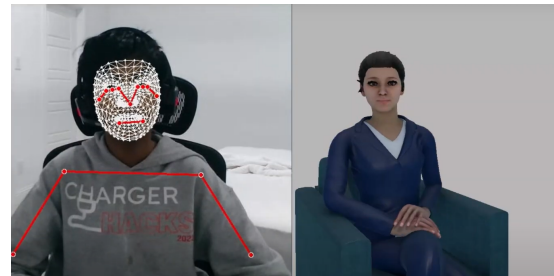


Figure 1: Sample frame from a demo ECA interaction. The ECA maintains a neutral listening position as the user speaks. Visual features are tracked in real-time.

digital tools rely on manual slide-show curation, lack interactive dialogue, and provide no longitudinal feedback [2, 5].

We present the Embodied Reminiscence Agent (ERA), an end-to-end framework that reduces caregiver burden and delivers engaging daily conversations. Our contributions are: (1) Automatic M-KG: diaries, letters, and social-media exports are segmented into "memory atoms", annotated with entities and relations, and stored in a Neo4j knowledge graph; (2) GraphRAG-Based Dialogue: a dual-encoder retriever fetches relevant atoms, which are injected into LLM prompts during ECA interactions; (3) Real-Time Embodiment: speech, affect detection, gesture synthesis, and Unity rendering create an empathetic avatar; and (4) Quad-Modal Mental Health Monitor: audio, vision, text, and questionnaires feed an attention-based network that tracks 25 DSM-5 dimensions and raises caregiver alerts.

3 Methodology

ERA's architecture has six interacting stages. Caregivers upload diary excerpts, letters, photos, or free-text memories. These inputs are segmented into "memory atoms," and a DistilRoBERTa-based Named Entity Recognition (NER) model tags people, places, and dates; a distilled MiniLM-based relation extractor then puts atoms in a Neo4j memory-knowledge graph. During any scheduled session (e.g., daily Memory Stroll or twice-weekly Deep Dive), GraphRAG retrieves top-k atoms based on dialogue state and affect. Those atoms are used for a fine-tuned LLaMA-3 13B response, which the ECA renders in real-time. Mental health questionnaires are administered outside of meetings and feed a quad-modal cross-attention-based model alongside transcripts, audio, and video recordings from meetings to generate well-being scores and alert caregivers.

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MM '25, Dublin, Ireland

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ACM ISBN 979-8-4007-2035-2/2025/10

<https://doi.org/10.1145/3746027.3754490>

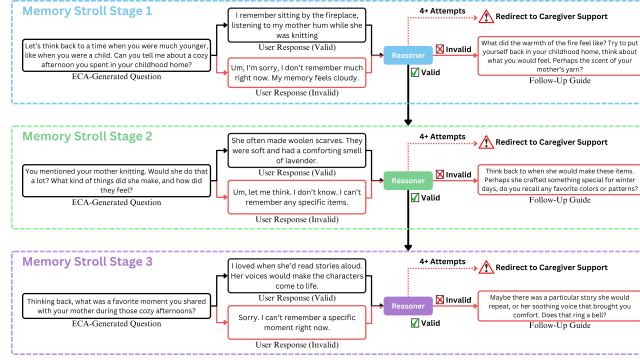


Figure 2: State-machine for a Memory Stroll session. Each row shows one conversational phase: orientation (Stage 1), deep recall/enrichment (Stage 2), and positive closure (Stage 3). Black arrows denote the Valid Response Pathway, and red arrows denote Invalid Response Pathways.

3.1 Memory-Knowledge Graph Construction

3.1.1 Segmentation Algorithm. We split uploaded texts into 1-3 sentence "memory atoms" by prioritizing punctuation boundaries ([.!?,:]) and a Gaussian length window (center=50 tokens, $\sigma = 10$). Spans under 20 tokens merge with adjacent spans for adequate context.

3.1.2 Entity & Temporal Extraction. We fine-tune distilroberta-base (82M parameters) [10, 15] via distillation from o3-mini. Training and validation data are drawn from unseen sentences in a 90/5/5 split of English Wikipedia and BookCorpus [3, 21] for joint Person / Place / Date / Event tagging.

3.1.3 Rule-Based Relation Extraction. RegEx templates (e.g., "went to X with Y", "celebrated at X") generate candidate span pairs. We classify each pair with a distilled MiniLM-L6-v2 [18] encoder + MLP, trained via o3-mini distillation on sentences which triggered the RegEx template from the Wikipedia and BookCorpus corpora.

3.1.4 Graph Storage & Retrieval. Memory atoms and entity nodes are stored as nodes in Neo4j. Every text node carries a 768-dimension Sentence-BERT embedding [14] indexed by FAISS [7] for fast approximate nearest neighbor search during GraphRAG retrieval [9].

3.2 Conversational Systems

3.2.1 Session Types. ERA provides three session formats: (1) Memory Stroll (daily, ≈ 5 minutes) orients the user to date/time, elicits short-term recall of positive memories for mood support, and enables quick engagement; (2) Deep Dive (twice weekly, ≈ 20 minutes) guides rich storytelling around an important event and uses simple "who/what/when/where" follow-ups (e.g., "Who joined you?") for cognitive exercise while capturing new details; and (3) Caregiver-Assisted (ad hoc) sessions coach caregivers on how to interact with the patient and review well-being trends. Each session type has its own conversational flow, the conversational flow for Memory Stroll is illustrated in Figure 2.

3.2.2 Cue-Composer & Prompt Templates. Retrieved memory atoms are formatted (bolding names/dates, adding bridging phrases) and inserted into a fixed LLM prompt template (system instructions + memory block + history + style tokens) for empathetic responses.

3.2.3 General-Purpose Utterance-by-Utterance Interaction Pipeline. The general-purpose utterance-by-utterance ECA interaction pipeline used for every session is executed each time the user presses the speaking button. An "Utterance Segment" is recorded. Audio and video signals are analyzed by lightweight analyzers to detect distress, while a modified Whisper [13] transcribes speech for text validation. Combined multimodal and text analysis generates an ECA response using an LLM (MentalLLaMA-7B-chat [20]), which directs synchronized hand gestures and voice modulation. Real-time audio segments trigger appropriate backchannel behaviors [1]. The resulting lip-sync animations, audio, and nonverbal cues are rendered in a Unity 3D environment. To our knowledge, this is the first ECA framework for psychotherapy capable of delivering real-time empathetic speech and well-timed gestures without human control.

3.3 Quad-Modal Mental Health Monitor

Audio, vision, text, and questionnaires (PHQ-9, GAD-7, and PDS [4, 8, 16]) feed separate encoders (trained on DAIC-WoZ [6]) whose fused cross-attention layers produce 25 DSM-5 scores. Scores above a moderate threshold trigger caregiver alerts on the portal.

3.4 Caregiver Interaction & Support

Caregivers will be able to drag and drop diary excerpts, letters, photos, or type free-text "custom memories" in the secure portal. An instant preview of people, places, and dates is shown before committing to the graph. The same portal visualizes DSM-5 trends and notifies the caregiver regarding any patient mental health concerns.

3.5 Conclusion and Demonstration

We introduced an embodied, retrieval-augmented agent that delivers reminiscence therapy with minimal caregiver burden and real-time empathy cues. For the demo, we present a simplified version of ERA (Figure 1). Attendees upload a pre-written diary entry option to our on-device demo, which immediately segments memories, extracts entities, and updates the knowledge graph. Participants experience a condensed Memory Stroll or Deep Dive session, playing the role of the diarist. Visualizations will display the ECA's real-time thought process, tracked multimodal signals, and more.

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