Background

Alzheimer's Disease and Dementia

In memory of my great-grandma Soonie Chae

- Her story inspires this effort
- Alzheimer's is not just a disease- it's a family story.

Alzheimer's and U.S. Healthcare

- By 2030, **all Baby Boomers** will be over 65
- Projected to reach 14 million by 2050, doubling the current number (CDC, 2024)

Background

Alzheimer’s Disease Statistics in Indiana

Understanding the scale of Alzheimer's impact on the population and healthcare

95-97%

of Alzheimer's cases occur in people age 65+

130k

Hoosiers aged 65+ affected by Alzheimer's in Indiana
(Alzheimer's Association, 2025)

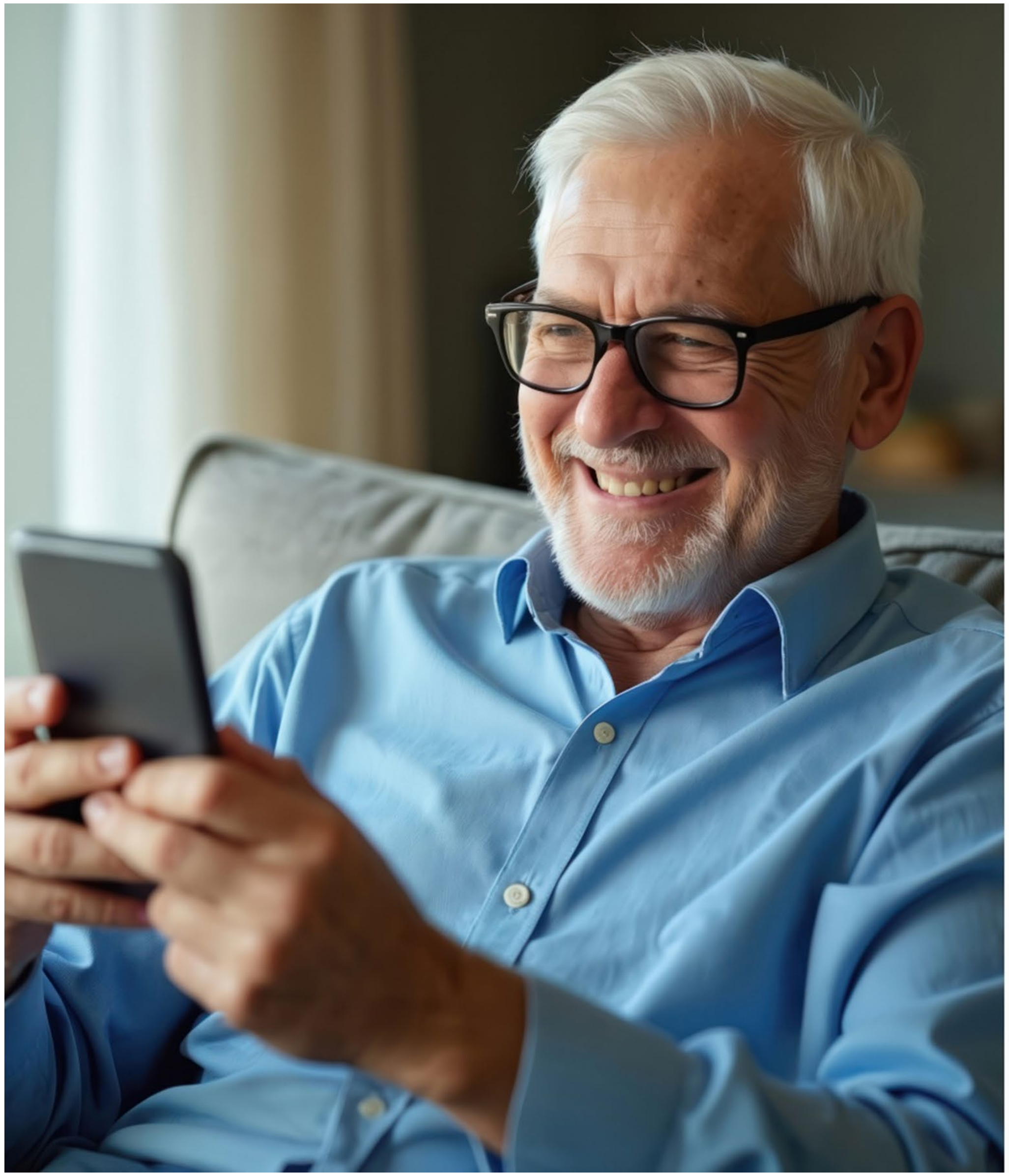
1 in 9

Older adults in Indiana have Alzheimer's

$1.3B
$6.9B

Medicaid spends; Unpaid family care value in Indiana
(Alzheirmer's Association, 2025)

Background



Access Barriers

- Only 1 in 4 receive formal diagnosis (Alzheimer's Association, 2024)
- Rural areas have 53% fewer specialists (Health Affairs, 2023)
- Medicare covers only 16% of care costs - $12k+ annual family burden (AARP, 2024)

Why Visual Memory Works

- 90% mood improvement with familiar photos/ videos (Am. Journal of Alz. Disease, 2022)
- Emotional memory > Factual memory retention (Neurology Research, 2023)
- Visual storytelling preserves connections text cannot

Background

Alzheimer's Disease and Aging

- Digital technologies are increasingly explored to support cognitive engagement among older adults. However, most existing tools focus on communication or entertainment rather than **AI-supported memory interaction and emotional engagement monitoring.**

→ RecallLive was developed to address this gap by combining structured memory videos, emotional response analysis, and AI-generated engagement summaries.

Research Questions

Can an AI-assisted mobile application integrating metadata-based clustering, real-time facial expression analysis, and language-model summarization be developed and evaluated for usability among senior adults?

Hypotheses

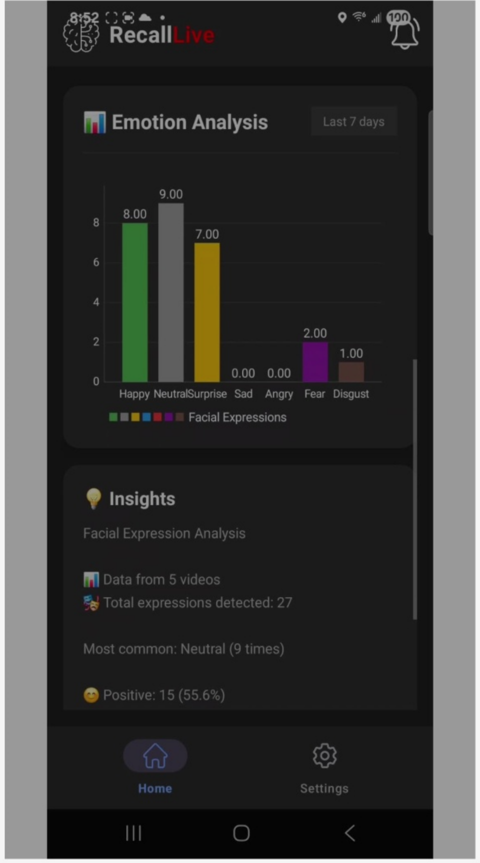
- **H1:** Older adults will report **high usability and engagement** when interacting with the RecallLive system.
- **H2:** Higher **perceived usefulness** will increase the **intention to use or recommend** the application.

Engineering Goals

1) Generate **structured memory videos** by clustering personal photos using time and location metadata.
2) Implement an on-device **CNN emotion classifier** to detect the user's real-time facial expressions (e.g., happy, sad) during video playback.
3) Use a **Large Language Model** to translate aggregated emotion data into an understandable summary report for caregivers.
4) Conduct **usability testing** with senior participants to evaluate system effectiveness and user satisfaction.

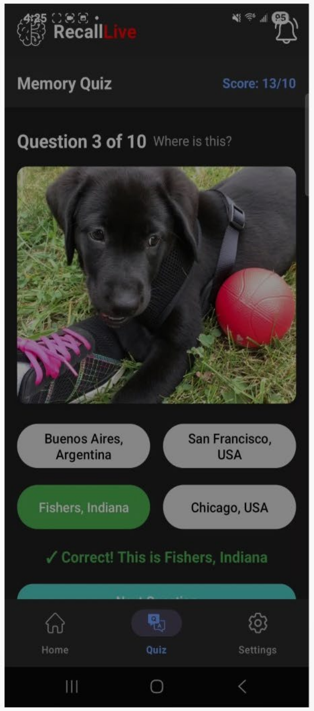
Comprehensive Guardian Dashboard

The Guardian Dashboard provides a powerful set of analytics tools that empower guardians to monitor emotional well-being and memory recall in patients. It features an emotion timeline for each video, allowing guardians to understand mood fluctuations and identify memories that elicit positive or negative responses.



Interactive Memory Quizzes: Engaging Cognitive Stimulation

RecallLive offers interactive memory quizzes designed to reinforce recall and stimulate cognitive engagement. These quizzes utilize photos from daily videos and location-based questions to actively engage users, encouraging better memory retention and recollection.



Firebase Realtime Database

Patient/Guardian accounts
Photo clusters (location, time, photos)
Emotion data per video
Real-time synchronization

System Architecture

- **RecallLive Cognitive Support System (RCSS)** consists of three integrated subsystems = **RVC + RRA + RRG**
- **Pipeline:**

Personal Photos

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Metadata-Based Clustering

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Memory Video Generation

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Real-Time Facial Emotion Recognition

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Emotion Timeline Construction

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LLM-Based Engagement Summary

- **ReLive Visual Composer (RVC)** clusters personal photos using metadata and generates structured memory videos.
- **ReLive Response Analyzer (RRA)** analyzes users' facial expressions during video viewing using a CNN model.
- **ReLive Report Generator (RRG)** converts emotion data into an interpretable summary for caregivers.

ReLive Visual Composer (RVC)

Metadata-Based Image Clustering

RVC extracts **EXIF metadata** from each photo, including:

• timestamp
• GPS location

Photos are grouped using rule-based clustering:

• **temporal clustering** – images captured on the same day or time window
• **spatial clustering** – images captured at nearby geographic locations

These clusters represent meaningful life events (e.g., family gatherings, vacations).

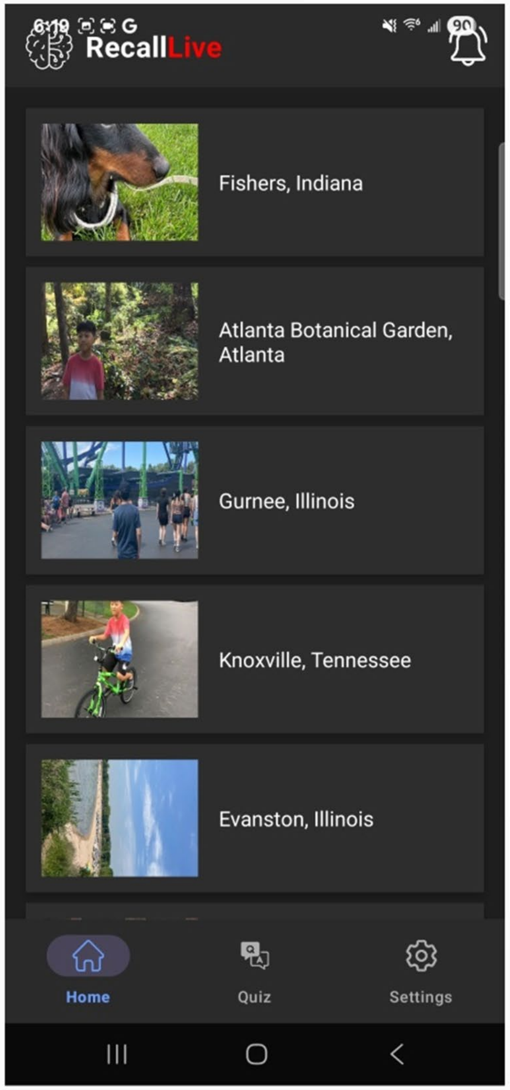
Video Generation

Clustered photos are sequenced into short videos using the **Google Media3 API**.

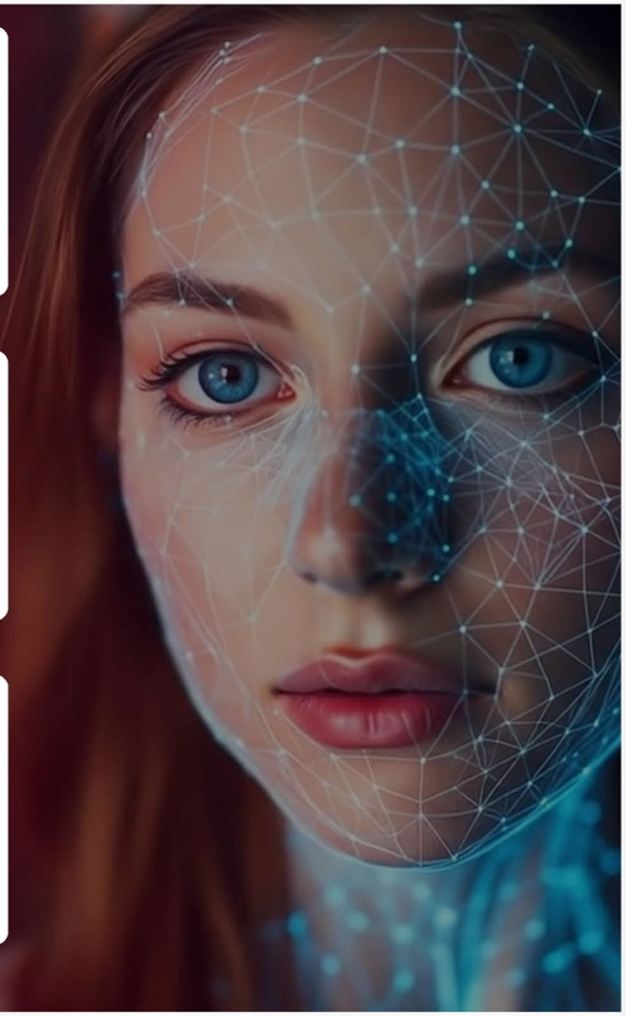
Features:

• chronological ordering of images
• simple transitions for visual continuity
• optimized duration to minimize cognitive overload for older adults

The output is a **structured "memory video"** designed to stimulate reminiscence.



ReLive Response Analyzer (RRA)



The **ReLive Response Analyzer** detects emotional responses while the user watches memory videos.

CNN Emotion Classification

A **convolutional neural network (CNN)** was trained on public facial expression datasets including: AffectNet, FER-2013, CK+

The network classifies facial expressions into **seven emotion categories**:

happy, sad, surprise, anger, fear, disgust, neutral

The model was converted to **TensorFlow Lite** and deployed directly on the smartphone.

Running inference **on-device** improves:

- privacy protection
- real-time processing speed

Emotion Timeline Construction

During video playback:

The smartphone's **front camera captures video frames**.

Each frame is processed by the CNN.

The model outputs a **probability vector for each emotion category**.

Example output for one frame: happy: 0.62 | neutral: 0.25 | sad: 0.08 | surprise: 0.05

These frame-level predictions are aggregated over time to build an **emotion timeline** for each memory video.

Temporal smoothing is applied to reduce noise in predictions.

ReLive Report Generator (RRG)

The **Engagement Report Generator** converts emotional signals into a human-readable report.

Inputs:

- aggregated emotion counts
- emotion timeline patterns
- video cluster metadata

These structured metrics are sent to a **large language model (LLM)** through an API.

The LLM generates a summary describing engagement patterns.

Example output:

> "Positive engagement was highest during recent family events. Neutral or reflective expressions appeared more frequently during older photo clusters. Overall emotional engagement remained positive.

- Reports help caregivers understand **emotional responses to memories**.

RecallLive Engagement Report

Generated by ReLive Report Generator (RRR)

Session Information

User Session ID: RL-0425
Video Duration: 42 seconds
Frames Analyzed: 1,260

Emotion Timeline

Time	Emotion	Confidence
0–10 s	Neutral	0.54
10–20 s	Happy	0.68
20–30 s	Happy	0.71
30–40 s	Neutral	0.49

Emotion Distribution

Emotion	Average Probability
Happy	0.61
Neutral	0.29
Surprise	0.05
Sad	0.03
Other	0.02

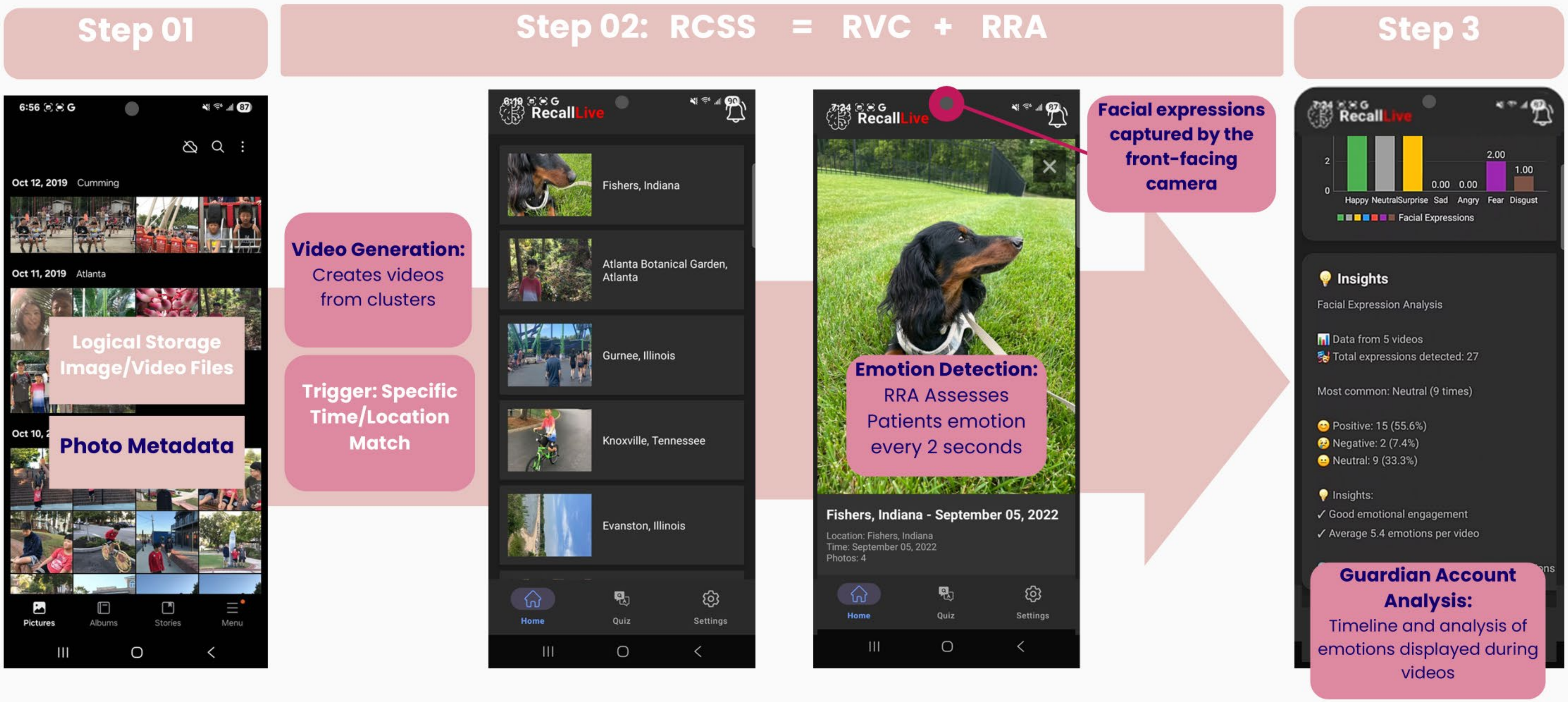
AI Engagement Summary

Positive engagement increased during Cluster 3 (family event photos)
Neutral expressions appeared more frequently during older photo clus
indicating reflective viewing rather than disengagement.
Overall engagement level classified as HIGH.

Caregiver Insights

- Memory videos triggered sustained positive engagement.
- Emotional peaks corresponded with recent family-related photos.
- User maintained attention throughout the viewing session.

RecallLive App Flow Diagram



Methodology

Evaluation Design

This project used a two-phase usability evaluation design to assess the developed system.

Phase 1 evaluated perceived usability and engagement at scale.
Phase 2 evaluated direct interaction usability through hands-on assessment.

This staged approach allows both broad feedback and deeper validation of system functionality.

Participants

Participants were adults aged 65 years or older residing in the United States.

Estimated Sample Size:

Phase 1: 202 senior adults (65+)

Phase 2: 10 senior adults (subset of Phase 1 participants)

Participants for Phase 2 are selected from Phase 1 respondents who indicate willingness to participate in follow-up assessment.

Recruitment

Participants will be recruited through CloudResearch, an online research participant recruitment platform.

Methodology

Phase 1: Video-Based Usability Assessment

This phase provided large-sample feedback on system clarity and perceived interaction quality.

Participants

Watched a structured walkthrough video (approximately 4 minutes) demonstrating the RecallLive system.

Completed an online usability and engagement survey.

Provided optional open-ended feedback.

Total time: approximately 10 minutes.

Measures

Perceived usability

Clarity of system design

Engagement

Perceived usefulness

Intention to use

Phase 2: Hands-On Usability Assessment

5 participants engaged in direct interaction with the application.

This phase strengthens validation beyond perception-based evaluation.

Participants

Used the RecallLive application on a smartphone device.

Interacted with core system components, including:

- Photo clustering and video generation
- Video viewing interface
- Interactive memory quiz
- Summary

Provided structured post-use feedback.

Total time: approximately 30 minutes.

Measures

Ease of navigation

Feature clarity

Interaction flow

User comfort

Results

Descriptive Statistics

Sample Characteristics

A total of N = 202 participants completed the Phase 1 survey. Participant ages ranged from 63 to 84 years (M = 70.5, SD = 4.4). The sample included 78 males (38.6%), 122 females (60.4%), and 2 participants who identified otherwise (2.0%). Participants were recruited through CloudResearch and viewed a structured walkthrough video of the RecallLive application prior to completing the survey.

Item-Level Means

Table 1 presents means and standard deviations for all 16 survey items. The highest-rated individual item was "The app looked interesting" (M = 4.37, SD = 0.72). The lowest-rated items were in the Ease of Use subscale, with the lowest item being "The instructions were clear and understandable" (M = 3.73, SD = 0.97).

Survey Item	M	SD
Section A: Ease of Use		
The app was easy to navigate.	3.77	0.81
The instructions were clear and understandable.	3.73	0.97
I was able to complete tasks without confusion.	3.75	0.92
The buttons and text were easy to read.	3.81	0.79
Section B: Engagement		
The photo/video features were engaging.	4.07	0.73
The app encouraged me to reflect on memories.	4.00	0.87
I found the experience enjoyable.	3.90	0.88
The app looked interesting.	4.37	0.72
Section C: Design & Accessibility		
The layout was simple and looked good.	3.82	0.83
The visual design of the app felt appealing.	4.01	0.75
The visual layout was comfortable for me.	3.87	0.82
Section D: Perceived Usefulness		
This app would be helpful for memory engagement in daily life.	4.01	0.85
Using this app feels beneficial for older adults.	4.10	0.88
The app felt appropriate for senior users.	4.07	0.94
Section E: Intention / Recommendation		
I would be willing to use this app regularly (daily or weekly).	3.65	0.96
I would recommend this app to other older adults or families.	3.79	0.97

Table 1. Item-Level Descriptive Statistics (N = 202)

Note. Scale: 1 = Strongly Disagree, 5 = Strongly Agree.

Results

Composite Subscale Scores and Reliability

Table 2 presents composite means, standard deviations, and Cronbach's alpha for each subscale and the full scale. All subscales demonstrated excellent internal reliability (α > .87). The full 16-item scale yielded α = .967, indicating strong internal consistency. Engagement received the highest composite mean (M = 4.16), while Intention to Use received the lowest (M = 3.77).

Subscale	N Items	M	SD	α
Ease of Use	4	3.77	0.78	0.919
Engagement	4	4.09	0.67	0.862
Design & Accessibility	3	3.90	0.74	0.917
Perceived Usefulness	3	4.06	0.82	0.909
Intention / Recommendation	2	3.72	0.90	0.863
Full Scale (all 16 items)	16	3.92	0.68	0.960

Table 2. Composite Subscale Scores and Cronbach's Alpha (N = 202)

Note. All alpha values indicate excellent reliability (α > .86).

Results

- All scales demonstrated strong reliability (Cronbach's α = .86-.92). Engagement (M = 4.09/5.00) and perceived usefulness (M = 4.06/5.00) were rated highly.
- **Results supported H1**

  Participants reported high usability (M = 3.77) and engagement (M = 4.09).
- **Results supported H2**

  Perceived usefulness strongly predicted intention to use or recommend the application ($R^2 = .634$, $F(1,200) = 346.18$, $p < .001$).
- Phase 2 included hands-on usability assessment with ten participants, confirming clarity of navigation and interpretability of emotional feedback.
- Results suggest that combining AI-driven emotional analysis with structured visual memory exposure is both technically feasible and scalable for real-world use. This study demonstrates how integrating machine learning with user-centered mobile design may support proactive cognitive engagement strategies for aging populations.

Results

Qualitative Feedback

Strengths

Ease of use: the simplicity of navigation and intuitive design, particularly for an older adult population.

Memory stimulation concept: Participants widely appreciated the photo clustering and video generation features as meaningful and emotionally resonant.

Caregiver value: Participants noted the potential benefit for caregivers monitoring emotional engagement patterns.

Visual design: The clean, uncluttered layout was frequently mentioned as appropriate for senior users.

Areas for Improvement

Setup concerns: A few participants raised questions about how photos would be loaded initially, particularly for seniors who may not be comfortable with smartphone file management.

Privacy: A small number of participants raised concerns about photo storage security and the nature of data collected by the app.

Suggested Improvements

Add a guided tutorial within the app for first-time users

Include background music

Add voice recognition for accessibility

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