# Personalized intelligent dialogue robot based on AIGC assists memoir writing for elderly people with cognitive impairment: a multi-method collaborative design framework

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Yibo Meng[1*]; Yuan Que[2*]; Zhe Yan[3*]; Bingyi Liu[4*]; Zixin Wang[5*]; Huidi Lu[6]

[1]Tsinghua University Tsinghua University Beijing CN
[2] Southwest Jiaotong University Chongqing CN
[3] The Chinese University of Hong Kong, Shenzhen Shenzhen CN
[4] University of Michigan, Ann Arbor Ann Arbor CN
[5] University of Pennsylvania Philadelphia US
[6]Tsinghua University University of Oxford Oxford GB
[*]these authors contributed equally

**Corresponding Author:**
Huidi Lu
Tsinghua University
University of Oxford
Park End Street, Oxford OX1 1HP, UK
Oxford
GB



## Abstract

**Background:** Elderly individuals with cognitive impairment often face significant challenges in memoir writing, including memory fragmentation, emotional loneliness, and language expression barriers. Although AI-generated content (AIGC) technologies such as GPT-3.5 show potential in content creation, they often lack the personalization and adaptability required for users with dementia.

**Objective:** This study aimed to design and evaluate a personalized AIGC-powered conversational robot to assist elderly people with cognitive impairment in memoir writing and emotional support.

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**Results:** The system achieved high usability (SUS score > 70) and significantly improved emotional congruence and memoir quality in the experimental group compared to controls. Participants with severe cognitive impairment (MMSE ? 18) benefited more from AI-driven narrative generation, while those with mild impairment (MMSE ? 22) preferred keyword-based prompts.

**Conclusions:** The personalized AIGC-based conversational robot effectively supports memoir writing and emotional well-being in elderly individuals with cognitive impairment. Its adaptive, multimodal design promotes meaningful human-AI collaboration and shows potential for enhancing cognitive rehabilitation and eldercare services.

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# Original Manuscript

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Keywords:
AIGC; elderly with dementia; memoir writing; multi-method design; conversational robot; cognitive impairment


## Introduction

Dementia affects over 50 million individuals globally, impairing memory, cognition, language, and emotional processing, and this number is projected to grow significantly with the aging population [12]. Among non-pharmacological interventions, memoir writing has been shown to support cognitive function and emotional healing by preserving personal narratives and enhancing identity [11]. However, traditional self-narration methods impose high cognitive demands, particularly for individuals with language difficulties and fragmented memory [14]. Emerging AIGC (Artificial

Intelligence Generated Content) technologies such as GPT-3.5 offer new opportunities for content generation with minimal user input [4], yet most current systems are not designed to adapt to the cognitive and emotional needs of people with dementia [20].

Recent studies in Human-Computer Interaction (HCI) and Computer-Supported Cooperative Work (CSCW) emphasize the role of asymmetric collaboration, where AI systems adapt dynamically to users with varying cognitive abilities [19]. For example, assistive technologies can act as “ability balancers,” helping dementia patients engage meaningfully despite limitations [5]. AIGC tools like Replika have been explored for emotional companionship and mental health applications [8], but they often lack medical adaptability and rigorous ethical safeguards required in dementia care [7]. Likewise, traditional dementia-assistive technologies emphasize personalization and usability [6], but seldom provide real-time narrative generation or emotion-sensitive feedback [9].

To address these limitations, we propose a personalized AIGC-powered conversational robot that dynamically adjusts its interaction based on cognitive states measured by MMSE scores [17], and responds to emotional needs such as loneliness and achievement using Kansei Engineering principles [16]. The system design integrates methods from mechanical engineering, packaging design, and HCI [1], aiming to support memoir writing, improve emotional well-being, and enable adaptive, human-centered AI experiences for elderly users with dementia.

## Objective

This study aims to design and implement a personalized AIGC-based conversational robot to support elderly individuals with cognitive impairment in writing memoirs and receiving emotional support. The system dynamically adapts its collaboration mode based on users’ Mini-Mental State Examination (MMSE) scores, offering keyword prompts for those with mild dementia and active narrative generation for those with severe cognitive decline. In addition to facilitating memory recall, the robot is designed to identify and respond to emotional needs such as loneliness and the desire for achievement through the application of Kansei Engineering principles, which translate emotional feedback into technical requirements. Furthermore, the research adopts an interdisciplinary approach by integrating human-computer interaction (HCI), mechanical design, and packaging engineering to ensure the system is usable and accessible across varying cognitive stages. By addressing both cognitive and emotional challenges, the system seeks to bridge current gaps in AIGC application for dementia care.

## Methods

## Multi-Stage Collaborative Design Framework

To develop a personalized AIGC-based system that supports memoir writing for elderly individuals with dementia, we adopted a multi-stage collaborative design framework that integrates Kansei Engineering (KE), Quality Function Deployment (QFD), Axiomatic Design (AD), and the TOPSIS decision model. In the first stage, KE was used to extract emotional and psychological needs through semi-structured interviews and field observations, identifying core affective themes such as “frustration from forgetting” and “the desire for recognition.” These emotional inputs were translated into design variables during the QFD phase, where emotional requirements were mapped to measurable technical specifications—for instance, ensuring an NLP response delay of less than 2 seconds or incorporating a comforting tone in audio feedback. Subsequently, the Axiomatic Design approach was employed to decompose the system into three functionally independent but complementary modules: memory triggering, narrative generation, and emotional feedback. This decomposition ensured modularity and flexibility for different cognitive stages. Finally, the TOPSIS decision-making method was used to evaluate and select among three intervention strategies (low, medium, and high AI proactivity). Emotional needs were weighted more heavily than technical complexity in the evaluation matrix to prioritize emotionally resonant interactions. This framework ensured the system could flexibly adapt to varying user profiles while maintaining both usability and emotional efficacy.

## System Implementation (Memoir-driven Human-AT Interaction)

The system is implemented using GPT-3.5 as its core AIGC engine, fine-tuned to receive user inputs such as MMSE scores and recorded life events. The core design goal is to help elderly users gradually build a structured and rich life memoir through continuous interaction with the AI, leveraging both voice guidance and a visual timeline interface. This multimodal interaction is designed to accommodate different cognitive stages and to reduce the barriers to memory retrieval and narrative generation.

### *AIGC Core*

The system's core is built on GPT-3.5, a powerful natural language processing model that is tuned to offer personalized collaboration strategies. The system responds dynamically based on the MMSE score of the user, adjusting the complexity of the generated content and offering personalized narrative assistance [21]. The main aim is to create an environment where the elderly can interact naturally with the AI, progressively developing their life stories.

### *Multimodal Interaction*

The system pairs voice guidance with a visual timeline interface [3], which helps users intuitively review and edit their autobiographical entries. This interface is designed to adapt to different cognitive stages, lowering the cognitive load for elderly users, especially those with dementia, by providing both auditory and visual cues. The timeline visually represents the user's life events, making it easier for them to recall and organize their memories [1].

## Evaluation Method

The system was evaluated through usability and emotional quantification measures to assess its effectiveness in assisting elderly individuals with dementia in memoir writing.

### *SUS Scale*

Usability testing on 10 participants aimed for a SUS score of 70, focusing on ease of narrative input and story review, ensuring the system's user-friendliness for individuals with cognitive impairments [2].

### *Emotional Standard Quantification*

The system's emotional consistency was measured using an emotional consistency index and a Memoir Quality Index, evaluating coherence, richness, and personal relevance of generated stories, ensuring emotional engagement along with cognitive support [13].

### *Effectiveness of Collaboration Model*

The system adapted well to different cognitive stages. The MMSE $\leq$ 18 group (severe dementia) preferred AI-driven active generation, while the MMSE 22 group (mild dementia) favored keyword prompts, demonstrating the system's ability to meet varying cognitive needs [17].

### *Memoir Construction Success*

Over 80% of participants successfully generated structured autobiographical records after two weeks, with qualitative feedback indicating enhanced accomplishment and improved intergenerational communication.

### *Intermediary Role Design*

The system dynamically switches between "assistance" (user-led recollection) and "agent" (AI-driven prompts), empowering users to take ownership of their stories and fostering a sense of agency [1].

### Asymmetric Collaboration Ethics

Transparency in AI-generated content and memory sources enhances trust, particularly in sensitive areas like personal history reconstruction, promoting trust with users and caregivers [22].

## HARDWARE DESIGN AND IMPLEMENTATION

The hardware architecture of the system consists of several modular components that support WiFi communication, voice interaction, and emotional recognition. These modules include a microcontroller, WiFi module, audio playback chip, and supporting circuitry. This section provides a detailed overview of the structure and functionality of each module, along with relevant diagrams and testing procedures.

Figure 1. AI-Generated VR Effect Diagra

### Main Controller (STC15L2K16S2)

The system uses the STC15L2K16S2 microcontroller as the central processing unit. This 8-bit MCU, based on the 8051 architecture, offers 16 KB of Flash memory and 2 KB of SRAM, with an operating voltage range of 2.2 to 3.6 V, making it compatible with peripheral components. The device features an integrated oscillator and reset logic, along with two UART serial interfaces, enabling simultaneous communication with both the WiFi and voice modules. It is responsible for parsing external commands, managing serial communication, and issuing control signals to the voice module and emotional feedback circuits.

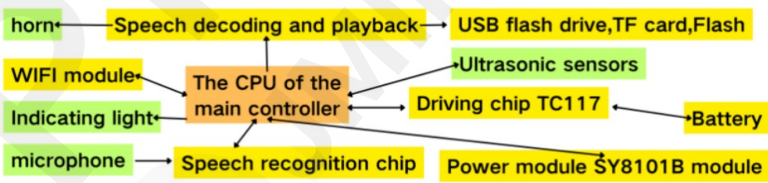



Figure 2. Microcontroller-based control unit schematic

### WiFi Module (ESP-01SF with ESP8266)

Wireless communication is enabled by the ESP-01SF module, which integrates the ESP8266 SoC. This 32-bit microcontroller includes a WiFi transceiver and full support for the TCP/IP protocol. It communicates with the main controller via UART. In this design, the ESP8266 is configured as a server, while the smartphone application acts as the client, enabling real-time control and data exchange. Its compact size and low power consumption make it highly suitable for embedded applications requiring wireless connectivity.

### Voice Module (GD5600 MP3 Decoder)

The robot utilizes the GD5600 MP3 decoder chip for audio output. It supports playback of MP3 and

WAV files stored in internal flash memory or a TF card. The chip interfaces with the main controller via UART and can be commanded to play specific audio tracks. In this system, it provides verbal responses and emotional cues in reaction to user input. The audio files are preloaded, with each file corresponding to a specific response or emotional state.

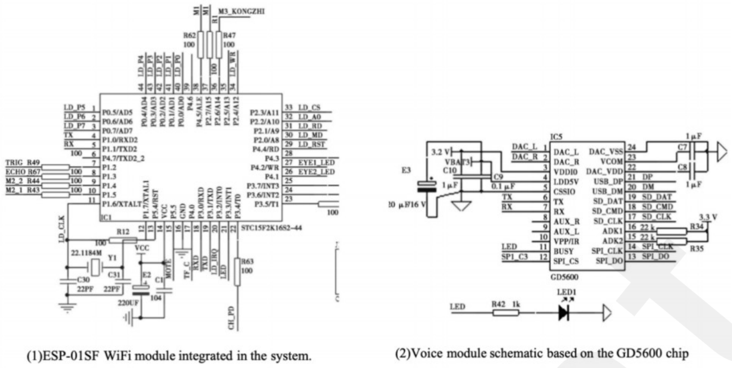



Figure 3. module schematic

## Audio Playback Control and Logic Table

Audio responses are triggered through simple serial commands. Playback control is managed through logical input combinations, as summarized in the accompanying control table. This ensures that the system responds appropriately to user commands, maintaining the flow of interaction and emotional feedback.

| **Input** | **Action** | **Audio Output** |
|---|---|---|
| High Low | Play command | Corresponding voice track |
| | No input | No input |

Figure 4. Voice Control Logic Table for GD5600 Module

## Assembly and Testing

Each module was soldered and tested independently to ensure proper operation. The microcontroller, WiFi, and voice modules were connected and verified using AT commands. The GD5600 voice module was tested with serial commands to trigger responses. After validation, the components were assembled onto the robot chassis and interconnected. A smartphone app was used to initiate interaction via WiFi, with the robot responding to voice commands and simulating emotional responses through audio and LED indicators. This version of the system does not include locomotion capabilities.

# Evaluation

## Study Design

### *Participants*

We recruited 20 older adults (aged 55–72, M = 63.4, SD = 12.1) with varying cognitive impairments through Xiaohongshu and offline outreach. Participants were divided into mild (MMSE 22) and severe (MMSE ≤ 18) impairment groups. Inclusion criteria included a clinical diagnosis of cognitive impairment, basic verbal communication, and voluntary participation, while individuals with severe conditions needing continuous care were excluded. Ten licensed psychiatrists were involved for emotional congruence assessments and emergency support.

### *Methodology*

We used a multi-stage participatory design framework, incorporating Kansen Engineering (KE) principles. Emotional journey maps were created through semi-structured interviews and field observations to identify key user needs, such as real-time prompting and emotional companionship. The system offered three AIGC interaction modes with varying proactivity (low, medium, high), and the optimal mode was selected using the TOPSIS model. The core system, based on a fine-tuned GPT-3.5 model, supports multimodal interaction with voice input and a visual timeline interface, with personalized collaboration strategies tailored to each user's MMSE score.

### Procedure

At T0, we recorded participant demographics (age, gender, MMSE) and assessed baseline emotional states through self-reports and clinical evaluations. Participants narrated a personal memory, which was evaluated by psychiatrists for completeness. Based on these evaluations, participants were assigned to the experimental and control groups (10 each), ensuring comparable baseline performance. At T1, the experimental group completed three memoir-writing sessions using the AIGC-based system, while the control group performed the same tasks without assistance. Psychiatrists evaluated emotional congruence and memoir quality for both groups. At T2, the experimental group completed the System Usability Scale (SUS) and qualitative interviews for in-depth feedback.

## Evaluation Metrics

We evaluated system performance across four core dimensions. Usability was assessed using the System Usability Scale (SUS), with a target threshold of 70. Emotional support effectiveness was measured through an Emotional Congruence Index derived from multi-perspective expert ratings. Memoir quality was assessed using a custom Memoir Quality Index, which considered content coherence, narrative richness, and personal relevance. Finally, we compared participants' emotional state scores before and after system use to evaluate changes in emotional well-being.

## Experimental Results

### Usability Dimension Analysis

The emotional value dimension achieved the highest score (M = 97.2, SD = 3.9, CV = 0.040), indicating consistent positive emotions during interactions. All emotional value scores exceeded 90, with minimal variation, highlighting strong emotional engagement support across cognitive profiles. The effectiveness dimension also scored well (M = 89.3, SD = 6.3, CV = 0.071), showing that participants found the system helpful in memoir creation. Scores ranged from 78 to 100, with seven participants scoring above 85. In contrast, simplicity (M = 81.2, SD = 7.2, CV = 0.089) and ease of use (M = 79.8, SD = 8.3, CV = 0.104) had lower scores and higher variability. Participant 5 reported the lowest ease of use score (approximately 65), indicating potential usability issues, especially for users with higher cognitive burdens or less tech familiarity.

A one-way repeated-measures ANOVA revealed significant differences across usability dimensions ($F(3,27) = 9.84$, $p < 0.001$), with emotional value rated higher than simplicity ($p = 0.004$) and ease of use ($p < 0.001$). The difference between effectiveness and simplicity was not significant ($p = 0.112$).

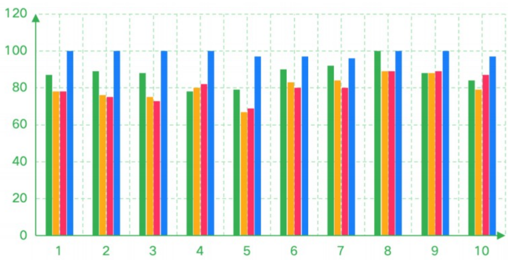



Figure 5. SUS scores of the experimental group(The horizontal axis is members, green is effectiveness score, orange is simplicity score, red is usability score, blue is emotional value score)

### Emotional Consistency Across Time Points

Emotional consistency scores measured at three time points (T1(1), T1(2), T1(3)) showed moderate variation, ranging from 4.0 to 5.0. The highest average score was at T1(1) (M = 4.7, SD = 0.3, CV = 0.064), indicating a stable emotional state initially. However, scores at T1(2) (M = 4.6, SD = 0.4, CV = 0.087) slightly declined, and T1(3) scores (M = 4.5, SD = 0.5, CV = 0.111) showed greater variability, suggesting increased emotional inconsistency over time. This trend indicates a slight decrease in emotional consistency and higher dispersion from T1(1) to T1(3). Most participants maintained consistent emotional responses, with exceptions such as

Participants 5, 7, and 9, who showed notable fluctuations. For example, Participant 5 had a significant drop in emotional consistency from T1(1) (M = 4.8) to T1(3) (M = 4.2), while Participant 9 showed an increase between T1(2) and T1(3).
A one-way repeated-measures ANOVA confirmed a significant effect of time on emotional consistency ($F(2,18) = 6.29$, $p = 0.008$). Post-hoc comparisons indicated that T1(1) scores were significantly higher than T1(3) ($p = 0.005$), but there was no significant difference between T1(1) and T1(2) ($p = 0.133$).


Figure 6. Emotional consistency scores of the experimental group(The horizontal axis represents the members of the experimental group, green represents the T1 (1) score, orange represents the T1 (2) score, and red represents the T1 (3) score.)

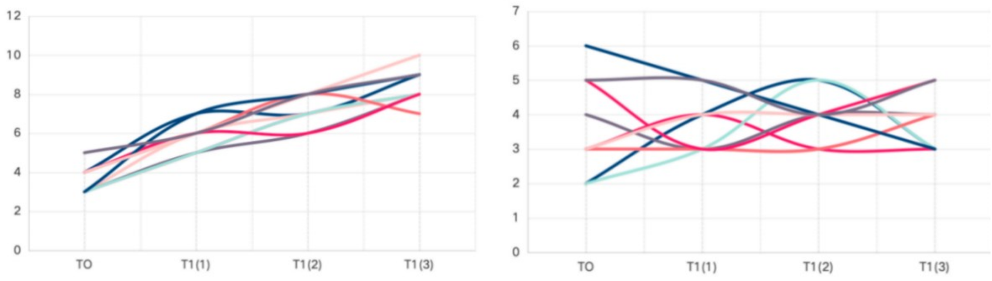
### Emotional Memory Changes in Experimental and Control Groups

Figures show the emotional memory scores across three time points (T0, T1(1), T1(2), T1(3)) for both the experimental and control groups, highlighting distinct trends in emotional memory improvement.

The experimental group showed a steady increase in emotional memory scores: 5.07 at T0, 5.38 at T1(1), 5.71 at T1(2), and 6.11 at T1(3), with minimal variation. The coefficient of variation (CV) decreased from 0.051 at T0 to 0.042 at T1(3), indicating consistent improvement.

In contrast, the control group showed more variability, with average scores of 4.13 at T0, 4.30 at T1(1), 4.47 at T1(2), and 4.63 at T1(3). While scores increased, the changes were less consistent, with the CV decreasing from 0.043 at T0 to 0.029 at T1(3).

A repeated-measures ANOVA showed significant improvements in the experimental group ($F(3,27) = 26.21$, $p < 0.001$) and the control group ($F(3,27) = 17.38$, $p < 0.001$), though with more variability in the control group. This highlights the intervention’s effectiveness in enhancing emotional memory in the experimental group.



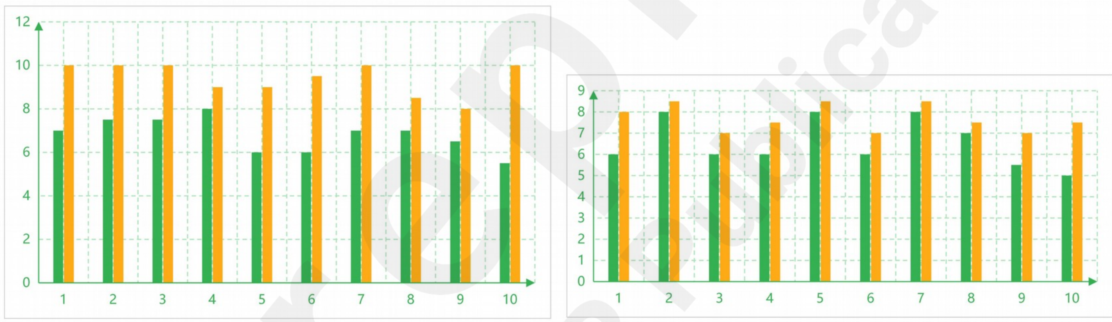

(1) Experimental Group's Memoirs Ratings (2) Control Group's Memoirs Ratings

Figure 7. Memoirs Ratings

### Emotional State and Enhancement Effect of Intervention

The experimental group’s emotional state scores improved significantly, from a pre-experiment score of M = 7.5 (SD = 1.2) to a post-experiment score of M = 8.5 (SD = 1.0). A paired t-test confirmed this improvement was statistically significant (t(9) = –5.63, p < 0.001), with a large effect size (Cohen’s d = 1.78). These results indicate a substantial positive effect of the intervention on emotional well-being.

In contrast, the control group exhibited minimal change, with pre-experiment scores of M = 6.5 (SD = 1.1) and post-experiment scores of M = 6.8 (SD = 0.9). A paired t-test revealed no significant change (t(9) = –1.31, p = 0.21), suggesting that the control group did not experience meaningful improvement.



A B

Figure 8. Emotional State Scores Before and After（A is the experimental group and B is the control group）

An independent samples t-test confirmed a significant difference between the experimental and control groups at the post-experiment time point (t(18) = –3.42, p = 0.003), with the experimental group showing significantly higher emotional state scores. The effect size for this comparison was Cohen’s d = 1.20, indicating a large effect.

Emotional enhancement scores also increased significantly in the experimental group (pre: M = 2.3, SD = 1.1; post: M = 3.7, SD = 1.3), with a statistically significant improvement (t(9) = –4.52, p < 0.001) and a large effect size (Cohen’s d = 1.32). In contrast, the control group showed minimal change (pre: M = 1.5, SD = 0.8; post: M = 1.8, SD = 0.7), which was not significant (t(9) = –1.22, p = 0.26). A follow-up independent samples t-test revealed a significant post-intervention difference (t(18) = –5.35, p < 0.001), with a large effect (Cohen’s d = 2.04).

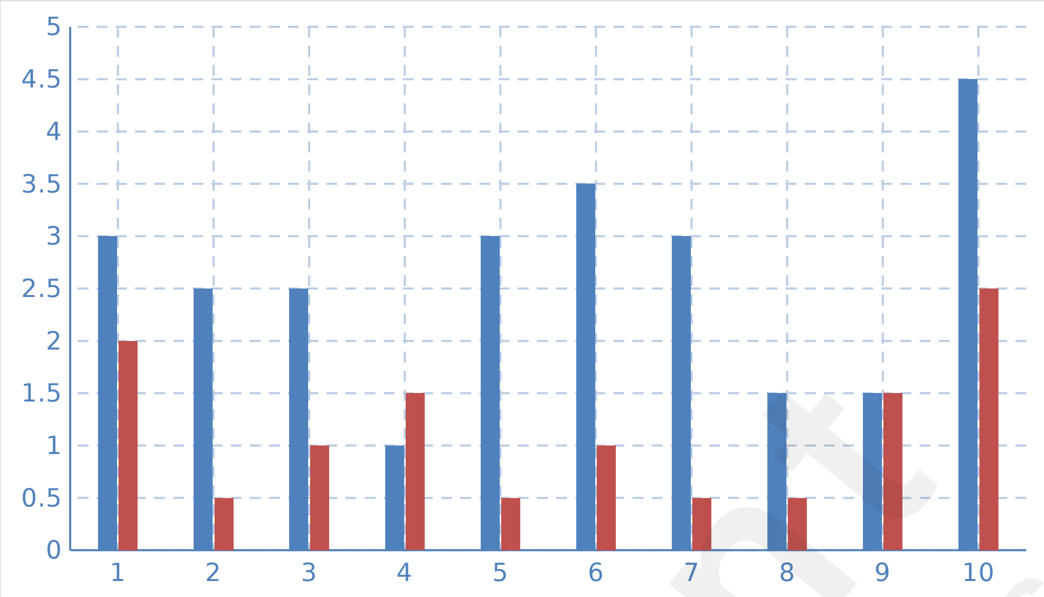



Figure 9. Emotional Enhancement Scores of Experimental and Control Groups(Green is the experimental group, yellow is the control group)

## Discussion

### System Effectiveness and Advantages

The AIGC-based system significantly supported elderly adults with cognitive impairments in memoir writing, producing higher-quality memoirs in the experimental group compared to the control group. Multimodal interaction and adaptive strategies, including voice input and a visual timeline interface, improved accessibility. Tailored support based on MMSE scores enhanced narrative outcomes across user groups.

### Emotional Support Outcomes

Emotional ratings post-experiment showed significant improvements in the experimental group, with high Emotional Congruence Index scores. The system provided emotional support through emotion maps and empathetic dialogue, alleviating anxiety and depression, thus transforming memoir writing into a beneficial experience [11].

### Usability Performance

The System Usability Scale (SUS) scores indicated high usability, with an intuitive interface that reduced barriers for elderly users. The system effectively supported memoir writing and enhanced user experience, confirming its role in facilitating both cognitive and emotional engagement [6].

### Limitations

The study had limitations, including a small sample size (20 participants) and a short duration, which hindered long-term effect assessment. Additionally, MMSE scores, while useful, have limitations in capturing the complexity of cognitive and emotional states in older adults, suggesting a need for more refined tools.

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