Towards Cognitively Aware Intelligent Systems: A Survey of Human Memory's Role in Shaping Adaptation Mechanisms

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Abstract

In an increasingly digital world, the ability of systems to adapt to individual users has become essential. Among cognitive variables informing such systems, the human short-term memory plays a crucial role, as it is responsible for perceiving, storing and retrieving data. This study explores the modalities in which various information about memory-related processes has been used in the field of Human-Centered AI (HCAI) by analyzing input methods, objectives, application domains and nature of implemented adaptations. By conducting a systematic literature review, the paper aims to address this gap, while identifying current trends and challenges. The 45 papers included in this study revealed that increasing or decreasing complexity of content or adjusting difficulty levels based on accuracy rates or time periods can improve human performance and support learning in computer-based environments. Such personalization are especially useful in the educational and healthcare domains. These results provide a basis of design guidelines for future research of adaptive mechanisms considering memory-related information. This survey is anticipated to be a starting point for upcoming developments in this field or succeeding reviews that could incorporate a wider range of the memory scope.

1 Introduction

Diverse systems and artificial intelligence are progressively integrated into daily life, from digital assistants and smart home devices to recommendation systems and autonomous technologies. As people rely more heavily on these systems, it becomes even more evident that a static and generalized system will not satisfy everyone. This leads to a necessity of tackling the one-size-fits-all approach and shifts the attention to personalizing these systems to the user[32].

The key feature of any adaptive technology is the user model that encapsulates observed information about the human interacting with it. These models allow the system to make informed decisions about how to respond to and aid the user based on sensed input, being the foundation for adaptive behavior. For more accurate profiling, systems have started integrating not only basic information such as background, interests and goals, but individual traits such as cognitive styles, extracted from specially designed psychological tests[12].

Understanding these traits often include examining fundamental cognitive mechanisms such as the human memory which is the main process this research focuses on. Memory plays a pivotal role in shaping how individuals engage and process information, meaning that accounting for individual memory differences can lead to a more effective and supportive interaction. While recent developments have begun to incorporate memory-related factors into system design, a comprehensive overview of current approaches remains lacking.

This paper aims to systematically review the mechanisms through which various systems obtain and use information related to the user's memory to adapt their behavior in meaningful, human-centered ways. The investigation is structured around a series of research questions that seek to be answered.

- **RQ-1:** What types of memory-related information are used in Human Collaborative AI (HCAI) research for system adaptation?
- **RQ-2:** For what objectives has this information been used?
- **RQ-3a:** How has this information been used?

- **RQ-3b:** Are there any trends or patterns observable in this usage?
- **RQ-4:** In which application domains is this information most commonly employed?
- **RQ-5a:** Are there any trends or patterns observable with respect to these aspects?
- **RQ-5b:** What challenges and trends exist in recent developments?

The remainder of the paper will introduce background information on human short-term memory and its concepts in section 2 and review previous work done in this area of research in section 3. The methodology in section 4 then outlines the protocol design for paper inclusion in subsections 4.1 to 4.4, the selection process in subsection 4.5, the search results in subsection 4.6 and the extraction strategy in subsection 4.7. The results are presented in section 5 and discussed in section 6. Section 7 will reflect upon the method used and discuss the ethical considerations. Finally, the research is summarized and potential future work is described in section 8.

2 Background

Human memory, as defined by Squire[41] consists of multiple systems with distinct operating principles and neuroanatomical structures that function in parallel to support behavior. It plays a critical role in learning, decision-making, and adapting to new environments. Typically, it is portrayed as three major stages:

- **encoding**: the process of acquiring information
- **storage**: the maintenance of information over time
- **retrieval**: the ability to access stored information when needed

However, the human memory is divided into two categories: declarative (conscious recall of facts and events) and non-declarative (unconscious memory processes such as skills and conditioned responses) memory. A lot of research, including this one, focuses on the declarative memory, in particular the short-term memory, also known as working memory. This subsystem allows individuals to recall information ranging from personal experiences (handled by the episodic memory) or general knowledge (managed by semantic memory).

3 Related Work

There has been a significant number of studies delving into the approaches used to evaluate and assess user's cognitive and memory-related capacities in digital environments. Thorpe et al.[49] investigated the methods used for empirically measuring the workload capacity of the users using digital systems. Although workload capacity (WLC) and working memory capacity (WMC) are both concepts that relate to the capacity of processing information, they differ in focus. WMC focuses on an individual's capacity to maintain and process information while WLC on the efficiency of the perceptual processing.[53]. Another study, conducted by Suzuki et al.[47], analyzes how cognitive load has been measured using physiological methods such as eye-tracking and electroencephalography (EEG), in the context of augmented reality (AR) systems.

Other studies have researched the intersection of cognitive abilities and digital interventions. For instance, Shaban et al. [36] studied the current applications aimed at training the working memory of children with learning disabilities and the effects they had on the cognitive abilities of the children. Moreover, certain guidelines and design principles were inspected. Baquero et al.[8] also aim their study towards computer-based training programs for people with mild cognitive impairment or mild dementia.

While aligned with previous contributions in evaluating how memory-related measurements are conducted, this paper centers around adaptive systems and explores the ways in which they take into account the memory of the user, regardless of their age or disabilities, to personalize their experience.

4 Methodology

This paper conducts a Systematic Literature Review, following the 2020 PRISMA guidelines[39]. This consists of systematically searching, filtering and synthesizing all relevant studies on the topic of adaptation for intelligent systems based on human memory. This method ensures a comprehensive and transparent search that can later be replicated and reproduced.

This section describes the main steps taken for the systematic literature review, including the eligibility criteria in subsection 4.1, the feasibility criteria in subsection 4.2, the literature databases in subsection 4.3, the search strategy of this study in subsection 4.4, the selection process in subsection 4.5, the search results in subsection 4.6 and the extraction strategy in subsection 4.7.

4.1 Eligibility Criteria

In the context of systematic literature reviews, the inclusion and exclusion criteria define the characteristics that determine whether a study is eligible or not to be included in the review. The eligibility criteria used for this study are presented in Table 5 and Table 2.

Inclusion Criteria	**Motivation**
System introduced in the paper is adapting based on the user's recorded memory.	The scope of the research.
The paper introduces a system that takes as input the user's memory and introduces ways to adapt the system based on them, even if not implemented yet.	If the system has the possibility to adapt to the memory, even if only in the future, than it falls under the scope of this research.

Table 1: Inclusion Criteria of the Study

Exclusion Criteria	**Motivation**
The paper introduces the concept of any computer-related memory (i.e., AI memory, organizational memory instead of human memory).	We are investigating how the human processes are influencing intelligent systems, not how intelligent systems mimic the human memory.

The paper is not in English.	Reproducibility could potentially be affected by using papers that are not understandable by everybody.
The paper focuses on mimicking the human memory in a machine, instead of taking the user's memory as input.	The research focuses on ways in which technologies adapt based on the human memory, taken as input, not on how we can imitate the human memory processes.
The paper is a survey or a review.	This paper relies on primary sources, instead of indirect information, helping eliminate bias in findings.
The paper introduces a systems that doesn't adapt itself in regard to the observed memory of the user.	The survey focuses on usage of the memory information in the adaptation of intelligent systems.
The paper introduces a Wizard-of-Oz approach of the system.	This study is focused on concrete research completed until this date regarding adaptations.
The paper aims to assess a certain characteristic of a system.	This focuses on the evaluation of that system, and not on the adaptability, falling out of our scope of research.
The paper is a retracted publication.	If the paper got retracted, it means it was faulty.

Table 2: Exclusion Criteria of the Study

4.2 Feasibility Criteria

Due to the limited time frame of the 10 week project, certain feasibility constraints had to be established when constructing the queries and extracting the papers. These are illustrated in Table 3.

Feasibility Criteria	**Motivation**
Restricted range of memory types.	During the scoping phase of this research, a pattern emerged in digital systems focusing on short-term memory types, such as working memory, procedural memory, and visual memory. These appeared the most relevant topics for this study, so only those were explicitly included in the query.
Only include papers from the Computer Science field.	As intelligent systems fall within the domain of Computer Science, this field was identified to be the most relevant for this research

Table 3: Feasibility Criteria of the Study

In Web of Science, the field of Computer Science is not a singular criterion that can be selected, but a series of categories. For this study, we include the following: Computer Science Theory Methods, Computer Science Information Systems, Computer Science Artificial Intelligence, Computer Science Interdisciplinary Applications, and Computer Science Software Engineering.

4.3 Search Engines

To perform the searches, the following bibliographic databases were used: Scopus[1], Web of Science[2] and ACM Digital Library[3]. This selection was made due to their extended coverage within the domain of Computer Science. The first two offer interdisciplinary access to high-impact journals, while the last one is recognized for its specialized access to a wide range of conference proceedings, journals, and technical magazines relevant to computing and information technologies.

4.4 Search Strategy

An essential part of the review process involved formulating a targeted search query to capture the most relevant studies. The final query used for this survey is found in Appendix A. In order for this to be developed, the topic had to be split into four key concepts: Human, Memory, Adaptation and Intelligent Systems. Such a division was made considering the research questions and topic of the study. The concept of *Intelligent Systems* supports the introduction of a system, framework or tool, while the *Adaptation* part ensures the previously mentioned technologies describe adaptive behavior or introduce ways to personalize the experience for the user. This leads to the remaining two concepts: *Human* and *Memory*, which should serve at least as input. They were separated to facilitate the mention of the various types of memory. The set of relevant papers is the result of the intersection of these concepts and their related terms, as illustrated in Figure 1.

[1] http://scopus.com
[2] https://www.webofscience.com
[3] https://dl.acm.org

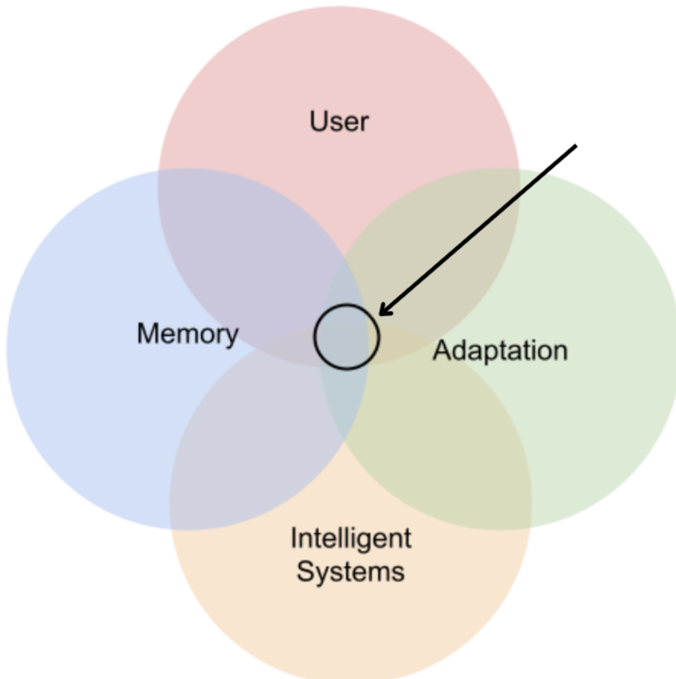

Figure 1: Main concepts of the search strategy

For each of these concepts, a list of synonym terms, word derivations and related terminologies has been used in the search. This can be observed in Table 4.

Concept	**Keywords**
User	user*, people
Memory	"working memory", "prospective memory", "visual memory", remember*, "visual spatial memory", "visual short term memory"
Adaptation	adapt*, interact*, influence
Intelligent Systems	model, interface*, framework*, robot*, coach, design

Table 4: Concepts and Associated Keywords Used in the Search Strategy

4.5 Selection Process

After the running the base queries and gathering papers from the three databases, these papers were filtered based on the eligibility criteria described in section 4.1 to asses if they fulfill the requirements to be included in the survey. This is a three-step process:

1. **Screening by title:** Based on the title of the paper, it is decided if the paper meeting the criteria previously defined. If the title is value, the paper is kept and further analyzed in the next steps.

2. **Screening by abstract:** The papers kept from step 1 are then kept or discarded based on their abstracts.

3. **Screening by full-text:** For each of the remaining papers, the entirity of the paper is read and their eligibility is decided.

4.6 Search Results

A total of 4152 results were retrieved on May 29, 2025 as follows: 1867 from Web of Science, 2064 from Scopus and 221 from ACM Digital Library. Of these, 2506 were not in the Computer Science field and 486 duplicates were removed. Based on the filtering described in 4.5, a number of 547 papers were excluded based on the title, 441 based on the abstract and 127 based on full-text, resulting in **45 included papers**. Figure 2 visually summarizes these steps.

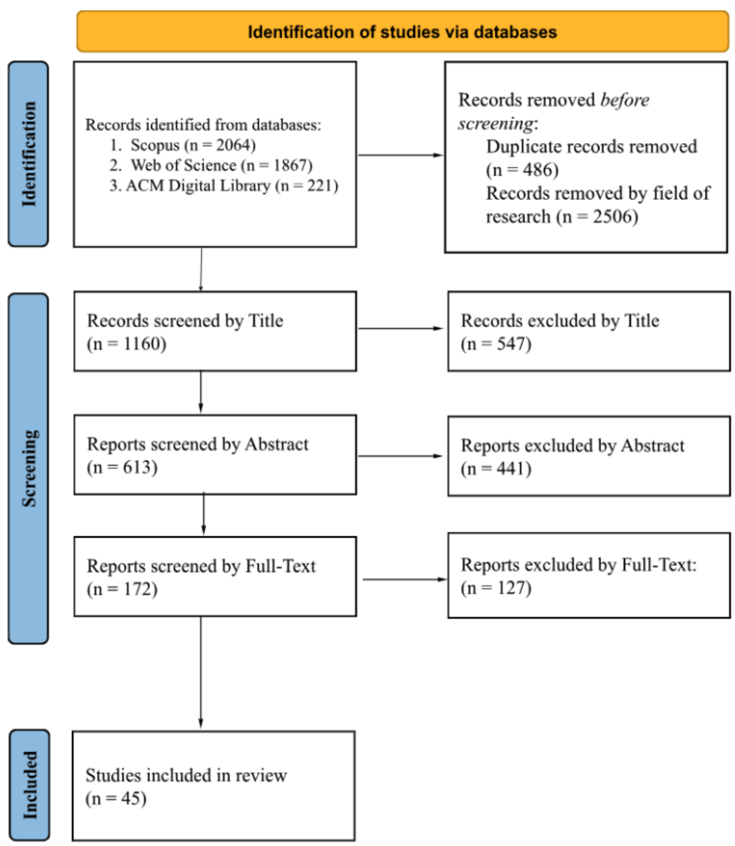

Figure 2: PRISMA flow diagram

4.7 Data Extraction

The papers that are decided eligible for the survey after the manual filtering are used for data extraction. References were stored into a management tool called Zotero[4] and the information necessary to answer the research questions mentioned in the introduction is listed below:

Information	Research Question
What does the system measure?	RQ-1
How is the input measured and, if applicable, with the help of what devices?	RQ-1
What does the user model predict?	RQ-1, RQ-3a
For what objectives has the system been designed?	RQ-2
What adaptations does the system implement based on the observed information?	RQ-3a, RQ-3b
Application domain	RQ-4
Type of system	RQ-5a, RQ-5b
Target audience	RQ-3b, RQ-5a, RQ-5b
Are the adaptations conceptual?	RQ-5b

Table 5: Research Questions of the Study and Their Motivation

5 Results

This chapter presents the results of the literature review conducted to explore how memory-related information is used to guide system adaptation. Section 5.1 outlines the input data and measurements related to the user's memory that the system collects to enable adaptive responses in subsequent phases, addressing **RQ-1**. Section 5.2 focuses on the nature of the adaptations implemented and the objectives they aim to fulfill, while highlighting any observable patterns. This answers **RQ-2**, **RQ-3a** and **RQ-3b**. Section 5.3 offers an overview of the application domains for which these systems were developed, covering **RQ-4**. Challenges and trends observed in recent years are introduced, responding to **RQ-5a** and **RQ-5b**, in section 5.4.

5.1 Memory-Related Input Data and Measurements

The first step of any adaptive system is to sense and interpret input data, forming its internal representation and driving adaptive behavior. This paper focuses on the type of memory-related information that has been used across the literature. An overview of these findings can be seen in Table 6.

[4]https://www.zotero.org

What does it measure	Number of papers	Papers
brain activity	8	[44], [37], [40], [52], [3], [54], [2], [27]
cognitive abilities	7	[30], [26], [43], [55], [50], [22], [20]
correct / incorrect answers	15	[7], [37], [35], [29], [5], [31], [16], [24], [23], [34], [54], [1], [9], [17], [15]
eye data	6	[5], [3], [43], [42], [18], [25]
time	10	[37], [16], [43], [54], [55], [9], [15], [5], [22], [10]
number of interactions with the system	2	[11], [6]
memory load	1	[28]
user performance	6	[14], [13], [34], [33], [18], [51]
user's password forget rate, recall threshold, write threshold	1	[4]

Table 6: Overview of inputs related to the memory used by the systems

The majority of the systems begin with an initial task designed to assess the user's mental state through various methods. The most common measurement is evaluating user responses to a predefined set of questions, ranging from math problems[23] to vocabulary[11].

Neurophysiological data is also a frequent choice. Among the brain activity measurement tools, functional near-infrared spectroscopy (fNIRS) has emerged as the most widely used[52, 3, 54, 2, 27].Others modalities include event-related potentials (ERP)[44], and electroencephalography (EEG)[37, 40].

In addition to accuracy and physiological metrics, many systems incorporate temporal indicators as proxies for memory performance. These consist of task completion time [37, 16, 43, 54, 55, 15], average response time[9], hesitation before response[5, 54, 22], and duration of task interruption[10].

Other measures identified in the literature range from cognitive abilities (perceptual speed, verbal working memory, visual working memory[26, 43, 50], spatial memory, visual scanning[26], and working memory capacity[22]), to various indicators of user performance (whether the user has eaten yet[14], game scores[34, 33], or results of psychometric tests[51]).

5.2 Adaptive Mechanisms

This section aims to give an overview of the adaptive mechanisms that intelligent systems have used in regard to human memory, as seen in Table 7. A wide range of adaptation strategies were identified, the most popular consisting of modifying the complexity and structure of the provided information. This included approaches such as simplifying visual content, reducing the number of interface elements, or providing additional instructions. Task difficulty adaptation is also a reoccurring behavior, where missions were scaled up or down in difficulty based on prior performance in game-like environments.

Adaptation	**Number of papers**	**Papers**
modify complexity and structure of provided information	18	[44], [45], [31], [3], [28], [26], [13], [22], [30], [33], [9], [50], [17], [15], [51], [25], [52], [20]
change difficulty level	9	[37], [40], [5], [24], [54], [55], [33], [27], [15]
add or remove reinforcement	7	[11], [48], [10], [43], [50], [42], [14]
adjust type of content provided	11	[7], [35], [4], [37], [5], [18], [29], [38], [21], [28], [1]
extend or cut out the exposure period	3	[52], [31], [34]
increase or decrease number of reminders	2	[20], [2]

Table 7: Overview of adaptation strategies implemented by the systems

An observable pattern in those adaptations is their focus on accommodating instead of challenging the user when performing a task or playing a game. This manifests as decreasing the difficulty, lowering the complexity, or adding more guidelines. Another trend is the attempt to predict the memory-related states in advance and validating them through the collected input. These interactions consist of constructing user clusters based on similar answers [34, 55, 9, 4] or dynamically adjusting internal parameters such as forget rate[11] and number of available quanta[35].

Pinpointing the objectives behind adaptive interventions allows for a deeper understanding of how memory-related measurements illuminate the rationale behind design decisions and the broader role of adaptation in supporting user needs. Table 8 summarizes the objectives extracted in this study.

Objective	**Number of papers**	**Papers**
cognitive training and rehabilitation	11	[7], [37], [19], [31], [16], [24], [38], [34], [21], [33], [17]
learning and education support	9	[40], [5], [11], [16], [10], [23], [54], [1], [27]
performance optimization	10	[44], [35], [52], [46], [40], [16], [3], [23], [22], [55]
user experience and interface adaptation	10	[45], [48], [28], [26], [13], [9], [50], [6], [42], [15]
assessment and monitoring	5	[29], [45], [34], [15], [51]
safety and daily life assistance	8	[52], [14], [22], [30], [2], [20], [18], [4]
person re-identification	2	[38], [21]

Table 8: Overview of the objectives of the systems

The table outlines high-conceptual domains, each consisting of a set of more granular and context-specific goals. For example, cognitive training and rehabilitation encompasses objectives ranging from post brain injury recovery processes[34] to memory enhancement programs for older adults[15, 24]. Similarly, educational support provided by the systems can vary from teaching children the basic shapes[5] to designing lessons for efficiently learning a foreign language[11]. An important aspect often lost by cognitive impaired patients is their ability to live independently. To address this, systems that ensure the individuals don't forget to eat meals[14], can choose a playlist by themselves[30], or are able to set passwords they will later remember[4] have been conceptualized.

5.3 Application Domains

While these systems are customized to the user's needs, it is particularly revealing to consider the application domains they are aimed to be used in. An overview can be found in Figure 3. As expected, most of them have clustered into domains such as healthcare and education. However, intriguing is the fact that more than 30% of the papers included in this study, do not mention anything about a specific domain for their systems.

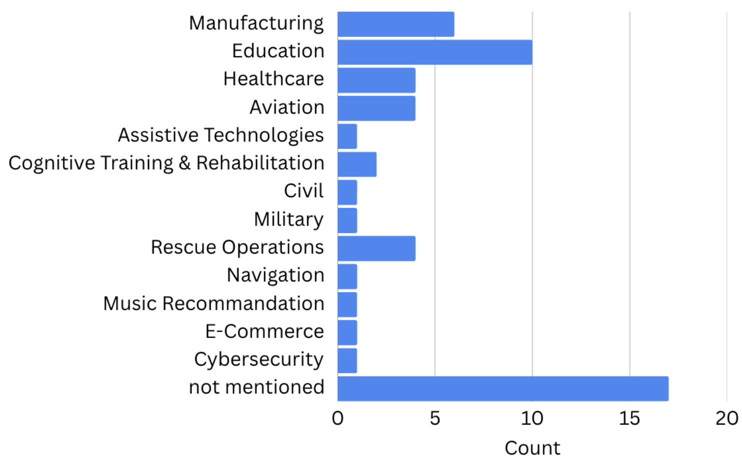

Figure 3: Application Domains Overview

5.4 Challenges and Trends in Recent Developments

When looking at papers from the last five years, there has been a clear shift toward implementing adaptive systems rather than merely proposing conceptual frameworks. However, the literature indicates that, even now, most of these systems provide only a starting point for development. This uncovers a large area of research that has not been yet explored.

In addition, a recurring limitation observed across much of the recent work is the narrow focus on memory as a singular source of input for driving system adaptation. While memory is undoubtedly a crucial component of cognitive function, its consideration in isolation overlooks the nuanced interplay it shares with other factors, such as attention, emotion, personality traits, motivation, and learning processes. Few systems attempt to integrate these variables in a cohesive framework, which may be due to both conceptual challenges and technical constraints. This gap raises the question of whether a single system is enough to conceptualize the multidimensionality nature of human beings.

The application domains for which these tools have been designed primarily cluster around manufacturing and education. In educational settings, these systems aim to support cognitive engagement and knowledge retention, while in manufacturing, the focus is often on maintaining worker effectiveness and reducing cognitive fatigue during complex or repetitive tasks. This focus reflects a growing emphasis on enhancing learning efficiency and sustaining productive performance over extended periods of time.

6 Discussion

This literature review aims to identify the current usage of human memory as a basis for adaptive behavior of various systems, exploring the input modalities, underlying motivations and application domains.

Given the dynamic and fallible nature of the human memory, it becomes necessary to develop measures that could assess specific memory states and levels of cognitive load. These often include tracking the accuracy of responses (i.e, correct or incorrect answers) or temporal data regarding delays or average response times. Moreover, brain activity can continuously be monitored using tools like fNIRS, allowing observation of neural signals over customized time intervals. This data can later be used to impose adaptation policies.

The findings also reveal a predominance in game-like scenarios incorporated in the systems, often in the form of serious games[35, 29, 45, 31, 24, 48, 33], challenges from a humanoid robot[7, 37, 5], or tasks in AR environments[44, 16, 17]. These adopted strategies improved content perception by the user by accommodating the cognitive state and mental load the user can manage, facilitating efficient performance and increased satisfaction.

However, many systems have not yet moved beyond the conceptualization stage, only proposing adaptation strategies, without full implementation[44, 45, 19, 10, 26, 23, 43, 1, 50, 27, 42, 18, 25]. This indicates a remaining gap in the potential new methods and effects of integrating memory information of the user into adaptive technologies.

The value of an adaptive system lies on its relevance to the human using it. While in the context of memory insights, it is expected that such frameworks primarily target individuals with cognitive impairments such as Alzheimer's Disease[30], Parkinson's Disease[33], or dementia[35, 14], the literature also reveals a different emphasis. A significant number of tools are designed to provide support for specialized workers such as pilots[52, 3, 29, 28] or manufacturers[44, 37, 16, 48, 27, 17], which closely ties to the application domains observed in section 5.

Regarding age, only a single paper[5] introduces a system designed explicitly for children, between the ages of 3 and 5. This is presented as an autonomous robot tutor with a personalization policy for when to increase or decrease the difficulty level of the lesson or change the tone of the feedback. In contrast, other studies that consider an age group as their target audience prioritize the elderly[31, 20, 15].

7 Responsible Research

Responsible research refers to the practice of conducting scientific work in a way that is ethical, transparent, and mindful of its social impact. This section addresses the methodology used in subsection 7.1 and discusses the ethical considerations in subsection 7.2.

7.1 Reflection upon method

The survey was conducted using a systematic literature review, with each step performed and reported according to the PRISMA guidelines. This ensures reproducibility to a certain extent. However, due to the research being carried out by a bachelor student with no prior experience with systematic reviews, potential errors may be introduced, particularly in the screening phase. To address this, detailed documentation was recorded throughout the filtering process to enhance transparency.

7.2 Ethical Considerations

Some existing research frameworks aim to detect, assess, or even diagnose an individual's mental state based on memory-related behavior. However, such assessments should involve qualified medical professionals, as they fall within the domain of clinical expertise. It is important to clarify that this survey does not attempt to diagnose or evaluate any individual, instead, it focuses solely on analyzing how various systems utilize user memory in adaptive and interactive contexts in previous research.

8 Conclusions and Future Work

This paper explores the integration of cognitive-affective information related to memory in adaptive technologies, examining how it has been used, for what purposes and in which application domains it proves most beneficial. It uncovers any trends or patterns that might have emerged across the literature regarding the usage and domains and pinpoints the challenges concerning memory in adaptations in the recent 5/10 years.

Those questions were answered through a systematic literature review conducted in accordance with the 2020 PRISMA guidelines, resulting in the inclusion of 45 relevant papers. The final selection was drawn from three major academic databases: Scopus, Web of Science and ACM Digital Library. The scope was restricted to the Computer Science field and inclusion was determined based on a clearly defined eligibility procedure. A complete study can be conducted without the feasibility criteria for a more accurate perspective on this topic.

The study outlines the reliance on external tests and serious games as indirect measures to infer user's memory state and cognitive load, given the abstract and inaccessible nature of the human memory. Most popular approaches include counting the number of errors or correct answers, as well as temporal indicators of performance, such as average response time or time needed to complete a task. However, some authors have pursued a more direct method by analyzing brain activity though means such as fNIRS or EEG, and tie these signals with user performance to guide system adaptations.

A correlation highlighted in numerous studies implies that as the user's cognitive load decreases, so does their performance and efficiency to perceive information. Building on that, those systems have adopted adaptive strategies regarding the actual content intended for the user, such as modifying the complexity, structure or type of information that is displayed. While such mechanisms are common in web-based platforms, a considerable number of studies presents game-like scenarios. For these contexts, the prevalent practice is dynamic difficulty adjustment, tailoring levels on user's scores and performance. Those adaptations aim to improve user satisfaction, support memory training and rehabilitation and facilitate digital-based education.

The nature of the systems' behaviors aligns with the reoccurring application domains such as healthcare and education. However, a gap still remains, as many papers omit the specification of the domain their system is intended to be used in. This lack of context limits the impact of the review and draws attentions to the necessity of future research to explicitly mention implementation domains.

In the future, this survey can be expanded by removing feasibility constrains and broadening the scope of memory constructs included. For example, adding literature from the *IEEE Xplore* database and not limiting the query to the Computer Science field. Moreover, the memory component of the current review has been composed of short-term memory concepts that relate to storage and retrieval of information. Incorporating studies that address semantic memory or long-term memory could offer richer insights into the role played by the human memory in adaptive context, expanding the results of **RQ-1**.

References

[1] A.M. Abdullahi, R. Orji, and J.C. Nwokeji. Personalizing persuasive educational technologies to learners' cognitive ability. volume 2018-October, 2018.

[2] D Afergan, SW Hincks, T Shibata, and RJK Jacob. Phylter: A System for Modulating Notifications in Wearables Using Physiological Sensing. volume 9183, pages 167–177, 2015.

[3] D Afergan, EM Peck, ET Solovey, A Jenkins, SW Hincks, ET Brown, R Chang, RJK Jacob, and ACM. Dynamic Difficulty Using Brain Metrics of Workload. pages 3797–3806, 2014.

[4] Y Al-Slais and W El-Medany. User-Centric Adaptive Password Policies to Combat Password Fatigue. *INTERNATIONAL ARAB JOURNAL OF INFORMATION TECHNOLOGY*, 19(1):55–62, January 2022.

[5] O. Almousa and S. Alghowinem. Conceptualization and development of an autonomous and personalized early literacy content and robot tutor behavior for preschool children. *User Modeling and User-Adapted Interaction*, 33(2):261–291, 2023.

[6] P. Andreou, P. Germanakos, A. Konstantinidis, D. Georgiadis, M. Belk, and G. Samaras. Towards user-centric social networks. pages 795–798, 2012.

[7] V Araujo, D Mendez, and A Gonzalez. A Novel Approach to Working Memory Training Based on Robotics and AI. *INFORMATION*, 10(11), November 2019.

[8] A. A. D. Baquero, R. M. Droes, M. V. P. Bartolome, E. Irazoki, J.M. Toribio-Guzman, M. A. Franco-Martin, and H. van der Roest. Methodological Designs Applied in the Development of Computer-Based Training Programs for the Cognitive Rehabilitation in People with Mild Cognitive Impairment (MCI) and Mild Dementia. Systematic Review. *JOURNAL OF CLINICAL MEDICINE*, 10(6), March 2021.

[9] M Belk, P Germanakos, P Andreou, G Samaras, and IEEE. Towards a Human-centered E-Commerce Personalization Framework. pages 357–360, 2015.

[10] U Bhandari and K Chang. Getting Interrupted? Design Support Strategies for Learning Success in M-Learning Applications. volume 10282, pages 32–43, 2017.

[11] M BielikovÃ¡ and P Nagy. Considering human memory aspects for adaptation and its realization in AHA! In W Nejdl and K Tochtermann, editors, *INNOVATIVE APPROACHES FOR LEARNING AND KNOWLEDGE SHARING, PROCEEDINGS*, volume 4227, pages 8–20, 2006.

[12] P. Brusilovsky and E. Millan. User Models for Adaptive Hypermedia and Adaptive Educational Systems. In *The Adaptive Web: Methods and Strategies of Web Personalization*, pages 3–53. Springer Berlin Heidelberg, Berlin, Heidelberg, 2007.

[13] A Caravantes. INTERACTION PROCESSING OF A COGNITIVE EDUCATIONAL SYSTEM. pages 387–390, 2010.

[14] W.-T. Chang, S. Wang, S. Kramer, M. Oey, and S. Ben Allouch. Human-Centered AI for Dementia Care: Using Reinforcement Learning for Personalized Interventions Support in Eating and Drinking Scenarios. volume 386, pages 84–93, 2024.

[15] A Costa, V Julian, and P Novais. Visual Working Memory Training of the Elderly in VIRTRAEL Personalized Assistant. In A Costa, V Julian, and P Novais, editors, *PERSONAL ASSISTANTS: EMERGING COMPUTATIONAL TECHNOLOGIES*, volume 132, pages 57–76. 2018.

[16] Sanika Doolani, Callen Wessels, and Fillia Makedon. Designing a Vocational Immersive Storytelling Training and Support System to Evaluate Impact on Working and Episodic Memory. In *Proceedings of the 14th PErvasive Technologies Related to Assistive Environments Conference*, PETRA '21, pages 268–269, New York, NY, USA, 2021. Association for Computing Machinery. event-place: Corfu, Greece.

[17] Sanika Doolani, Callen Wessels, and Fillia Makedon. vIIIS: A Vocational Intelligent Interactive Immersive Storytelling Framework to Support Task Performance. In *Proceedings of the 14th PErvasive Technologies Related to Assistive Environments Conference*, PETRA '21, pages 527–533, New York, NY, USA, 2021. Association for Computing Machinery. event-place: Corfu, Greece.

[18] A Gomaa, A Alles, E Meiser, LH Rupp, M Molz, G Reyes, and ACM. What's on your mind? A Mental and Perceptual Load Estimation Framework towards Adaptive In-vehicle Interaction while Driving. pages 215–225, 2022.

[19] LM Hirshfield, ET Solovey, A Girouard, J Kebinger, RJK Jacob, A Sassaroli, and S Fantini. Brain Measurement for Usability Testing and Adaptive Interfaces: An Example of Uncovering Syntactic Workload with Functional Near Infrared Spectroscopy. pages 2185–2194, 2009.

[20] JH Hou, CY Miao, and Y Liu. Prospective Memory Aid Reminder System Design for Group Tasks. pages 433–438, 2016.

[21] A. Jain, M. Shah, S. Pandey, M. Agarwal, R.R. Shah, and Y. Yin. SeekSuspect: Retrieving suspects from criminal datasets using visual memory. 2021.

[22] Anthony Jameson, Ralph Schaefer, Thomas Weis, Andre Berthold, and Thomas Weyrath. Making systems sensitive to the user's time and working memory constraints. pages 79–86, 1999.

[23] V. Kellen, S. Chan, and X. Fang. Improving user performance in conditional probability problems with computer-generated diagrams. volume 8006 LNCS, pages 183–192, 2013. Issue: PART 3.

[24] A Koivisto, A Lindstedt, S Merilampi, and K Kiili. Designing Working Memory Games for Elderly. volume 10056, pages 311–320, 2016.

[25] T Kosch, M Hassib, PW Wozniak, D Buschek, F Alt, and ACM. Your Eyes Tell: Leveraging Smooth Pursuit for Assessing Cognitive Workload. 2018.

[26] S Lalle, C Conati, G Carenini, and ACM. Impact of Individual Differences on User Experience with a Visualization Interface for Public Engagement. pages 247–252, 2017.

[27] Katharina Lingelbach, Daniel Diers, and Mathias VukeliÄ. Towards User-Aware VR Learning Environments: Combining Brain-Computer Interfaces with Virtual Reality for Mental State Decoding. In *Extended Abstracts of the 2023 CHI Conference on Human Factors in Computing Systems*, CHI EA '23, New York, NY, USA, 2023. Association for Computing Machinery. event-place: Hamburg, Germany.

[28] WE Marsh, JW Kelly, J Dickerson, and JH Oliver. Fuzzy Navigation Engine: Mitigating the Cognitive Demands of Semi-Natural Locomotion. *PRESENCE-TELEOPERATORS AND VIRTUAL ENVIRONMENTS*, 23(3):300–319, 2014.

[29] Bruno Massoni Sguerra and Pierre Jouvelot. "An Unscented Hound for Working Memory" and the Cognitive Adaptation of User Interfaces. In *Proceedings of the 27th ACM Conference on User Modeling, Adaptation and Personalization*, UMAP '19, pages 78–85, New York, NY, USA, 2019. Association for Computing Machinery. event-place: Larnaca, Cyprus.

[30] Bruno Massoni Sguerra, Pierre Jouvelot, and Samuel Benveniste. Oblivion Tracking: Towards a Probabilistic Working Memory Model for the Adaptation of Systems to Alzheimer Patients. In *Adjunct Publication of the 25th Conference on User Modeling, Adaptation and Personalization*, UMAP '17, pages 253–256, New York, NY, USA, 2017. Association for Computing Machinery. event-place: Bratislava, Slovakia.

[31] L Nguyen, K Murphy, and G Andrews. Design and development of a gamified cognitive training program targeting executive functions for older adults. *ENTERTAINMENT COMPUTING*, 52, January 2025.

[32] E. Purificato, L. Boratto, and E. W. De Luca. User modeling and user profiling: A comprehensive survey. *arXiv preprint*, 2024.

[33] M Ratto, JE Harrison, KT Sparrowhawk, and PB Cliveden. The Clinical Potential of a Cognitive Training Program Embedded in an Adaptive Video Game. pages 10–13, 2017.

[34] R SalmerÃ^3$n, S\ Crespo, F\ L^3pez, MT\ Daza, andF\ Guil.\ ITAWARDprimeIT\ : AnAdaptiveWebBased-ToolPrototypeforNeurocognitiveIndividualizedAssessmentandTraining.volume668$ $-549, 2011.$

[35] BM Sguerra, A Benamara, S Benveniste, P Jouvelot, and IEEE. Adapting Human-Computer Interfaces to Working Memory Limitations Using MATCHS. pages 1309–1314, 2018.

[36] A. Shaban, V. Chang, O. D. Amodu, M. R. Attia, and G. S. M. Abdelhamid. A Systematic Review of Working Memory Applications for Children with Learning Difficulties: Transfer Outcomes and Design Principles. *EDUCATION SCIENCES*, 14(11), November 2024.

[37] A Sharifara, AR Babu, A Rajavenkatanarayanan, C Collander, and F Makedon. A Robot-Based Cognitive Assessment Model Based on Visual Working Memory and Attention Level. volume 10907, pages 583–597, 2018.

[38] H. Shrivastava, P.V.N.S. Rama Krishna, K. Aggarwal, M.P. Ayyar, Y. Yin, R.R. Shah, and R. Zimmermann. Facefetch: An efficient and scalable face retrieval system that uses your visual memory. pages 338–347, 2019.

[39] C. Sohrabi, T. Franchi, G. Mathew, A. Kerwan, M. Nicola, M. Griffin, M. Agha, and R. Agha. Prisma 2020 statement: What's new and the importance of reporting guidelines. 2021.

[40] M. SpÃŒler, T. Krumpe, C. Walter, C. Scharinger, W. Rosenstiel, and P. Gerjets. Brain-computer interfaces for educational applications. In *Informational Environments: Effects of use, Effective Designs*, pages 177–201. 2017.

[41] L. R. Squire. Memory and brain systems: 1969-2009. *The Journal of Neuroscience*, 29(41):12711–12716, October 2009.

[42] Ben Steichen, Giuseppe Carenini, and Cristina Conati. User-adaptive information visualization: using eye gaze data to infer visualization tasks and user cognitive abilities. In *Proceedings of the 2013 International Conference on Intelligent User Interfaces*, IUI '13, pages 317–328, New York, NY, USA, 2013. Association for Computing Machinery. event-place: Santa Monica, California, USA.

[43] Ben Steichen, Cristina Conati, and Giuseppe Carenini. Inferring Visualization Task Properties, User Performance, and User Cognitive Abilities from Eye Gaze Data. *ACM Trans. Interact. Intell. Syst.*, 4(2), July 2014. Place: New York, NY, USA Publisher: Association for Computing Machinery.

[44] S Stork, C Stossel, HJ Muller, A Wiesbeck, MF ZÃ€h, A SchubÃ¶, and IEEE. A neuroergonomic approach for the investigation of cognitive processes in interactive assembly environments. pages 745–+, 2007.

[45] A Streicher and M Aydinbas. Bayesian Cognitive State Modeling for Adaptive Serious Games. volume 13332, pages 14–25, 2022.

[46] M. Suryani, D.I. Sensuse, H.B. Santoso, R.F. Aji, S. Hadi, and R.R. Suryono. An initial user model design for adaptive interface development in learning management system based on cognitive load. *Cognition, Technology and Work*, 26(4):653–672, 2024.

[47] Y Suzuki, F Wild, and E Scanlon. Measuring cognitive load in augmented reality with physiological methods: A systematic review. *JOURNAL OF COMPUTER ASSISTED LEARNING*, 40(2):375–393, April 2024.

[48] P. Taylor, N. Bilgrien, Z. He, and H.T. Siegelmann. EyeFrame: Real-time memory aid improves human multitasking via domain-general eye tracking procedures. *Frontiers in ICT*, 2(SEP), 2015.

[49] A Thorpe, K Nesbitt, and A Eidels. A Systematic Review of Empirical Measures of Workload Capacity. *ACM TRANSACTIONS ON APPLIED PERCEPTION*, 17(3), November 2020.

[50] Dereck Toker, Cristina Conati, Giuseppe Carenini, and Mona Haraty. Towards adaptive information visualization: on the influence of user characteristics. In *Proceedings of the 20th International Conference on User Modeling, Adaptation, and Personalization*, UMAP'12, pages 274–285, Berlin, Heidelberg, 2012. Springer-Verlag. event-place: Montreal, Canada.

[51] N Tsianos, P Germanakos, Z Lekkas, C Mourlas, and G Samaras. Working Memory Span and E-Learning: The Effect of Personalization Techniques on Learners' Performance. volume 6075, pages 64–+, 2010.

[52] S. Wen, M. Middleton, S. Ping, N.N. Chawla, G. Wu, B.S. Feest, C. Nadri, Y. Liu, D. Kaber, M. Zahabi, R.P. McMahan, S. Castelo, R. McKendrick, J. Qian, and C.T. Silva. AdaptiveCoPilot: Design and Testing of a NeuroAdaptive LLM Cockpit Guidance System in both Novice and Expert Pilots. pages 656–666, 2025.

[53] Ju-Chi Yu, Ting-Yun Chang, and Cheng-Ta Yang. Individual differences in working memory capacity and workload capacity. *Frontiers in Psychology*, Volume 5 - 2014, 2014.

[54] BF Yuksel, KB Oleson, L Harrison, EM Peck, D Afergan, R Chang, RJK Jacob, and ACM. Learn Piano with BACh: An Adaptive Learning Interface that Adjusts Task Difficulty based on Brain State. pages 5372–5384, 2016.

[55] Y. Zhang and W.-B. Goh. Personalized task difficulty adaptation based on reinforcement learning. *User Modeling and User-Adapted Interaction*, 31(4):753–784, 2021.

A Search Query

(adapt* OR interact* OR influence) AND
(user* OR people) AND
("working memory" OR "prospective memory" OR "visual memory" OR remember* OR "visual spatial memory" OR "visual short term memory") AND
(model OR interface* OR framework* OR robot* OR coach OR design)