

Living Memory: AI-Generated Characters as Digital Mementos

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Figure 1: Left (A&B): The user interface for a living memory of Leonardo Da Vinci chatbot that participants interacted with using our system. The experience started with a 40 second long animated video of Leonardo Da Vinci introducing himself generated using an open-source AI-generated character pipeline. **Right:** Potential applications of Living Memories to (C) help people remember and mourn, and (D) preserve culture and learn about people from the past.

ABSTRACT

Every human culture has developed practices and rituals associated with remembering people of the past - be it for mourning, cultural preservation, or learning about historical events. In this paper, we present the concept of "Living Memories": interactive digital mementos that are created from journals, letters and data that an individual have left behind. Like an interactive photograph,

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living memories can be talked to and asked questions, making accessing the knowledge, attitudes and past experiences of a person easily accessible. To demonstrate our concept, we created an AI-based system for generating living memories from any data source and implemented living memories of the three historical figures "Leonardo Da Vinci", "Murasaki Shikibu", and "Captain Robert Scott". As a second key contribution, we present a novel metrics scheme for evaluating the accuracy of living memory architectures and show the accuracy of our pipeline to improve over baselines. Finally, we compare the user experience and learning effects of interacting with the living memory of Leonardo Da Vinci to reading his journal. Our results show that interacting with the living memory, in addition to simply reading a journal, increases learning effectiveness and motivation to learn about the character.

CCS CONCEPTS

- Human-centered computing → Interaction design theory, concepts and paradigms; Empirical studies in interaction design; Empirical studies in HCI; HCI theory, concepts and models.

KEYWORDS

AI, Human-AI Interaction, AI-Generated Characters

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1 INTRODUCTION

Have you ever wondered what historical figures like Leonardo Da Vinci or your very own great grandparents were like? What did they value and what were their attitudes towards life? Did you ever get to meet them? Did you wish you could hear their stories or ask them for advice?

From science fiction to literary classics, there is a recurring theme of someone talking to a postmortem being, a living memory, or a spirit mentor that supports and interacts with the main character throughout the story. This mentor often appears as a ghostly figure or a disembodied voice that provides wisdom and serves as the person's moral compass [50]. Examples of this spirit advisor range from the force spirits of Jedi masters that, beyond their death, continue to watch over their trainees in the sci-fi epic, Star Wars [54], to the ghost of Hamlet's father who comes back to visit his son in the classical work by William Shakespeare [3]. This recurring literary motif demonstrates how a valued person's wisdom can have a long-lasting impact and continue to be a guiding force for generations.

Every human culture has developed practices and rituals associated with responding to death and creating mementos of the deceased for the living [23] - be it prehistoric burial mounds, statues, biographies, portraits, movies and digital memorials. Given the rapid digitization of most aspects of our lives, technology is increasingly intersecting with these practices. For example, over the last couple of years, Zoom has been streaming memorial services and funerals for family members unable to attend in person due to COVID-19 [7]. Research in HCI has traditionally explored distinct parts of the human lifespan, with a new call in the last decade, for technologies to support practices such as "collaborative acts of remembrance, bequeathing of digital data, or group reflection on the digital residuals of a life" [22, 23]. We believe that living memories, in the form of interactive conversational agents that resemble a person of the past and are based on the journals, letters and data that the person has left behind, could provide a new form of "technological heirloom" and a novel way for reflection and meaning-making [23], adding to the repertoire of current mementos such as photographs, videos and personal objects.

A recent example of a digital memento is a chatbot created by Eugenia Kuyda of her deceased friend, Roman Mazurenko [8]. Kuyda

claimed that for many people, interacting with the bot had a therapeutic effect and a significant impact on the lives of people who knew the deceased. Roman's mother told Kuyda, "I am getting to know him more. This gives the illusion that he is here now." Eterni.me is a related technology with a similar goal of creating and preserving memories through interactive conversations with the departed [21]. In another recent example, photogrammetry was used to enable the parents of a deceased child to revisit her and cope with their traumatic loss by enabling one last goodbye in 3D [11]. More recently, Amazon also announced an upcoming feature of their Alexa conversational agent platform that lets you get stories read aloud in the voice of your (past) grandparent[10].

The field of HCI has been further exploring research that both acknowledges and engages with end-of-life issues. For example, Kirk et. al. [15] introduced the idea of a technology heirloom that is designed to be inherited and cherished across multiple generations. Odom et. al. [30] explored the issue of keeping digital remains as valuable, self-defining possessions. While difficult, it is becoming increasingly important to design "thanatosensitive" technologies that support different ways of remembrance and reflection with the digital residuals of a life [23]. These projects demonstrate how the concept of a living memory could be of great interest to people to either create novel educational and personal experiences, assist with end-of-life practices as they increasingly intersect with technology, preserve culturally significant figures, events and stories, and support the mental health of grieving friends and family.

1.1 Living Memory

We believe the time is right to explore the human impact of interactive "Living Memories" built from the journals, letters and data people leave behind upon their death, including pictures, videos, social media posts, interviews, blog posts, and other digital remains. We define a **Living Memory** as an interactive AI-generated *portrayal* of a person's stories, attitudes, personality, and wisdom. We envision living memories to take the form of anything from a chatbot to an embodied, animated, and interactive photograph. Rather than "bringing the person back to life" or being "a clone of the person", we conceptualize living memories as being similar to a photograph; like photographs, living memories are snapshots of people at specific moments in time and should not be thought of as the person themselves. Hence it is important that they are authentic and well-represent the data that they are trained on.

1.2 Motivation: Why Create a Living Memory?

While we acknowledge that this type of research may feel uncanny and it is controversial as it touches upon sensitive topics of death, identity, and authenticity, we believe, if done correctly, living memories, like other mementos, could be a meaningful way of celebrating the life of a person, sharing their stories, and passing the portrayed individual's wisdom on to later generations. For this to happen safely, living memories should always deliver information that is authentic to the data extracted from the archives of the person. Given recent advances in generative language models and natural language processing along with the exponential rise of personal data being stored online, creating intelligent systems that can reliably portray an individual has become increasingly feasible. Last,

we anticipate the possible misuse of living memories for malicious reasons, e.g., tricking people into believing the person is still alive, that they are talking to the real person, or manipulating the living memory to say things that are inauthentic to the portrayed person in order to persuade. Like current concerns about deepfakes [52], living memories require careful consideration and methods for mitigating harm.

In this paper, we present the concept of “Living Memories”, the use of AI-generated characters as digital living mementos. To demonstrate our concept, we created an AI-based pipeline for generating living memories from any data source and generated living memories of the three historical figures “Leonardo Da Vinci”, “Murasaki Shikibu”, and “Captain Robert Scott”. Since these kinds of systems are still in their infancy, as a second key contribution, we present a novel metrics method for evaluating the accuracy of living memories in terms of question-answering capability. Based on 600 question-answer pairs generated from our living memory pipeline, we show that our architecture outperforms baselines on accuracy, style, understanding and grammar, and highlights its capability to represent the characters authentically. Finally, to demonstrate the concept of living memory in action, we conducted a user study with 90 participants evaluating the user experience and learning effects of interacting with the living memory of Leonardo Da Vinci. Our results show that interacting the living memory in addition to simply reading a journal increases learning effectiveness and motivation to learn about the character. These results highlight the purpose of the living memory system as a meaningful and interactive way to learn stories and wisdom from people in the past.

2 RELATED WORK

2.1 Computing and Cultural Heritage

Innovative interactive applications and storytelling techniques in augmented and virtual reality are becoming more widespread in “communicating and enhancing tangible and intangible cultural heritage” [20]. Traditionally, this work has focused on the recreation of cultural sites through 3D reconstruction for storytelling and generating new experiences, whether location-based or in virtual reality. Recent work has started to explore the creation and interaction with virtual characters as a form of experiencing cultural heritage [1, 19, 34, 43] through historical daily life scenarios. For instance, Dalí Lives [26] is a recent exhibit that uses deepfake technology to recreate Salvador Dalí’s face and voice from archival footage. In the exhibit, a life-sized Dalí appears before museum visitors, tells them stories about his life, and takes selfies with them. In another example, a system based on documentary video allows anyone to talk to a holocaust survivor and ask them questions [41, 46, 49]. In comparison to these methods that rely on curated data, our work explores how data that is already available from books, social media, interviews, and more, can be leveraged and reshaped to create a living memory that is authentic to the source knowledge but is easier to create and more expressive.

2.2 Conversational AI Agents

Conversational AI allows people to communicate with devices or automated systems using natural language in the same way they communicate with a real person. The interaction may be speech

or text based and the automated system may be in the form of a device, part of an operating system or integrated into a website or application [40]. Examples of conversational agents (CAs) include: chatbots for casual conversation or question-answer systems; embodied agents (e.g., virtual avatars or agents) for face-to-face conversation; and conversational interfaces such as Apple Siri or Amazon Alexa [16, 24, 36, 40]. Researchers have also begun exploring CAs for novel applications. For example, Wearable reasoner is a system that uses natural language processing to talk to the user and teach them to think critically about information[6]. Wearable Wisdom presents an intelligent, audio-based system for mediating wisdom and advice from mentors and personal heroes to a user [35]. The idea of a virtual mentor has also been explored in MentorPal, a framework for rapid creation of virtual mentors for high school students in a question-answer system based on recordings from real STEM professionals. Students showed increased career knowledge and reacted positively to the helpfulness of virtual mentors [29]. Our work is inspired by these recent applications.

2.3 Conversational Agents based on the Deceased

While there have been numerous examples demonstrating opportunities for CAs to assist in human knowledge acquisition in an educational context, CAs have also been explored in the context of assisted mourning, remembrance and cultural heritage. For example, “HereAfter” (<https://hereafter.ai>) is a platform that allows you to create a chatbot to leave behind for your family to interact with after death, powered by more than four hours of conversations with an interviewer about your life and memories. Similarly, Dalí Lives uses vast amounts of curated archival footage to enable simple interactions with a virtual Salvador Dalí [26]. UneeQ’s digital Einstein (<https://digitalhumans.com/digital-einstein/>) is a video CAs that uses WolframAlpha to give him “computational intelligence” so he can answer a broad range of science questions. Lastly, StoryFile is a company that specializes in making CAs by manually recording video footage of someone answering as many questions as possible before their passing to create an embodied video chatbot of them.

While these systems technically allow people to talk to representations of people from the past, they heavily rely on pre-recorded or curated data that specifically match a pre-defined set of questions and answers. For instance, both Dalí Lives and StoryFile (<https://storyfile.com/>) [26] have all their questions and answer pairs pre-scripted with samples manually curated from massive amounts of text passages, or taken from recordings that took days to produce. While this format ensures that the passages spoken by the system have been uttered by the person depicted and are 100% authentic, it is extremely time-consuming and limits the scope of possible interactions with reduced dynamism in the interaction. Moving beyond these limitations requires *living memories* that can accurately understand and represent the portrayed person’s knowledge and conversational style from any available, non-curated data to allow it to respond to any questions and contextualize the knowledge into a natural and unscripted dialogue.

Recently, large language models (LLMs) like “chatGPT” have gained high popularity as CAs due to their language capabilities and easy prompting, enabling them to engage in conversations with an unprecedented human-likeness and common-sense understanding[2]. Due to these capabilities, there have also been attempts at using them to create living memories. For instance, Project December (now discontinued) enabled users to finetune an LLM, “GPT-3”, from a biography and quotes of a loved one to create a chatbot with their likeness [9, 39]. However, despite the popularity of large language models, they struggle with representing knowledge accurately and can produce convincing but inaccurate answers [2]. This becomes a significant problem when the chatbot of the deceased starts to make up knowledge about the deceased and respond inauthentically. To minimize model inaccuracy, researchers have explored increasing language models knowledge representation through model fine-tuning [2], data-curation [47], and weight editing [25] but the problem still persists. Instead, our work explores the combination of large-language models with another semantic knowledge extraction model to overcome the challenge of inaccurate model output. In contrast to other approaches, the LLM is only used for fitting the knowledge extracted by the semantic model to the dialogue flow instead of having the knowledge be embedded within the model.

3 IMPLEMENTATION OF LIVING MEMORY

As we conceptualize a Living Memory as an interactive AI-generated portrayal of a person’s stories, attitudes, personality, and wisdom, in this section, we go over the methods we use to implement living memories including data and system architecture.

3.1 Data

Numerous people have written about their lived experience in journals, diaries, online blogs, autobiographies, letters, autobiographies, online messages and social media posts. Personal writings can also be found in everyday life through private and public messages, texts, and call logs exchanged with friends, family members, or partners. Due to their content, these writings can be seen as authentic, intimately written transcriptions of the knowledge and attitudes of their author. Our implementation of an AI-generated living memory makes use of this type of written content to gather context and information about the life of an individual, and to fit their personality and writing style.

In particular, we demonstrate how a text can be converted into a living memory by sampling the journals of three famous historical figures: (1) Leonardo Da Vinci through “The Complete Notebooks of Leonardo Da Vinci” (1.279.994 tokens)[38], (2) Murasaki Shikibu through “The Diary of Lady Murasaki” (223.744 tokens)[44], and (3) Captain Robert Scott through “Scott’s Last Expedition” (1.003.123 tokens)[42].

To prepare the data for our model and to ensure the model is more likely to rely on the data rather than the name of the character, we automatically replaced the character’s name in the data source with “I” or “my”. We then split the data into smaller paragraphs based on new lines and natural paragraphs. For paragraphs that were longer than 2000 tokens, we split them into smaller paragraphs.

We did this as some models of our pipeline could only take inputs of less than 4000 tokens.

To provide the model with more knowledge about the context of the character, the original source text (*Primary Source*) is also augmented with background information (*Secondary Source*) about the character. In our case, we chose to include the secondary source introductions already in the journals we used, but this background information could also be extracted from online sources like Wikipedia, or provided by a third party. The data preparation steps were done automatically using a script.

3.2 System Architecture

In order to implement an accurate and convincing AI-generated living memory, we made use of recent advancements in natural language processing, that enable us to select meaningful information and precisely answer questions. As such, our system architecture consists of two transformer-based language models: all-MiniLM-L6-v2 (BERT) is used to respectively extract knowledge from the source document (Knowledge Extraction) and GPT-3 is used to generate answers based on this knowledge (Text Generation). The two models work jointly to ensure the relevant information is extracted and used authentically in the generated answers with respect to the source document (See Figure 2)

3.2.1 Knowledge Extraction. To perform Knowledge Extraction, we use the pretrained all-MiniLM-L6-v2 sentence transformer model [37] which maps sentences and paragraphs to a 384 dimensional dense vector space. Through this mapping, we can use the model to perform semantic search and find the paragraphs that are most likely to contain the answer to the question in the primary pre-processed source data (see Section 3.1). The paragraphs are then held in memory in the second step of the pipeline to be used by the text generation model.

3.2.2 Text Generation. The Text Generation features provided by large language models such as GPT-3 produce convincing outputs that are likely to address the specific questions asked by users. For our text generation step, we use GPT-3 [2] with the davinci pretrained model. In our pipeline, relevant paragraphs that are extracted by the knowledge extraction model are fed into the prompt given to the text generation model together with an instruction. The final prompt given each time the user asks a question was of the following form: “[Insert extracted paragraphs] Convert the above journal paragraph into a conversation between an interviewer and the author of the paragraph. Interviewer: [question] Author:[GPT-3 will generate the answer here]”. To prevent GPT-3 from using external knowledge about the character, we automatically transform the source text by replacing every occurrence of the character’s name with the first-person pronoun “I”. We also replace every genitive (e.g. “Leonardo Da Vinci’s”) with corresponding first-person possessive determiners (e.g. “my”). In order to help the model keep track of and “remember” the conversation, we also inject the last 10 questions and answers back into the query of subsequent GPT-3 calls.

3.2.3 Authenticity Verification. While large language models, such as GPT-3, can generate very convincing answers with implicit knowledge on a wide variety of topics, they are known to generate

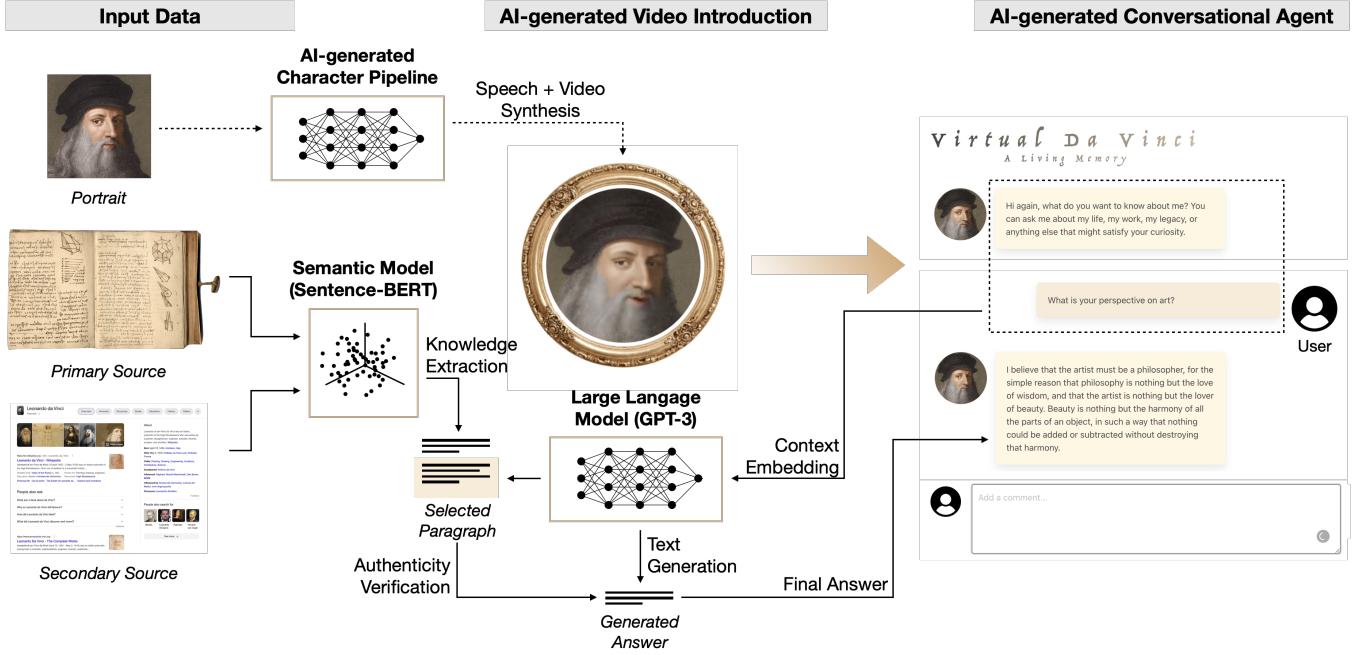


Figure 2: The architecture for our implementation of an AI-generated living memory, showing the interactions between the Semantic Model and the Large Language Model. The additional AI-generated Character Pipeline is used as an introductory step in the User Study described in Section 5.

hallucinatory content, which is defined as content that is “nonsensical or unfaithful to the provided source content” [12]. In order to make sure that the living memory does not make any wrong inferences about the knowledge or attitudes of the character portrayed by the living memory, the responses need to be authentic. To do so, the Knowledge Extraction stage of our pipeline is used to compute the semantic similarity between the generated answer and the extracted paragraph using the same sentence transformer as for extraction (all-MiniLM-L6-v2). If the computed similarity is below a certain threshold (empirically defined in our pipeline as a cosine similarity of 0.3), we output a scripted answer stating that the living memory is unable to answer the question (e.g. “I am sorry, I am unable to answer this question.”). Examples generated by our living memory system together with the extracted source text can be seen in Figure 4

4 TECHNICAL EVALUATION

We compare the capabilities of our system that combines text extraction with text generation by performing a Technical Evaluation on three different architectures:

1. A **all-MiniLM-L6-v2** sentence transformer, which uses Sentence-BERT [37] to search for semantic similarity to extract paragraphs from the source document related to the question asked.
2. A **Finetuned GPT-3**, which uses a finetuned GPT-3 model to generate answers for a given question. The GPT-3 uses the curie base model, and was finetuned on the source document of each character for 4 epochs, with a prompt loss weight of 0.01.

3. **GPT-3 + all-MiniLM-L6-v2 (our model)**, which combines the all-MiniLM-L6-v2 sentence transformer with the large language model GPT-3 (as described in Section 2.)

Figure 3 illustrates the procedure of our Technical Evaluation, which we describe in this section.

4.1 Evaluation Dataset

To evaluate the three architectures, we generated a test set of 600 Question and Answer pairs using GPT-3 with manual curation (procedure is described in Section 4.1.1 & Section 4.1.2). Of the 600 Q&A pairs, 300 questions were generated to cover information that was included in the source document, while 300 questions included information that was not present in the source document. This was meant to evaluate how different architectures are able to approach known and unknown information. We detail the generation of both categories of questions.

- 4.1.1 *In-source Questions & Answers.* We used GPT-3 to automatically generate questions on the information contained within the source document of each character. To do so, we randomly sampled paragraphs from each source document (see overview of exact sources in Section 3.1), and queried GPT-3 with the prompt “Convert the following journal paragraph into a conversation between an interviewer and the author of the paragraph”. We then manually removed every question or answer that included relative temporalities (e.g. words such as “today”, “yesterday”, “next”, “lately”), implicit contextual temporalities (e.g. “what did you do?”), implicit pronouns and adverbs (e.g. “her”, “him”, “here”, “there”), long quotations from the paragraph, or question/answer pairs that were too

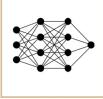
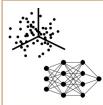
Architectures	Characters	Question Types	Participant Evaluation Criteria
	 Leonardo Da Vinci Italian Artist/Engineer	 In-source Question e.g. Where were you born?	Generated Text VS Ground Truth
	 Murasaki Shikibu Japanese Writer/Poet	 Out-of-source Question e.g. When did the Space Race start?	Content Success Rate (CSR) To what extent does the generated answer match the ground truth? Style Success Rate (SSR) To what extent is the style of the ground truth preserved in the generated answer? Understanding Success Rate (USR) To what extent is the generated answer understandable? Grammar Success Rate (GSR) To what extent is the grammar of the generated answer correct?
	 Robert Scott British Explorer		

Figure 3: We perform our Technical Evaluation on 3 different architectures, with 3 different characters, 2 different question types, and we measure 3 different participant evaluation criteria.

Question	Leonardo Da Vinci Italian Artist/Engineer	Murasaki Shikibu Japanese Writer/Poet	Robert Scott British Explorer
What is your most profound experience?	Generated Answer: I was working on a project to develop a machine that would allow people to stay underwater for extended periods of time. As I was working, I realized that this machine could also be used for nefarious purposes, such as assassinations. Source: How by a certain machine many may stay some time under water. I do not publish nor divulge these, by reason of the evil nature of men, who would use them for assassinations at the bottom of the sea by destroying ships, and sinking them.	Generated Answer: The death of my husband. It was a very sudden and unexpected death but led me to shortly thereafter begin writing my most famous work. Source: I married around the turn of the century, had one daughter and was widowed soon after. During the next four or five years it seems to have begun writing The Tale of Genji, the work of fiction that was to bring her fame	Generated Answer: I would say that the most profound experience of my life was when I was chosen to command a great Antarctic expedition. It was a great responsibility Source: It was a serious responsibility to induce him to take up the work of an explorer; yet no man living could be found who was so well fitted to command a great Antarctic Expedition

Figure 4: Examples of answers generated with our model to the question “What is your most profound experience?” for three different characters and the extracted source text.

close to other question/answer pairs. In the end, we collected a total of 100 pairs of questions and answers per character (300 total). These answers were then marked as “ground truth”.

4.1.2 Out-of-source Questions & Answers. To generate questions about information that was not covered in source documents, we used GPT-3 to generate questions about events that happened after the year of death of each character. To do so, we queried GPT-3 with the prompt “List of questions about 100 events, people and technologies after [year of death] in random non-chronological order”. This gave us a list of 100 out-of-source questions that neither of the characters could possibly know. Since we the characters would not know the answers, we paired each question with the answer “I am not sure...”. In the end, we collected a total of 100 pairs of questions and answers per character (300 total). These answers were then marked as “ground truth”.

We used the questions from our evaluation test set to generate answers using each of the three architectures that we could then compare against the ground truth. Running each architecture model on the combined in-source and out-source questions (600 total), we generated a total of 600 answers per model.

4.2 Answer Evaluation

To compare the generated answers of each model against the ground truth, we performed human evaluations using the online Prolific platform. In the surveys, 86 subjects were asked to compare the generated answers to the ground truth according to four different criteria, inspired by [55]: **Content Preservation:** To what extent does the generated answer match the ground truth? **Style Transfer:** To what extent is the style of the ground truth preserved in the generated answer? **Understanding:** To what extent

is the generated answer understandable? And **Grammar Fluency**: To what extent is the grammar of the generated answer correct? Each criterion was rated on a 5-point Likert scale by each participant (See appendix for specific questions and Likert descriptions: <https://github.com/mitmedialab/livingmemory>). Each generated answer was evaluated 3 times, 1 time by 3 different subjects with the median of the 3 evaluations being picked as the final value.

Following [17] and [55], we mark an answer as being successful if it has a rating with a score of 4 or 5 as rated by participants. We then collect five success rates to evaluate the output of each architecture:

1. **Content Success Rate (CSR)**: the percentage of answers that receive a score of 4 or 5 in the Content Preservation criterion.
2. **Style Success Rate (SSR)**: the percentage of answers that receive a score of 4 or 5 in the Style Transfer criterion.
3. **Understanding Success Rate (USR)**: the percentage of answers that receive a score of 4 or 5 in the Understanding criterion.
4. **Grammar Success Rate (GSR)**: the percentage of answers that receive a score of 4 or 5 in the Grammar Fluency criterion.
5. **Overall Success Rate (OSR)**: the percentage of answers that receive a score of 4 or 5 in all four criteria.

4.3 Technical Evaluation Results

Based on our human evaluation results in the table in Figure 5, we find that our model outperforms the finetuned GPT-3 Curie model and all-MiniLM-L6-v2 BERT model in every task. In terms of staying true to the content of the source material (and not hallucinating new answers outside of the source material), we found that our model outperformed both the Finetuned GPT-3 Curie model (43%) and all-MiniLM-L6-v2 BERT model (53%) with an accuracy of 60% on the content preservation metric (CSR). Similarly, we found that our approach had a higher preservation of style (SSR) compared to both the Finetuned GPT-3 Curie model (37%) and all-MiniLM-L6-v2 BERT model (47%) with a score of 60%. In terms of how well the answers were understandable, we also found our model to outperform the Finetuned GPT-3 Curie model (63%) and all-MiniLM-L6-v2 BERT model (67%) but by a smaller margin than the other metrics with a score of 70%. Lastly, we found that our model also produced more grammatically fluent answers compared to the Finetuned GPT-3 Curie model (80%) and all-MiniLM-L6-v2 BERT model (67%) with a score of 93%. Overall in the Overall Success Rate score (OSR), our model was found to outperform both the Finetuned GPT-3 Curie model (56%) and all-MiniLM-L6-v2 BERT model (59%) with a score of 0.71%, way above the comparison scores.

While the accuracy of our model can be further improved in terms of outputting the correct content (CSR), our results demonstrate a metric for evaluating the accuracy of living memories. The results also show how infusing knowledge into large language models, by combining such models with semantic search models, can lead to improvements over both large language models and semantic search models alone.

5 STUDY ON USER EXPERIENCE OF LIVING MEMORIES

To demonstrate our living memory model in action, we deployed our living memory as a chatbot and conducted a user study with

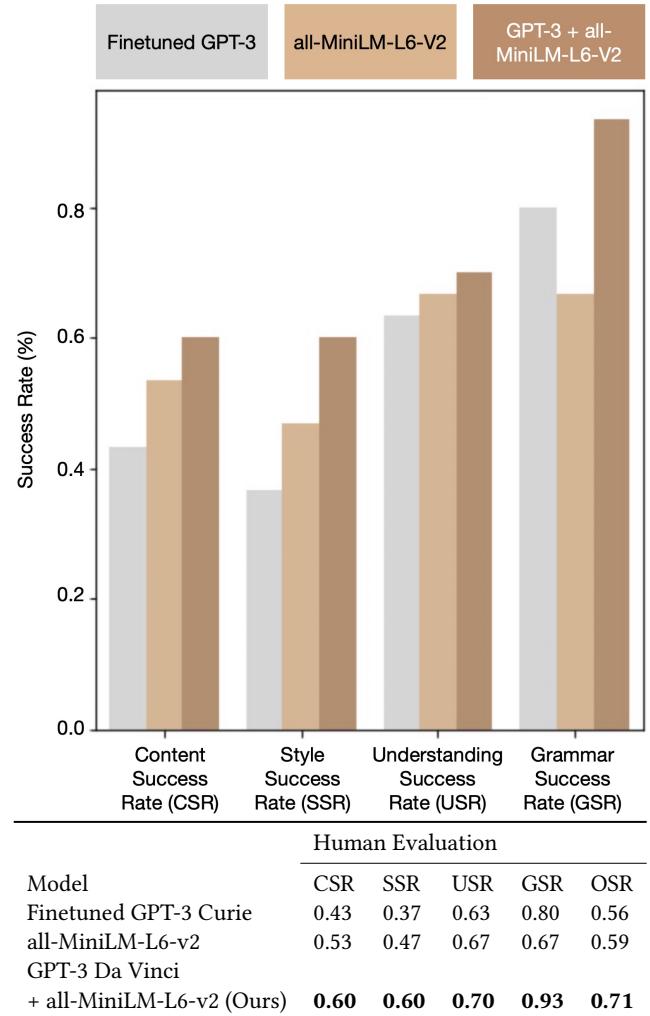


Figure 5: Technical results: Content Success Rate (CSR), Style Success Rate (SSR), Understanding Success Rate (USR), Grammar Success Rate (GSR), and Overall Success Rate (OSR)

90 participants interacting with the living memory of Leonardo Da Vinci. The participants were screened to have not taken part in the human evaluation part of our experiment (see Section 4.2). Figure 6 describes the procedure for this experiment.

5.1 Conditions

Participants were automatically assigned to one of two conditions. Participants in the first condition interacted with a living memory *chatbot* of Leonardo Da Vinci, while participants in the second condition read a PDF about Leonardo Da Vinci and then interacted with the living memory chatbot of Leonardo Da Vinci. Allowing participants to first read about Da Vinci before interacting with Da Vinci's living memory was performed in the hope that learning about Da Vinci would engage their curiosity and help them ground their questions. This also helped balance out concerns arising from

all participants engaging with the chatbot first and text second or the other way around.

5.2 Chatbot implementation

The chatbot that participants interacted with, which used our **GPT-3 + all-MiniLM-L6-v2** model to generate answers to participants' questions. The experience started with a 40 second long animated video of Leonardo Da Vinci introducing himself generated using an open-source AI-generated character pipeline [31].

"Hello, I am an AI-generated living memory of Leonardo da Vinci, an Italian Renaissance polymath. I have had a wide range of interests and have made significant contributions in many fields. In science, I made important observations in the fields of anatomy, physiology, and optics. People also know me for my famous paintings, such as the Mona Lisa and The Last Supper. As an engineer, I also designed many practical inventions, such as the parachute and the helicopter. If you have any questions about my life, please feel free to ask me."

The participants were then directed to a chatbot interface where they could type their questions and get answers. We ran the model on an in-house server with NVIDIA Titan V GPUs (although a weaker GPU will possibly work as well), and implemented a Flask API to integrate it with the chatbot interface.

5.3 Procedure

When participants enrolled in the study, subjects were directed from Prolific to an online Qualtrics survey platform. First, the web platform introduced the study ("You will learn about a historical character and answer survey questions"), and asked for the participants' consent and their Prolific ID so that they could be paired with their demographic data (see Figure 6). Next, if they consented, subjects were then asked to answer two pre-screener attention checks that if failed would exclude them from the rest of the survey so as to make sure that we only recruited subjects who were paying attention. The first pre-screener attention check asked them to input the number "15", while the second attention check asked subjects to pick two specific values. Next, subjects were assigned to either (1) a Text and Living Memory condition, or (2) a Living Memory only condition. In the analysis the "Text and Living Memory" is split into "Text" and "Text and Living Memory". In the experiment, depending on which condition they were assigned to, subjects were taken to either an interface where they could read a piece of text from Leonardo Da Vinci's journal [38] (text condition and text + living memory condition) or interact with the living memory of Leonardo Da Vinci (living memory condition). The participants were unable to skip ahead in the survey until five minutes had passed. During the interaction, participants were asked to "Please spend 5-10 minutes learning about Leonardo Da Vinci. If you don't know what to ask him, here are some examples: (1) "Tell me more about science", (2) "What did you invent?", (3) "Do you like drawing?", and "What do you think about animals?". This was done to get a better understanding of how people would engage with Leonardo Da Vinci to learn more about him, his thoughts, and his inventions. After the interaction, participants were asked to fill out a Curiosity measure,

Learning Effectiveness measure and Motivation measure (See more details about the measurements in Section 5.4). In addition, subjects who interacted with the living memory were additionally asked to fill out an Interactive Personal Agents measure. After answering the questionnaires, subjects in the "Text & living memory" condition were asked to interact with the living memory interface and fill out the above listed questionnaires, while the subjects in the "Text" and "Living memory" conditions proceeded to the hypothetical answer evaluation. Finally, we asked participants to provide open ended feedback and suggestions along with reporting any technical issues they experienced.

5.4 Measurements

- Curiosity: We measure the in-the-moment curiosity level as an average of the ratings to the 20 questionnaire items based on the state-curiosity inventory [27] on a 4-point Likert (1-Not at all to 4-Very much so).
- Learning Effectiveness: Following [4], we adapted the questionnaire used to measure the perceived learning effectiveness from video games for our study. We measure Effectiveness on a 7-point Likert scale (1-Strongly disagree to 7-Strongly agree).
- Enjoyment/Motivation: Following the scale developed by [5], we measure the level of enjoyment and motivation on a 7-point Likert scale (1-Strongly to 7-Strongly agree).

5.5 Analysis

The purpose of this experimental study is to understand the user experience and influence of interacting with living memories on user curiosity, learning effectiveness and enjoyment/motivation. To investigate these effects, Kruskal Wallis test, Welch analysis of variance (ANOVA), or basic ANOVA were used to analyze the main effects depending on sample normality and homogeneity with relevant post hoc analysis. In the analysis, we first assessed if the normality assumption was met for each distribution using the Shapiro-Wilk test due to the relatively small group sample sizes. If the normality assumption was not met, we performed a Kruskal-Wallis test followed by a post-hoc Dunn test using the Bonferroni error correction. If the normality assumption was met, we then conducted a homogeneity test using a Levene test to assess whether the samples were from populations with equal variances. If the samples were not homogeneous, we ran a Welch analysis of variance (ANOVA) and a Games-Howell post-hoc test. If the samples were homogeneous, we ran a basic ANOVA test with a Tukey post-hoc test.

5.6 Participants

Participants were recruited from Prolific, an online research participant pool¹. The total number of participants that enrolled in our study was 90 people. All participants were from the United States and fluent in English with a balanced sex distribution (50% female and 50% male). The age range of the final group of participants was

¹<https://prolific.co/>

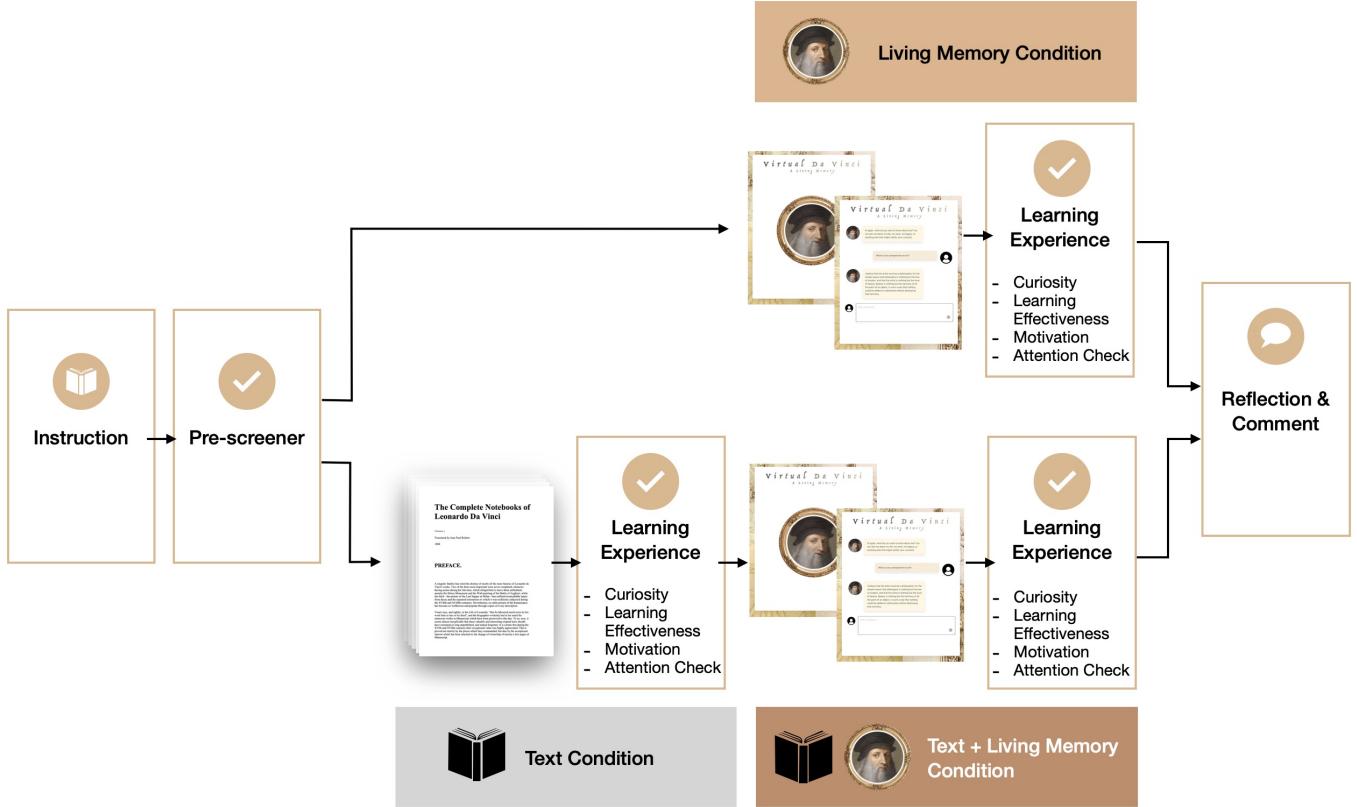


Figure 6: The procedure of our User Study, with the two different conditions used.

between 18 to 65+. Participants were randomly assigned to each condition, and could complete the study only on their computer.

6 USER STUDY RESULTS

Here we present the results from the user study with 90 participants for the dependent variables curiosity, effectiveness, enjoyment/motivation, facilitated learning, credibility, human-likeness, and engagement between the conditions “Text”, “Living Memory”, and “Text & Living Memory” (See Figure 7). Our results show that while there is no significant effects between just interacting with a living memory and reading a text (although there is a trend), having a conversation with a living memory of a historical figure in combination with reading a text about them significantly enhances effectiveness and motivation to learn about the character compared to just reading a text (the character’s journal).

6.1 Learning effectiveness

The sample has satisfied sample size sufficiency and equal distribution among conditions, thus basic ANOVA test was performed. The test reveals statistical significance among the conditions ($p=0.001$). Tukey post-hoc test reveals that participants in the “Text & Living Memory” condition ($M = 5.48$, $SD = 1.57$) have significantly reported the effectiveness of the intervention to be higher than the “Text” control group ($M = 4.11$, $SD = 1.49$). However, we observed no statistical difference between the hybrid group and the group

that solely interacted with the living memory system ($M = 4.71$, $SD = 1.58$).

6.2 Enjoyment/Motivation

The sample has satisfied sample size sufficiency and equal distribution among conditions, thus basic ANOVA test was performed. The test reveals statistical significance among the conditions ($p=0.0006$). Tukey post-hoc test reveals that participants in the condition that interacted with the living memory after reading the text ($M = 5.45$, $SD = 1.63$) had significantly higher learning motivation than the control group ($M = 3.78$, $SD = 1.84$) that was reading the text alone. However, we observed no statistical difference between the hybrid group and the group that solely interacted with the living memory system ($M = 4.67$, $SD = 1.95$).

6.3 Curiosity

The sample has satisfied sample size sufficiency and equal distribution among conditions, thus basic ANOVA test was performed. The test reveals no statistical significance among the conditions ($p=0.21$), with the highest rating in terms of curiosity being the group that interacted with the living memory after reading the text ($M = 2.84$, $SD = 0.71$) follows by the group that solely interacted with the living memory system ($M = 2.76$, $SD = 0.72$), and finally the control group ($M = 2.56$, $SD = 0.73$).

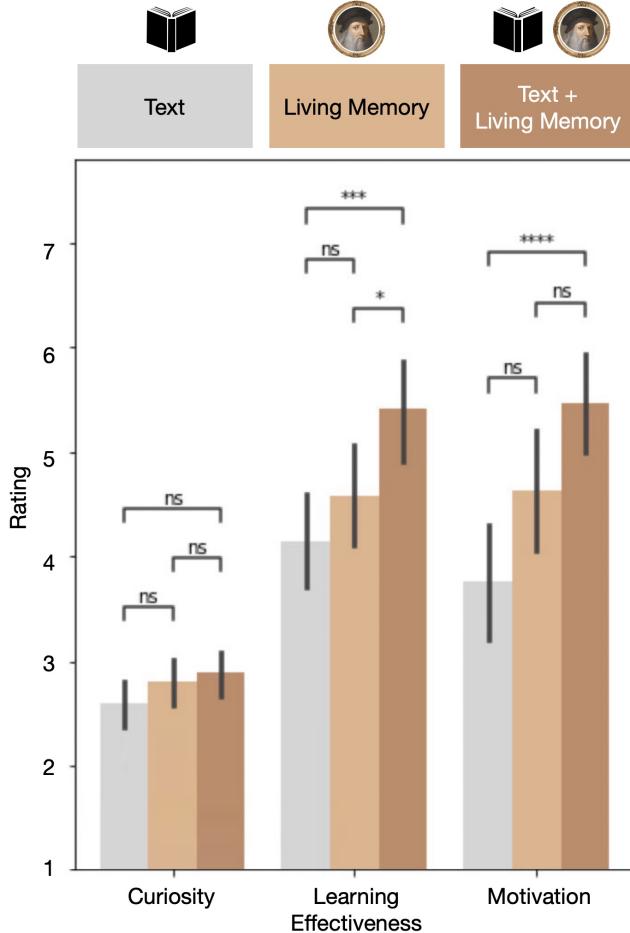


Figure 7: Overview of the user experience results. Left: The difference in learning experience between interacting with text, the living memory, and both text and living memory with regards to (i) the user’s state of curiosity, (ii) how effectively it made them learn, and (iii) their motivation for learning.

7 DISCUSSION

7.1 Living Memories and System Accuracy

In this paper, we presented a method to evaluate the content preservation, style transfer, understanding, and grammar fluency of the answers generated by our living memory architecture. Our results showed that our GPT-3 + all-MiniLM-L6-v2 combined architecture outperforms both all-MiniLM-L6-v2 semantic search and finetuned GPT-3 models across metrics of content preservation, style, understanding and grammar fluency.

We acknowledge the concerns over identity and authenticity. We can broadly classify the concerns into two categories. The first category deals with how closely the model resembles the target human. If the model is prone to be inaccurate, it may lead to misrepresentation of the human, which is highly undesirable as it goes against the

idea of a living memory. A robust system needs to always maintain the integrity of the person.

While large language models (like GPT-3) have become very popular lately due to their ability to be applied across a variety of tasks, they are notoriously known to hallucinate knowledge [12]. This makes them ineffective for authentic knowledge representation. Our results demonstrate a way to circumvent this limitation to a certain extent by explicitly infusing knowledge as context into the LLM prompt prior to question answering.

In addition to improving accuracy, our approach also makes the living memory explainable. Since we know the paragraph from the source text that is used to generate an answer, users are then able to manually check the authenticity of a generated answer by inspecting the paragraph that it is based on. Specifically, if an answer seems somewhat off, it is possible to check the source that has been used in the generation of the answer and ensure that it is correct and meaningful. While this was not made available to users in the study, future systems should allow users to see this source text for each generated answer. We believe that this will further add to the verification of authenticity.

Lastly, while our approach is more successful across metrics than the baseline models, our model was still only successful at content preservation and style preservation in about 2/3 attempts. This is still a very low success rate that requires future work and refinement to truly ensure that living memories become a successful type of digital mementos.

7.2 Inferring knowledge and evaluating answers

Attempting to capture the entire personality of an individual through written testimonies is a complex task which raises particular questions when there is no record of a specific topic, attitude or knowledge in the source text. In our implementation, we choose the living memory to respond with “I am not sure...” when an answer was not semantically similar enough to its source paragraph (less than 0.3) to prevent our model from generating inaccurate answers. However, one question is whether future Living Memory-like systems should be dotted with the capability to make inferences based on the source documents. For instance, although Leonardo Da Vinci has no knowledge about iPhones, one might argue that the living memory should be able to infer from his liking of mechanics mentioned in the source text, that he would like the iPhone. However, for a living memory to make such a statement would be to deviate from the source material. Similarly, others might also argue that the living memory should be able to remember previous interactions and learn new concepts when explained in conversation.

Going forward, we will have to question the needed capabilities of living memories. Should the living memory be able to make inferences from the source data? How do we define the validity and authenticity of such an inference? Should people be allowed to teach the living memory? Should the living memory be able to learn? Enabling the living memory to synthesize new knowledge through inferences and by learning would seemingly make the living memory go beyond being an “interactive photograph” which we previously defined it as, and get nearer to bringing the person “back to life” or “making a clone”. These are hard questions that require more research and ethical consideration.

7.3 Experience with Living Memory

Based on the results from 90 participants on the user's experience and learning effects of interacting with the living memory of Leonardo Da Vinci. Our results show that even though living memory increases learning effectiveness and motivation compared to reading the journal alone, interacting with the living memory in addition to simply reading a journal significantly increases learning effectiveness and motivation to learn about the character. These results reflect our vision to introduce living memories as a new medium for storytelling and knowledge sharing that does not replace reading and other methods of learning. We believe that the main reason behind this result is that once people learn more about the background of the character before they interact with the living memory, they have enough prior knowledge to ask better and more in depth questions, which would result in a more meaningful dialogue. Thus, our work suggests the use of living memory as complementary media to augment the experience of reading and learning about historical characters.

8 LIMITATIONS & FUTURE WORK

8.1 Beyond Text-based Living Memories

Advancements in machine learning for generating highly realistic virtual humans offer novel opportunities for creating interactions with digital portrayals of individuals that can inspire and intrigue us. AI-generated portrayals of characters can feature synthesized faces, bodies, and voices of anyone from a fictional character to a historical figure to living person. We believe that the immersive experience of Living Memories could be greatly improved by a combination of state-of-the-art generative AI models that convert text-to-audio, audio-to-video, and video-to-video to create the appearance and voice of the deceased through a variety of audio and video outputs based on the available data.

Speech Synthesis and Voice Replication could be developed using a neural network-based system with text-input to synthesize speech audio in the voice of different speakers as demonstrated in [13]. Additionally, Facial Animation Video Synthesis could be integrated into our pipeline as an ensemble model with (i) a temporal generative adversarial network (GAN) for generating a face that lip-syncs the input audio with natural facial expressions such as blinks and eyebrow movements [51], and (ii) a self-supervised learning algorithm to transfer face motion from the lip-synced video to a target image of the replicated person [45].

Through this paper, we aim to pave the way for more accurate text generation through the use of extracted context. Although the results are promising, using a semantic model is a simple approach, and we envision that using more performant Knowledge Extraction technologies (e.g. Knowledge Graph extraction approaches like Modular QA [14]) could expand the potential and accuracy of Living Memories in the future.

8.2 Applications

The examples of Living Memories put forth in this paper represent only the beginning. Some potential use cases for such a system could include mourning and remembrance, cultural preservation, or learning about historical characters and events. Like photographs

or letters left by the deceased might bring comfort or preserve memorable moments and help in the grieving process, we envision Living Memories to give people a new way of remembering and mourning, as an interactive photograph. Another application includes the use of living memories for preserving cultures. Every 14 minutes, a language dies and with it, the oral traditions and cultural values embedded within the language [28]. Beyond personal use, living memories that use voice cloning to copy someone's voice [56] could help preserve those traditions and values beyond the extinction of the language. Living memories could also assist individuals in learning about historical events and characters [31, 33], or advanced concepts through a conversation with the living memory of a historical figure, pioneer or an expert in an area. For example, a student may ask Dr. Einstein's AI to explain Relativity. This has the potential to make learning more interactive and potentially more engaging. The user could also gain multiple perspectives by talking to multiple living memories of various mentors. This will help users understand the challenges faced by these target humans and the approaches they took to overcome them. Researchers have shown that learning about the struggles that great scientists have gone through helps improve science learning and makes the students feel connected to the lesson and the scientists [18]. Finally, a living memory can also be created to capture a person's attitude and perspective at a point in time by training the model on a personal diary. This would allow a person to look at themselves from a second perspective and talk to different versions of themselves as they have grown over their life time [32].

9 ETHICAL CONCERNS

As mentioned in the introduction, we acknowledge the concerns that many people might feel that this type of research is uncanny and controversial as it is touching on sensitive topics. For one, critics may argue that having an AI portray a person in the form of a Living Memory would devalue the integrity of the historical figure that it is based on. Rather than using the narrative of "Digital Immortality" that aims to bring the person back to life or create a clone of the person, we think of living memories as analogous to an actor playing a historical figure in a biographical film, based on the figure's autobiography. It offers a way of celebrating life, sharing the story, and passing on an important figure's life lessons to later generations.

However, if the model is highly accurate in resembling the target human, we may encounter issues similar to those around deepfakes [48]. There could be potential misuse leading to scams, fraud, and fake news. How would people be able to tell a living memory from a real person? What if people changed the data source of the living memory, making it say things or have opinions that the original person never did? Lastly, adequate permissions must always be acquired from the living target humans or from the family of deceased target humans for these systems. These systems must always be built for positive use cases and abide by any governmental policies in the region where they are being built. As with deepfakes, we do expect more regulation in other areas of AI use. In 2018, for instance, the "Malicious Deep Fake Prohibition Act" was introduced to the US Senate and in 2019 the "DEEP FAKES Accountability Act" was introduced in the House of Representatives[53]. Several states have

also introduced legislation regarding deepfakes, with California signing into law Assembly Bills No. 602 and No. 730 that provide individuals a cause of action against deepfake content creators and the ability to prohibit distribution of malicious deepfake audio or visual media targeting them. We acknowledge that the concerns presented here might not be an exhaustive list of all potential misuses of living memory, and urge the researchers working in this area to ensure to further investigate and ensure the ethical use of the technology.

10 CONCLUSION

Every human culture has developed practices and rituals associated with remembering people of the past - be it for mourning, cultural preservation, or learning about historical events. In this paper, we presented the concept of “Living Memories”: interactive digital mementos that are created from journals, letters and data that an individual has left behind. Our results show that interacting with living memories in addition to simply reading a journal increases learning effectiveness and motivation. Together with our proposed evaluation metrics for living memory, we envision living memories as immersive mementos that effectively assist people in learning about historical events, cultural preservation, and remembering the past.

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