A Survey on Working Memory Capacity, Think-aloud Method, Cognitive Processes, Verbal Protocols, Cognitive Load, and Memory Recall

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Abstract

This survey provides a comprehensive analysis of the intricate relationships among working memory capacity, the think-aloud method, cognitive processes, verbal protocols, cognitive load, and memory recall, all of which are crucial for understanding information processing and retention. The survey highlights the pivotal role of working memory capacity (WMC) in cognitive performance, emphasizing its influence across domains such as education, sports, and technology. The executive control model underscores the importance of attentional control in optimizing task performance. The think-aloud method is showcased as an effective tool for capturing real-time cognitive processes, particularly in educational and usability contexts, enhancing comprehension and problem-solving abilities. The integration of physiological measures like EEG and eye-tracking provides a nuanced understanding of cognitive load and memory processes, offering potential for personalized interventions in healthcare and education. Advanced models combining physiological and behavioral data elucidate the relationship between cognitive load and memory processes, improving multitasking performance. The survey also explores context-dependence in memory recall, highlighting the need to align cognitive processes with environmental demands to optimize learning outcomes. Future research directions include refining cognitive models to better mimic human cognition, exploring long-term effects of cognitive interventions, and integrating emerging technologies for enhanced cognitive load detection and management. This survey underscores the dynamic interplay between cognitive constructs, providing a foundation for developing interventions that optimize cognitive performance and enhance real-world applications.

1 Introduction

1.1 Structure of the Survey

This survey meticulously explores the intricate relationships among working memory capacity, the think-aloud method, cognitive processes, verbal protocols, cognitive load, and memory recall. It begins by establishing foundational concepts essential for understanding information processing and retention. Section 2 delves into the background of cognitive psychology, defining key terms such as expertise, cognitive processing, and task characteristics. This section underscores the interrelations among these concepts, utilizing qualitative research methods and verbal protocols to demonstrate how cognitive processes influence knowledge acquisition and performance across varying levels of expertise. It also highlights the significance of understanding thought processes in task performance and the methodologies employed in expertise studies, thereby enhancing comprehension of cognitive psychology's core principles [1, 2, 3].

Section 3 investigates working memory capacity, detailing its conceptual framework, measurement techniques, and crucial role in cognitive processes. The section reviews theoretical and empirical

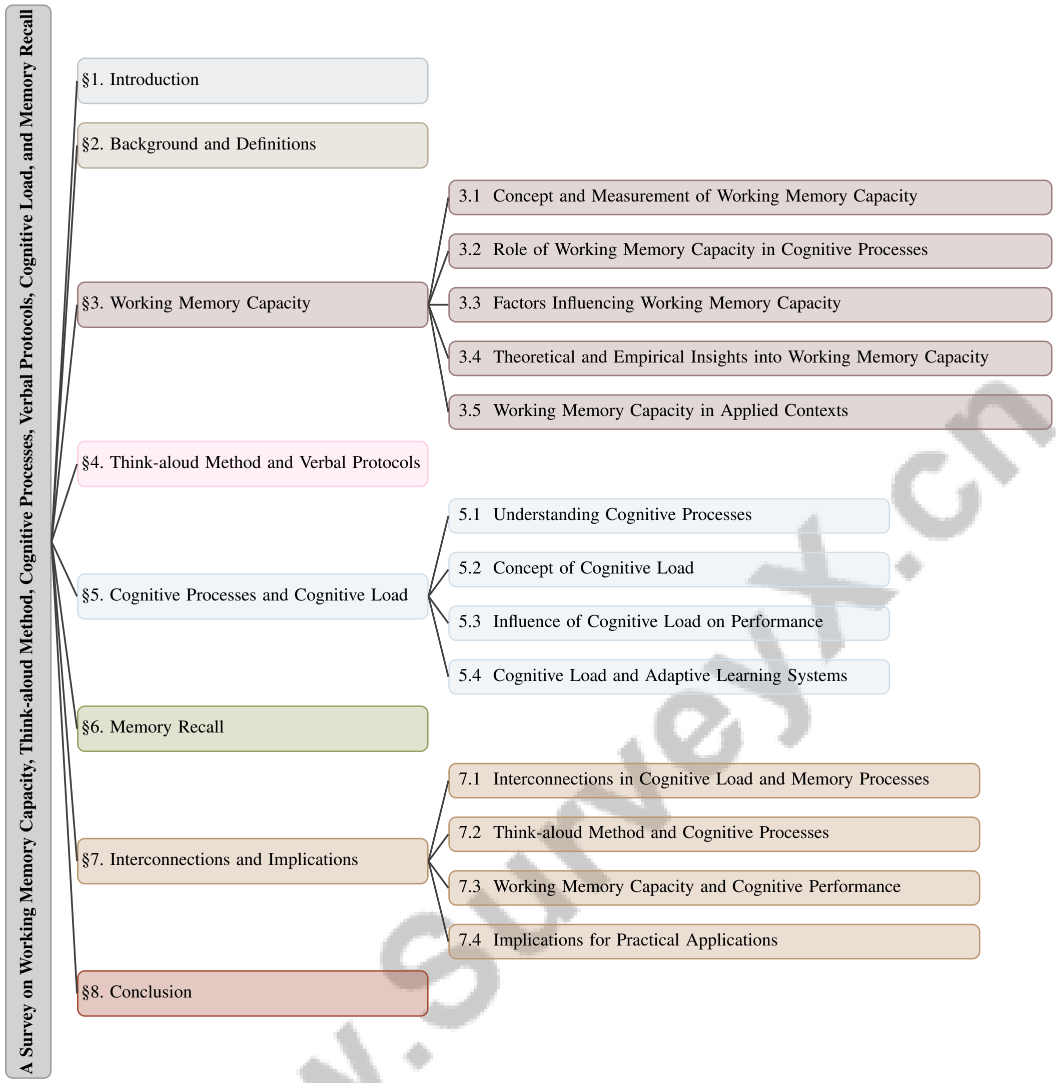

Figure 1: chapter structure

insights while discussing factors that influence working memory capacity and its applications in real-world contexts.

In Section 4, the think-aloud method is analyzed as a means to gain insights into cognitive processes, particularly focusing on verbal protocols. This section critically assesses the strengths and limitations of the method in cognitive research, examining the interplay between knowledge, cognitive processing, and task characteristics through interviews and verbal protocols. These approaches facilitate the exploration of expertise development, particularly how experts navigate critical incidents and employ strategies during tasks. Although interviews yield valuable insights into learning processes, they may not capture immediate cognitive representations as effectively as verbal protocols. This analysis emphasizes the necessity of integrating various qualitative research methods to enhance data quality and interpretation in cognitive studies [1, 4].

Section 5 addresses cognitive processes and cognitive load, elucidating their impact on performance and relevance in adaptive learning systems. It incorporates findings from studies like Minadakis et al. [5], which explore cognitive load measurement in human-machine interactions.

Section 6 examines memory recall mechanisms, emphasizing their dependence on working memory capacity and cognitive load. This section discusses factors affecting recall accuracy and context-dependent memory recall.

Section 7 synthesizes the discussed concepts, analyzing their interconnections and implications for cognitive research and practical applications. It emphasizes their significance in educational contexts and human-computer interaction, illustrating how insights from cognitive load theory, multimedia learning, and expertise development can inform teaching methodologies and AI system design to enhance learning outcomes [6, 1, 4].

Section 8 concludes by synthesizing the survey's main findings, highlighting critical insights regarding redundancy, cohesion, and informativeness in extractive summarization. It proposes future research avenues to enhance the practical application of these findings, particularly in optimizing summary generation methods based on cognitive processing theories [1, 7, 4].The following sections are organized as shown in Figure 1.

2 Background and Definitions

2.1 Background and Definitions

Understanding cognitive processes and their mechanisms is essential for comprehending how individuals acquire, process, and retain information, particularly in contexts requiring analysis, comprehension, and decision-making. Cognitive process classifications, such as Anderson and Krathwohl's taxonomy, highlight the link between learning objectives and cognitive strategies, emphasizing the need for tailored cognitive tools to improve information processing and retention in various learning environments [8, 3, 9, 10]. This survey focuses on key concepts like working memory capacity (WMC), the think-aloud method, cognitive processes, verbal protocols, cognitive load, and memory recall, each contributing to the understanding of cognitive psychology and information processing.

WMC, the capacity to hold and manipulate information simultaneously, is fundamental to cognitive processes, affecting information processing and retention. Sweller's cognitive load theory suggests that WMC is limited, necessitating the processing of new information within this capacity before long-term storage, thereby influencing cognitive functioning [11]. Factors such as childhood maltreatment can affect WMC, leading to cognitive deficits in adulthood. The development of auditory working memory is crucial for tasks like reading and writing, underscoring the importance of understanding WMC across sensory modalities. Studies link WMC to creativity, with verbal, visual-spatial, and dual-task WMC categories contributing to creative processes, challenging the notion that fluid intelligence is merely an extension of working memory.

The think-aloud method, a qualitative technique, provides insights into cognitive processes by having participants verbalize thoughts during tasks. Analyzing transcribed verbal protocols reveals underlying cognitive mechanisms [1]. While effective in various domains, its application in cross-cultural psychology remains limited, indicating potential for expansion. This method is instrumental in reconciling differing learning theories regarding procedural learning, particularly in understanding how writers engage with next-phrase suggestion systems.

Cognitive processes involve mental activities like problem-solving, decision-making, and information processing. The Mental Rotation Test (MRT) examines whether spatial imagery processes rely solely on spatial strategies or incorporate additional strategies. Mind wandering can significantly affect user engagement during tasks like data visualization. Large language models (LLMs) have been studied for their ability to simulate human cognitive processes, prompting evaluations of their utility in understanding human cognition. Reviews highlight both the similarities and differences between LLMs and human cognitive abilities, suggesting that while LLMs model certain cognitive processes and provide insights into memory and language use, they have limitations. Studies indicate that LLMs can predict human memory performance and simulate cognitive loads during reading, yet their contextual access capabilities differ from humans, raising questions about their validity as substitutes for human participants in psychological research. The integration of LLMs into cognitive research opens avenues for exploring the interplay between artificial and human intelligence, identifying challenges and future research directions [12, 13, 14, 15]. Additionally, cognitive demands of conversation require effective information management by speakers and real-time processing by listeners. Understanding the complex organization of cognitive processes in the brain remains challenging due to the vast number of neurons involved. In software testing, cognitive processes entail analysis, reasoning, decision-making, abstraction, and collaboration, emphasizing the intellectual complexity of these activities. Recent advancements in models like GPT-4 demonstrate their potential to emulate and predict aspects of cognitive functions, providing valuable insights into human cognition and memory mechanisms. Examining these models on established cognitive psychology datasets can enhance understanding of the relationship between artificial intelligence and human cognitive processes, paving the way for innovative psychological research and applications [16, 14, 1, 17].

Cognitive load refers to the mental effort required for tasks, significantly impacting performance. Monitoring cognitive load is crucial in learning environments to optimize outcomes [11]. Investigating the effects of different time windows on physiological data predictive performance in estimating cognitive load is critical. In game-based learning, managing cognitive load enhances learning efficiency. Assessing cognitive load is vital for evaluating user interface usability across software, information systems, and virtual reality applications. Cognitive load estimation through EEG signals, influenced by psychoacoustic parameters, highlights the limitations of traditional visual data representation methods and the necessity for effective auditory displays. Unique eye movement patterns related to cognition necessitate cognitive load assessment, particularly in gaze-based typing. This survey explores thermal imaging as an unobtrusive cognitive load estimation method, addressing the limitations of traditional self-reporting and obtrusive physiological sensors. Continuous cognitive load monitoring during complex tasks, such as laparoscopic surgery training, is essential for optimizing training outcomes and overcoming methodological limitations. Cognitive load also influences misinformation discernment, as seen in reading COVID-19 news headlines. The interplay between cognitive load, prior knowledge, and learning engagement is mediated by help-seeking behaviors, underscoring the need for integrated research frameworks. The unclear impact of multimedia design principles on cognitive load and learning outcomes, particularly through their effects on neural mechanisms, remains a challenge.

Memory recall involves retrieving stored information from long-term memory, influenced by WMC and cognitive load during tasks. Research shows that WMC is critical for functions like problem-solving and language comprehension, essential for coordinating information retrieval. Individual differences in WMC affect recall performance, with higher capacity often leading to better outcomes under varying cognitive load conditions [18, 19, 20, 21]. Recall context can impact accuracy; for instance, transitions between virtual reality and reality can affect memory recall. Advanced techniques like EEG and fMRI have enhanced understanding of brain regions involved in memory processes. The challenge of catastrophic forgetting, where new learning interferes with existing knowledge, highlights memory functions' complexity. Effective memory retrieval requires dynamic manipulation of memories to align with current contexts rather than relying on static results. The necessity for effective long-term memory in dialogue systems is recognized, particularly concerning emotional and contextual factors crucial for human-like interactions.

The interrelationships among these concepts are significant in cognitive psychology. WMC influences cognitive processes and memory recall, while cognitive load affects performance and recall accuracy. The think-aloud method and verbal protocols provide valuable insights into these processes, fostering a deeper understanding of information processing. Collectively, these concepts establish a framework for exploring the intricate dynamics of cognition, with implications for research and practical applications across various domains [9]. Additionally, virtual reality (VR) has emerged as a valuable training tool in advanced manufacturing, albeit with potential high cognitive load due to factors like VR hardware or task complexity. The epistemological approach to immersive virtual and augmented reality further investigates their roles in learning processes, information management, cognitive processing, and neurophysiology. The integration of machine learning algorithms into healthcare systems for enhanced decision-making and patient outcomes reflects the core issues explored in this survey. This research systematically reviews EEG-based cognitive workload (CWL) estimation methods, identifying experimental paradigms and deep neural network (DNN) approaches used for cognitive load detection, focusing on how the topological features of functional connectomes in the human brain relate to different cognitive states, particularly in working memory tasks.

In examining the complexities of Working Memory Capacity (WMC), it is essential to understand its multifaceted nature. Figure 2 illustrates the hierarchical structure of WMC, detailing its measurement techniques, theoretical models, roles in cognitive processes, and influencing factors. This figure highlights how WMC is measured using various tasks and neuroimaging methods, demonstrating its application across diverse fields, including writing and sports. Furthermore, it emphasizes the cognitive, environmental, and physiological factors that significantly affect WMC, thereby providing a comprehensive overview of its implications in cognitive research and practical applications.

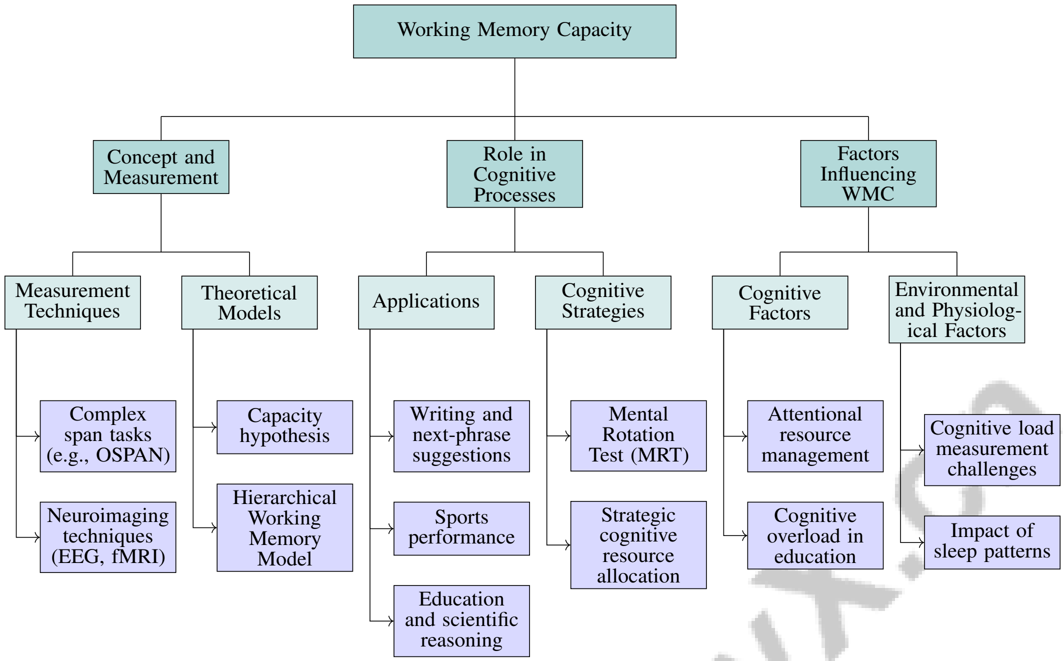

Figure 2: This figure illustrates the hierarchical structure of Working Memory Capacity (WMC), detailing its measurement techniques, theoretical models, roles in cognitive processes, and influencing factors. It highlights how WMC is measured using tasks and neuroimaging, its application in various fields like writing and sports, and the cognitive, environmental, and physiological factors affecting it.

3 Working Memory Capacity

3.1 Concept and Measurement of Working Memory Capacity

Working memory capacity (WMC) is pivotal in cognitive psychology, representing the ability to temporarily hold and manipulate information for tasks like reasoning, learning, and comprehension. The capacity hypothesis suggests that higher WMC allows individuals to process and retain more information concurrently, thereby enhancing task performance [22]. Complex span tasks, such as the operation span (OSPAN), are commonly used to measure WMC by requiring simultaneous information processing and storage [23]. These tasks are crucial for understanding individual differences in WMC.

Neuroimaging techniques like EEG and fMRI have elucidated the neural correlates of working memory, identifying brain areas involved in maintaining and manipulating information [24]. EEG offers high temporal resolution, while fMRI provides spatial resolution to identify brain areas activated during memory tasks. The reliability of these methods is corroborated by benchmarks such as the change detection task, which assesses visual working memory capacity by matching items with previously viewed stimuli [25].

Artificial systems highlight the limitations of human working memory. The Hierarchical Working Memory Model illustrates how information is chunked into hierarchical representations to enhance WMC [26]. Despite cognitive load theory's insights into the interaction between working memory and long-term memory, its impact on instructional design remains limited [27].

Individual differences in WMC are influenced by familiarity with stimuli, with less familiar stimuli requiring more resources, complicating problem-solving [28]. Anchors or default options can affect decision-making by influencing cognitive load, particularly in low-stakes scenarios [29]. Cognitive biases arise from assigning value to outcome-irrelevant features [30]. Accurately defining and measuring WMC during free recall tasks, especially regarding the serial position curve, remains a research focus [18].

In sports psychology, WMC mediates attention and performance relationships across different expertise levels, highlighting its role in high-performance activities [20]. Using EEG data to extract functional connectivity metrics and applying machine learning algorithms illustrates the intersection of neuroscience and computational methods in understanding WMC [31].

Ongoing research combines behavioral tasks and advanced neuroimaging techniques to explore working memory dynamics, limitations, and effects on cognitive performance. This research enhances cognitive psychology's theoretical frameworks and informs applications in education and clinical psychology. Findings suggest that meaningful information can expand memory capacity and improve recall. Moreover, individual differences in WMC influence how effectively intentions are offloaded to the environment, mitigating deficits associated with lower WMC [19, 32, 24, 21].

3.2 Role of Working Memory Capacity in Cognitive Processes

Working memory capacity (WMC) is vital for cognitive processes and performance, essential for tasks requiring information manipulation and integration. Higher WMC enables better attentional resource management, crucial for maintaining focus and optimizing task performance. In writing, WMC facilitates interactions between writers and next-phrase suggestion systems, as analyzed through the Hayes Cognitive Process Model of Writing [33].

In sports, WMC mediates attention and performance, allowing athletes with greater control and capacity to harness attentional resources, enhancing performance during demanding activities [20]. In education, WMC supports heuristic and analytical thought processes, particularly in physics, requiring scientific reasoning.

In tasks like the Mental Rotation Test (MRT), individuals with higher WMC effectively use spatial and analytic strategies, improving outcomes [34]. This dual strategy exemplifies WMC's multifaceted role, allowing adaptive management of cognitive demands for optimal performance.

In software testing, WMC influences cyclical problem-solving processes. The brain's small-world and scale-free network architecture facilitates efficient information organization and management, providing functional advantages in cognitive tasks [16]. Strategic cognitive resource allocation, such as partitioning options into categories, aids in managing cognitive load effectively, preventing overload and maintaining performance [29].

WMC is integral to executing cognitive processes, facilitating attentional resource management and strategic thinking, enhancing information processing and recall capabilities. This relationship influences task outcomes, as evidenced by the correlation between WMC, control, and athletic performance across expertise levels [32, 20, 33, 21, 4].

3.3 Factors Influencing Working Memory Capacity

Working memory capacity (WMC) is influenced by cognitive, environmental, and physiological factors. Cognitive factors, including attentional resource management, are crucial in determining WMC. Individuals with lower WMC struggle with delayed intentions, impairing task management requiring sustained attention [19]. This challenge is exacerbated by cognitive overload in educational settings, necessitating innovative strategies for learning efficiency [6].

Environmental factors, particularly cognitive load, significantly affect WMC. Real-time cognitive load measurement complexity poses challenges, as methods like heart rate and eye movement often lack sensitivity for transient load changes [35]. This inadequacy is pronounced in contexts like surgical simulator training, where precise real-time measurement is vital for readiness assessment [36]. Multimedia content design can influence cognitive load, with varying designs affecting learning efficiency, necessitating further exploration through network neuroscience [37].

Physiological factors, including sleep patterns and neurological conditions, impact WMC. Investigating the brain's capacity to compensate for reduced sleep without performance decline is crucial, as sleep deprivation negatively affects WMC [38]. EEG signal variability across sessions complicates cognitive state assessments [39].

Eye-tracking technology in education reveals existing methods often fail to differentiate cognitive load types, limiting effectiveness in accurately assessing demands [40]. This limitation underscores the need for nuanced approaches to measure cognitive load, crucial for optimizing learning environments.

The main challenge in cognitive workload classification is the inability of existing methods to capture spatial features and temporal dependencies effectively [41].

The interplay of cognitive, environmental, and physiological factors significantly impacts WMC. Research indicates individual differences in working memory influence attention and performance, particularly in athletics where expertise mediates these effects. Athletes with higher expertise exhibit enhanced working memory control and capacity, correlating with performance in cognitively demanding tasks, highlighting these factors' importance in understanding working memory variations [19, 20, 21]. Understanding these factors is essential for developing strategies to optimize cognitive performance, enhancing educational outcomes and applications in healthcare and technology.

3.4 Theoretical and Empirical Insights into Working Memory Capacity

The exploration of working memory capacity (WMC) has advanced through theoretical frameworks and empirical studies, providing a comprehensive understanding of this cognitive construct. Theoretical models, like Baddeley's, emphasize working memory's dual role in integrating storage and processing functions, highlighting adaptive cognitive resource allocation for complex tasks [21].

Empirical studies have elucidated WMC's multifaceted nature. Research shows working memory operations deplete resources more for less familiar stimuli, affecting performance. This aligns with the hierarchical working memory model, suggesting hierarchical chunking enhances effective capacity by organizing information into manageable units [26].

Reliability in measuring WMC is crucial, with experiments showing high reliability estimates and significant correlations across sessions, indicating stability over time [25]. This reliability is vital for understanding WMC's consistent role in cognitive performance, evidenced by its correlation with mathematical ability [23].

Cognitive load's role in WMC has been explored through benchmarks. For example, assessing cognitive load during complex tasks like driving under adverse conditions provides insights into working memory demands [42]. Benchmarks focusing on cognitive load and complexity offer a nuanced understanding of performance across demands, differing from previous assessments lacking depth in evaluating capabilities [43].

Theoretical advancements propose working memory and secondary memory belong to the same store, each with distinct recall roles [18]. Comparative analyses reveal studies on design as search and exploration differ significantly in terminology and conceptualization of cognitive processes [44].

In artificial intelligence, evaluating large language models (LLMs) using cognitive psychology benchmarks highlights potential for simulating human-like processes. However, existing benchmarks lack sophistication for thorough capability evaluation, as many tests are overly simplistic [17]. This underscores the need for refined assessment tools to fully understand cognitive processes underlying WMC.

Recent studies on brain network topological features suggest distinct integration and segregation patterns during cognitive states [45]. Mastered tasks can be executed within a segregated network, challenging assumptions that integration is necessary [46]. Innovations in machine learning models applied to EEG-derived connectivity metrics show promise in predicting multitasking performance, particularly post-tDCS interventions [31].

The combined theoretical and empirical insights from recent WMC studies elucidate its critical role in cognitive processes, revealing that factors like meaningfulness and familiarity of stimuli enhance memory capacity. These insights underscore the importance of reliability and stability in memory assessments, guiding future research and practical applications in cognitive psychology. Emphasizing cognitive load considerations, attentional control, and neural correlates in studying working memory is essential for advancing this field [32, 25, 21, 4].

3.5 Working Memory Capacity in Applied Contexts

Working memory capacity (WMC) is integral to real-world applications, influencing cognitive performance across domains like education, technology, and healthcare. In education, collaborative learning approaches combining self-explanation with example-problem alternation enhance outcomes by leveraging WMC. This method encourages step-based tutoring, fostering deeper comprehension through interaction and engagement [47].

In technology, particularly in dialogue systems, Transformer-based models' WMC limitations are evident due to self-attention mechanism constraints, affecting N-back task performance as complexity increases. Advancements like the MADial-Bench introduce novel evaluation metrics, enhancing dialogue systems' assessment by incorporating memory injection and intimacy measures [45]. These metrics provide insights into augmenting WMC to improve system performance and user interaction, highlighting network dynamics' importance in cognitive processing.

Healthcare applications also benefit from WMC insights. Integrating games like Scavenger Hunt (SH) offers innovative ways to assess executive functions by utilizing game mechanics to monitor cognitive processes in real-time [18]. This approach provides an engaging environment for continuous cognitive performance assessment, underscoring WMC's utility in monitoring and enhancing cognitive health.

Wearable device-based real-time monitoring frameworks have been developed to adaptively manage WMC in dynamic environments like finance, healthcare, and autonomous systems. These frameworks enhance WMC applicability by enabling real-time adaptation, improving performance in rapidly changing domains compared to static models [47]. This adaptability is crucial for optimizing task outcomes and addressing complex cognitive challenges in real-world settings.

The application of WMC in real-world contexts underscores its significance in enhancing cognitive performance and optimizing task outcomes. By utilizing WMC across diverse fields, researchers and practitioners can devise innovative strategies to tackle intricate cognitive challenges. This approach not only enhances individual performance but also optimizes system-level efficiency, as evidenced by the correlation between WMC and creativity, varying across cultural contexts. Integrating qualitative methods, such as cognitive task analysis and verbal protocols, allows for a deeper understanding of expertise development and cognitive processes, informing the design of more effective interventions and tools [33, 17, 1, 48].

4 Think-aloud Method and Verbal Protocols

4.1 Introduction to the Think-aloud Method

The think-aloud method is a qualitative research approach that requires participants to verbalize their thoughts during task performance, providing direct insights into cognitive processes [7]. Widely used in cognitive psychology, this method uncovers cognitive strategies and mechanisms during task execution. By capturing real-time verbalizations, researchers gain valuable data on problem-solving, decision-making, and learning processes.

In educational settings, the think-aloud method enhances comprehension through metacognitive awareness. Students articulating their thoughts while reading engage in metacognitive processes that improve understanding and retention [49]. This technique not only identifies individual reasoning patterns but also fosters critical thinking skills.

The method involves stages of data collection: preparation (formulating research questions and task familiarization), conducting (interviews and verbal protocols), and analysis (coding and reporting) [1]. This framework allows for a thorough examination of cognitive processes, enhancing our understanding of interactions with complex tasks.

The versatility of the think-aloud method across research settings underscores its importance in cognitive research. By analyzing cognitive processes such as analysis, comprehension, evaluation, and decision-making, it highlights limitations in current cognitive process classifications and the need for comprehensive models. These insights are crucial for designing effective cognitive tools and understanding writer interactions with suggestion systems and expertise development through nuanced task performance and cognitive strategies [33, 1, 10].

4.2 Application of Verbal Protocols

Verbal protocols, derived from the think-aloud method, are instrumental in analyzing cognitive processes across various contexts. By capturing participants' verbalizations during task engagement, researchers gain insights into the cognitive strategies employed. In educational settings, verbal

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Method Name	Cognitive Insights	Diverse Contexts	Performance Optimization
TAM[50]	Cognitive Processes Verbalizing	Various Fields Including	Enhance Learning Processes
TA[51]	Verbalizing Their Thoughts	Different Sports Contexts	Enhance Understanding Stress
TAM[7]	Verbalizing Thoughts	Different Sports Contexts	Analyze Cognitive Processes

Table 1: This table presents an overview of various methods utilizing verbal protocols to gain cognitive insights across diverse contexts and optimize performance. The methods, including those applied in educational and sports settings, highlight the verbalization of cognitive processes to enhance understanding and analysis.

protocols reveal translanguaging strategies used by learners. For example, when learning Chinese characters, the think-aloud method has illuminated cognitive processes, showcasing how learners navigate and integrate multiple language systems [50].

In sports psychology, verbal protocols capture real-time stress and coping responses during athletic performance. Tennis players, for instance, verbalize thoughts between points, providing direct measures of cognitive responses to stress and coping strategies [51]. This approach evaluates how athletes manage cognitive load and maintain focus under pressure, offering insights into performance optimization.

Additionally, studies on motor skills, such as golf putting, have analyzed verbal reports to assess cognitive processes involved in fine motor control and decision-making [7]. Verbal protocols deepen our understanding of cognitive processes by detailing mental activities during tasks, facilitating comprehensive investigations into expertise development, writing processes, and knowledge work. By employing interviews and verbal protocols, researchers capture cognitive strategies, decision-making processes, and interactions between knowledge and task characteristics that experts utilize in their fields [33, 4, 1, 10]. Table 1 provides a comprehensive comparison of methods employing verbal protocols to investigate cognitive processes and performance optimization in different contexts.

4.3 Strengths of the Think-aloud Method

The think-aloud method is a robust qualitative research tool with several strengths, making it invaluable in cognitive research. Its primary advantage is providing real-time insights into cognitive processes, enhancing understanding of complex activities such as stress and coping mechanisms in sports [51]. By capturing verbalizations during task performance, this method offers detailed accounts of cognitive strategies, crucial in fields like sports psychology and education [7].

In educational research, the think-aloud method enhances student engagement and comprehension by fostering interactive and reflective learning experiences [49]. This interactive nature allows educators to better understand students' cognitive processes, enabling tailored instruction to meet individual learning needs. Integrating eye-tracking technology with the think-aloud method further enhances its utility, allowing non-intrusive monitoring of cognitive load, which can inform instructional adjustments [40].

The method's adaptability is evident in its integration with digital tools and advanced technologies. For example, mobile devices augment learning experiences and provide structured evaluations of digital tool impacts in educational research [52]. Furthermore, the application of deep neural networks (DNNs) for automatic feature extraction in conjunction with the think-aloud method shows promise in classifying cognitive workload levels from EEG signals, highlighting innovative cognitive load classification frameworks [39].

Moreover, the think-aloud method supports rich qualitative data collection, as studies involving diverse cognitive processes yield comprehensive insights into search behaviors and cognitive strategies, advancing cognitive research [9]. Its capacity to handle multiple tasks through unified frameworks, as seen in models like the M&M model, underscores its versatility and efficiency in research applications [53].

The think-aloud method's strengths lie in its ability to engage participants actively, integrate with other data collection techniques, and provide comprehensive insights into cognitive processes. These attributes are essential for deepening our understanding of how individuals process and interact with information, facilitating advancements in cognitive research and instructional design. Insights from studies on next-phrase suggestion systems, cognitive load theory, and multimedia learning contribute to a nuanced understanding of learning dynamics and effective educational interventions [33, 6, 1, 9, 11].

4.4 Limitations and Challenges

Despite its utility in revealing cognitive processes, the think-aloud method presents several limitations and challenges that must be addressed to optimize its application in research. A primary concern is the potential alteration of participants' natural performance due to the requirement to verbalize thoughts, which may lead to discrepancies between observed and actual cognitive strategies, affecting data validity [7].

Logistical challenges arise in educational contexts, where teachers may struggle to manage time effectively and ensure inclusive participation among students [54]. Without structured implementation strategies, the think-aloud method may fail to engage all students meaningfully, limiting its effectiveness as a pedagogical tool.

The complexity of interface designs used alongside the think-aloud method can exacerbate cognitive load, detracting from participants' ability to engage thoughtfully [29]. This necessitates user-friendly interfaces that minimize cognitive overload.

Variability in cognitive routes chosen by individuals complicates the prediction of specific thought sequences, posing challenges in analyzing verbal protocols [3]. This variability requires flexible analytical frameworks capable of accommodating diverse cognitive pathways.

The applicability of the think-aloud method is limited due to its focus on specific environments or demographic groups, such as pharmacy settings or university students. This specificity restricts the generalizability of findings, complicating the application of insights gained from these contexts to broader populations. For instance, research on pharmacists' clinical reasoning has highlighted unique cognitive processes relevant to their practice, which may not translate effectively to other professional fields or layperson experiences [55, 7]. This demographic specificity necessitates caution when extrapolating results to other contexts.

Finally, the labor-intensive nature of manual data labeling and reliance on small datasets hinder the scalability and generalizability of research findings [56]. These challenges underscore the need for innovative solutions to streamline data processing and enhance the robustness of the think-aloud method across diverse research settings.

5 Cognitive Processes and Cognitive Load

5.1 Understanding Cognitive Processes

Cognitive processes involve essential mental activities for acquiring, processing, and utilizing information, including problem-solving, decision-making, and learning. These processes are often modeled hierarchically, similar to neuronal connections in the brain, facilitating efficient information processing and retrieval [57]. The think-aloud method is instrumental in elucidating these processes, particularly in educational settings, by enhancing metacognitive awareness and comprehension. Through verbalization during tasks like reading, students reveal their cognitive strategies, enabling educators to tailor instruction for improved learning outcomes [49, 54].

In artificial intelligence, the limitations of working memory capacity in large language models (LLMs) offer insights into human cognitive processing. The constraints of self-attention mechanisms in LLMs mirror human cognitive limitations, especially in managing multiple information streams simultaneously [58, 15]. Cognitive processes are also influenced by intuitive heuristics, such as associative activation and processing fluency, which are frequently employed in scientific reasoning, demonstrating the role of cognitive shortcuts in decision-making [8]. Additionally, cognitive hypergraphs capture complex interactions in human memory by allowing concepts to associate with multiple nodes simultaneously [57].

Environmental context significantly shapes cognitive processes, particularly in memory recall, as contextual factors can influence cognitive performance. This adaptability is evident across various tasks, where aligning processes with contextual demands enhances performance and retention [59]. The exploration of these processes through methodologies like the think-aloud method has improved

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reading comprehension by enabling students to articulate their thoughts, addressing challenges faced by educators and learners [54, 49, 7]. Such insights are vital for advancing cognitive psychology and developing applications to enhance cognitive performance across diverse domains.

5.2 Concept of Cognitive Load

Cognitive load refers to the mental effort required to process and manage information during tasks, significantly impacting performance and efficiency. Cognitive load theory categorizes load into intrinsic, extraneous, and germane types [11]. Intrinsic load is inherent to task complexity, extraneous load arises from information presentation, and germane load pertains to processes facilitating learning and schema development. This framework emphasizes optimizing instructional design to manage cognitive load effectively, enhancing learning outcomes [11].

Assessment of cognitive load has evolved from subjective evaluations to physiological measures like EEG and pupil size, reflecting cognitive processing intensity [5]. EEG band ratio analysis, particularly theta band activity, captures nuanced changes in brain activity associated with mental workloads, providing a reliable method for continuous measurement. However, task-stimulus ordering and presentation modality are often overlooked, potentially leading to misleading results [17]. Additionally, physiological sensors can be intrusive, and self-reported measures may introduce bias, complicating accurate assessment.

Cognitive load impacts performance across domains. In education, high cognitive load can hinder problem-solving skills, especially in subjects like physics, where fragmented knowledge structures exacerbate difficulty [60]. Integrating cognitive theories with artificial intelligence holds promise for optimizing learning and personalizing education [47]. In dynamic environments like driving, hybrid models combining CNN and RNN architectures have improved cognitive load prediction accuracy, highlighting advanced computational methods' potential [42].

The interplay between emotions and cognitive load is significant, as emotions can influence cognitive load, warranting consideration in instructional design [61]. Cognitive load affects attention control, with arousal impacting focus and distraction avoidance, influencing working memory capacity [25]. Understanding these dynamics is crucial for developing adaptive systems that respond to users' cognitive states, enhancing efficiency and task outcomes across domains. The scalability of cognitive load assessments is challenged by increasing task complexity, necessitating sophisticated methodologies [62]. Analysis of functional brain networks derived from EEG data provides insights into multimedia design's effects on cognitive load and learning outcomes, emphasizing higher integration in brain networks during cognitive load for effective processing.

Recent advancements suggest combining text with visualization can reduce cognitive load and improve understanding, particularly in complex reasoning tasks [63]. Cognitive load theory can inform design choices to minimize load during programming tasks, enhancing reasoning performance [64]. The classification of cognitive workload using fNIRS data expands our understanding of cognitive states, providing a nuanced approach to assessment [41]. However, the lack of standardized methods for cleaning and processing pupillary data remains a challenge, highlighting the need for reliable measures [65].

5.3 Influence of Cognitive Load on Performance

Cognitive load significantly affects cognitive performance by influencing the allocation of mental resources for task execution. High cognitive load can reduce efficiency and accuracy as the system struggles to manage demands exceeding its capacity. This impact is pronounced in educational contexts, where neglecting cognitive load in instructional methods can impede learning and hinder knowledge transfer [11].

Studies illustrate short-term memory limitations and their effects on cognitive tasks, showing how restricted memory capacity can impair information organization and retrieval, leading to suboptimal strategies [60]. Effective instructional design must minimize extraneous cognitive load for maximum learning efficiency.

Advanced methodologies for assessing cognitive load and its performance implications include hybrid deep learning models, which have shown improved accuracy in workload classification [41]. These models address traditional methods' limitations, which often rely on single modalities or simplistic

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measures, failing to capture cognitive load's complexity [53]. However, the limited availability of labeled EEG datasets for cognitive load hampers deep learning models' training, which typically requires large datasets [66].

The relationship between cognitive load and emotional states affects performance. For example, cognitive load associated with different presentation formats of Bayesian problems significantly impacts reasoning accuracy [63]. This necessitates reevaluating traditional cognitive load theories to incorporate affective factors in performance assessments.

In dynamic environments like virtual reality, assessing cognitive load is challenging due to variability in user interactions. Eye-tracking technology provides insights into cognitive states by measuring cognitive load types in real-time, enabling adaptive systems that respond to users' needs and enhance performance [65]. This approach underscores the correlation between eye-tracking metrics and cognitive load, facilitating the creation of systems that optimize training effectiveness.

Cognitive load influences multitasking scenarios, where secondary tasks can detract from primary task performance, such as driving under high load conditions and adverse weather [59]. The influence of cognitive load on decision-making processes is evident, with studies demonstrating that it mediates the relationship between attention and performance, providing empirical support for theoretical claims [20].

Understanding cognitive load's influence on performance is crucial for developing strategies to enhance performance across contexts. Optimizing instructional design by integrating adaptive learning systems and utilizing real-time cognitive load assessment techniques can effectively reduce extraneous load and promote efficient long-term memory storage. This approach leverages cognitive load theory insights, recognizing the importance of managing intrinsic, extraneous, and germane loads to facilitate deeper understanding and improve learning efficacy [27, 67].

5.4 Cognitive Load and Adaptive Learning Systems

Integrating cognitive load considerations into adaptive learning systems is essential for optimizing educational outcomes and enhancing learner engagement. These systems dynamically tailor educational experiences to individual learners by adjusting information complexity and presentation based on real-time cognitive load assessments. This approach aligns with cognitive load theory, emphasizing the need to balance intrinsic, extraneous, and germane loads to improve learning efficiency [53].

Recent advancements in cognitive load measurement techniques have significantly enhanced adaptive learning systems' development. The MM model effectively integrates audio and video features for load assessment, demonstrating competitive performance [53]. Utilizing a multimodal-multitask framework that incorporates audiovisual data through specialized streams and a cross-modality attention mechanism enables accurate assessment, enhancing educational platforms' adaptability.

Eye-tracking technology in adaptive systems provides objective, continuous load measurements, allowing for immediate feedback and instructional design adjustments [65]. This capability is valuable in dynamic learning environments, where real-time adaptation is essential for maintaining engagement and optimizing outcomes.

Incorporating problem-solving tutorials that actively engage students and help them build coherent knowledge structures is another effective method for managing load in adaptive environments. These tutorials guide students through structured problem-solving processes, integrating quantitative and conceptual approaches, enhancing learning efficiency by reducing extraneous load [60].

Challenges remain in integrating new technologies into educational settings. Addressing the risk of cognitive overload and ensuring proper training for educators to utilize these technologies effectively is crucial for successful implementation. Additionally, variability in load measurements across demographics, such as age-related differences in pupil response, may affect assessment reliability [65].

Future research should explore domain-specific outcomes of load management and investigate the effects of different working memory tasks on learning efficiency. Examining varying load levels' impact on decision-making across populations and contexts is crucial, enhancing our understanding of cognitive demands' effects on individuals' search behaviors during complex tasks, as evidenced by studies revealing significant load variations throughout web search stages and individual differences in mental effort [68, 69, 70].

The integration of load assessments into adaptive systems represents a significant advancement in educational technology. By utilizing real-time data and advanced measurement techniques, these systems can create tailored learning experiences that enhance cognitive engagement and lead to significant improvements in educational outcomes, as demonstrated by studies showing reduced load and enhanced understanding through interactive multimedia and game-based learning environments [52, 71, 43, 72, 73].

6 Memory Recall

6.1 Mechanisms of Memory Recall

Memory recall involves retrieving stored information, framed within dynamic cognitive models. A mathematical framework for memory consolidation allows agents to recall context-relevant information, showcasing memory systems' adaptability [74]. Working memory capacity (WMC) is critical in recall, as higher WMC reduces mind wandering, enhancing comprehension and performance [22]. Repeated exposure and practice improve recall, as evidenced in surgical training where cognitive load management optimizes retrieval [36]. Environmental context and cognitive strategies, such as translanguaging in learning Chinese characters, enhance information organization and retrieval [49]. Non-principal multimedia designs engage brain networks, promoting efficient recall through global processing [37]. Technological advancements like eye-tracking in virtual reality training predict cognitive load, deepening our understanding of memory processes [31]. These mechanisms, involving cognitive strategies, contexts, and neural adaptability, are crucial for retrieval efficiency, influencing educational methodologies and cognitive research. Next-phrase suggestion systems and summarization techniques illustrate interactions impacting writing and decision-making, while cognitive load during web searches suggests tailored interfaces to enhance user experience [33, 70, 4].

6.2 Influence of Cognitive Load on Memory Recall

Cognitive load significantly impacts memory recall, influencing accuracy and efficiency. High cognitive load can overwhelm cognitive systems, reducing retrieval capacity, especially in transitions between virtual and real environments [63]. EEG recordings reveal cognitive load's effect on neural activation during recall [66]. Eye-tracking technology offers real-time cognitive load assessment, differentiating load types and enhancing understanding of its influence on recall [40]. Strategies like interactive tutorials and visualization techniques mitigate cognitive load, enhancing recall accuracy [60, 63]. The complex relationship between cognitive load and recall involves task demands, emotional states, and instructional strategies, with implications for educational methodologies. Effective strategies in video lectures can reduce extraneous load, enhancing learning outcomes [68, 75, 70].

6.3 Context-Dependence and Memory Recall

Context-dependence is vital in memory recall, affecting retrieval effectiveness. Learning and recall phase context shifts, such as between virtual and real environments, often reduce performance [63]. Cognitive processes must align with environmental demands, as illustrated by translanguaging strategies enhancing retention in language learning [49]. Cognitive systems' adaptability to environmental changes underscores context's influence on recall. Technologies like virtual reality and eye-tracking assess context-dependent cues, enhancing memory processes [40]. Understanding context-dependence allows for strategies leveraging prior knowledge and engagement techniques to improve learning outcomes and cognitive performance [71, 72, 33, 75].

6.4 Factors Influencing Recall Accuracy

Recall accuracy is influenced by cognitive, instructional, and contextual factors. Cognitive hypergraphs outperform pairwise networks in predicting word concreteness, emphasizing modeling complex interactions to enhance recall [57]. Instructional strategies, like problem-example sequences, affect learning outcomes and self-explanations [76]. Prior knowledge influences recall accuracy,

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highlighting the need for tailored instructional approaches [72]. Diverse strategies during learning, such as inference and summarization, facilitate robust encoding and retrieval, enhancing recall [77]. However, generalizability across tasks and contexts is limited; future research should explore these factors across diverse settings to extend understanding [25].

7 Interconnections and Implications

7.1 Interconnections in Cognitive Load and Memory Processes

Understanding the interaction between cognitive load and memory processes is essential for examining how mental effort influences information encoding, storage, and retrieval. Cognitive load, representing the mental effort required for processing, directly impacts memory by affecting available capacity for retrieval and manipulation, with individual differences like frustration tolerance and personality traits shaping task load perception and memory performance [11]. Empirical studies demonstrate cognitive load's influence on attention and memory, with design elements and mind wandering acting as intermediaries. Advanced models using EEG functional connectivity and machine learning enhance multitasking cognitive performance [31]. These models enable precise predictions and interventions by elucidating cognitive load's interaction with memory processes.

Real-time feedback, such as pupil diameter metrics, supports adaptive strategies that optimize user performance by minimizing cognitive load, crucial during information retrieval in web searches and multimedia learning. Managing extraneous and germane cognitive loads effectively allows efficient mental effort allocation, enhancing retrieval and manipulation capabilities. Techniques that regulate information flow during video lectures and consider cognitive load's dynamic nature significantly improve learning outcomes and search experiences [69, 70, 6, 75, 4]. Strategic content engagement in education mitigates extraneous load's adverse effects on germane load, enhancing learning outcomes.

The interconnections between cognitive load and memory processes involve dynamic interactions among cognitive strategies, individual differences, and environmental factors. Investigating relationships between prior knowledge, cognitive load, and help-seeking behaviors can lead to tailored interventions that enhance cognitive performance and memory processes, reducing cognitive load and fostering better learning outcomes. Studies show that students with greater prior knowledge experience lower cognitive load, facilitating effective help-seeking strategies and enhancing engagement and learning quality [33, 72, 9].

7.2 Think-aloud Method and Cognitive Processes

The think-aloud method is a pivotal tool in cognitive research, providing insights into real-time cognitive processes during task execution by requiring participants to verbalize their thoughts [7]. Particularly valuable in educational settings, it enhances comprehension and retention, as seen in language learning where it reveals cognitive strategies for memorizing Chinese characters [50]. This method not only identifies effective memorization techniques but also helps learners develop metacognitive strategies, boosting learning outcomes.

In mathematics, the think-aloud method supports problem-solving by refining cognitive processes underlying mathematical reasoning [78]. By articulating thought processes, learners improve problem-solving strategies and performance. In usability studies, it identifies usability issues through verbalization, enriching understanding of user-system interactions [79]. Compared to retrospective accounts, it offers a more accurate depiction of cognitive processes [51].

Additionally, the think-aloud method is employed in testing environments to analyze testers' problem-solving approaches. Verbal protocol analysis captures cognitive strategies used by testers, providing insights into effective testing practices [80]. This method is invaluable for exploring cognitive processes across domains, enhancing cognitive research and practical applications in education, usability, and problem-solving contexts [54].

7.3 Working Memory Capacity and Cognitive Performance

Working memory capacity (WMC) significantly influences cognitive performance by determining an individual's ability to manage, process, and retrieve information. The executive control model suggests that individuals with higher WMC exhibit superior attentional control, enabling them to inhibit distractions and focus on task-relevant information, thus enhancing performance across various domains [20]. This capacity is crucial in complex cognitive activities like learning, decision-making, and sports, where focus and resource management are essential for optimal outcomes.

Research indicates that WMC is influenced by the number of retained information chunks and their meaningfulness and familiarity [18]. Structuring information into hierarchical chunks enhances WMC, facilitating efficient retrieval and cognitive performance [26]. The quantization of working memory into discrete items further affects recall patterns, highlighting structured information's importance in memory processes [18].

In sports psychology, WMC mediates the relationship between attention and performance, with stronger effects in experienced athletes [20]. This mediation underscores WMC's critical role in high-performance activities, where attentional resource management is vital. Brain region adaptability to compensate for cognitive deficits, such as sleep deprivation, illustrates WMC's dynamic nature in sustaining cognitive performance [38].

WMC's influence extends to cognitive load classification, with EEG-based advances significantly improving accuracy and F1 scores, highlighting the potential for leveraging WMC insights to enhance cognitive performance [66]. Understanding WMC mechanisms is crucial for developing strategies that optimize cognitive efficiency.

Working memory capacity plays a critical role in cognitive performance by influencing an individual's ability to process, store, and retrieve information, essential for tasks like problem-solving, language comprehension, and executing delayed intentions, impacting overall learning and recall efficiency [19, 20, 21]. Exploring WMC and cognitive processes interconnections enables researchers to devise interventions enhancing cognitive performance, improving learning outcomes and task efficiency.

7.4 Implications for Practical Applications

Interconnections among working memory capacity, cognitive load, and cognitive processes have significant implications for practical applications in education, healthcare, and technology. In education, understanding these interconnections guides instructional strategies aligning with students' cognitive capacities, optimizing learning outcomes. Singh's approach emphasizes active engagement and cognitive needs, enhancing problem-solving skills and knowledge retention [60]. This underscores instructional design's importance in reducing extraneous load and enhancing germane load, as discussed by Klepsch et al. [11], resulting in better learning outcomes.

Integrating artificial intelligence into educational practices improves learning by providing personalized feedback tailored to individual cognitive loads, facilitating effective engagement and deeper understanding of complex concepts. This aligns with educational theories like Cognitive Load Theory and Multimedia Learning, leveraging AI systems that adapt to cognitive demands and prior knowledge, fostering critical thinking and advanced cognitive skills essential for contemporary learning environments [33, 72, 6, 43]. This highlights the need for refined cognitive load assessment techniques, as suggested by Khan et al., to improve cognitive workload assessment and inform education and human-computer interaction practices. AI technologies enable educators to create adaptive learning environments catering to students' unique cognitive profiles, fostering deeper engagement and comprehension.

In healthcare, employing physiological measures like EEG and eye-tracking enhances cognitive load and memory process assessments, leading to personalized interventions improving patient outcomes. Developing non-invasive measurement techniques, emphasized by Bez et al., is crucial for clinical applications, ensuring comfort and accuracy. Finc et al.'s findings on brain network reconfiguration during cognitive training provide insights into brain adaptation to task demands, highlighting increased modularity and integration as individuals master complex tasks like the dual n-back. This understanding informs therapeutic strategies harnessing network segregation to enhance cognitive performance, especially in contexts requiring improved working memory and task efficiency [45, 81, 46].

Technological applications, particularly in user interface design, benefit from insights into cognitive load dynamics. Interface nudges, explored by Menon et al., enhance deliberation in online interactions, with effectiveness varying by nudge type. Exploring cognitive control hypotheses in real-world scenarios, like driving, informs adaptive systems design responding to users' cognitive states, improving safety and performance. Future research should expand task scope beyond shortest path finding and incorporate diverse network structures to validate Yoghourdjian et al.'s findings comprehensively. This exploration enhances understanding of cognitive processes in knowledge work, as existing classifications are insufficiently detailed for practical application. By examining different tasks and network configurations, researchers can better analyze how cognitive tools support decision-making and problem-solving in complex environments [33, 10].

These practical applications underscore the potential for leveraging insights into working memory capacity, cognitive load, and cognitive processes to enhance educational practices, healthcare interventions, and technological systems. By integrating these insights, researchers and practitioners can develop targeted strategies optimizing cognitive performance and improving outcomes across domains. Future research could explore mechanisms connecting working memory capacity (WMC) with voluntary and involuntary mind wandering, investigating interventions enhancing WMC, particularly for individuals with lower capacity, as higher WMC is associated with reduced mind wandering, positively influencing task performance [22, 19].

8 Conclusion

This survey provides an in-depth analysis of the multifaceted relationships among working memory capacity, the think-aloud method, cognitive processes, verbal protocols, cognitive load, and memory recall, offering valuable insights into the field of cognitive psychology. A key discovery is the pivotal role of working memory capacity in enhancing cognitive performance across diverse areas such as education, sports, and technology. The executive control model underscores the significance of attentional control in optimizing cognitive performance, with notable implications for instructional design and adaptive learning systems.

The think-aloud method has proven effective in capturing real-time cognitive processes, particularly in educational and usability contexts, thereby enriching the understanding of cognitive strategies and enhancing comprehension and problem-solving skills. Moreover, the integration of physiological measures like EEG and eye-tracking provides a deeper understanding of cognitive load and memory processes, paving the way for personalized interventions in healthcare and education.

Advanced models that combine physiological and behavioral data have elucidated the relationship between cognitive load and memory processes, boosting cognitive performance in multitasking scenarios. The exploration of context-dependence in memory recall emphasizes the importance of aligning cognitive processes with environmental demands to optimize memory performance and learning outcomes.

Future research should aim to refine cognitive models, such as large language models, to better align with human cognition and enhance their applicability in real-world settings. Additionally, investigating the long-term effects of cognitive interventions and integrating emerging technologies like wearable sensors can improve cognitive load detection and management, leading to better outcomes across various domains. The potential of wearable device-based real-time monitoring frameworks to surpass traditional methods in adaptability and accuracy suggests promising directions for dynamic learning environments.

This survey underscores the importance of understanding the dynamic interplay between cognitive constructs, laying the groundwork for developing targeted interventions that optimize cognitive performance and enhance real-world applications. Ongoing exploration of these interconnections, leveraging technological advancements, will refine cognitive models and improve practical outcomes across education, healthcare, and technology.

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