Decision Fatigue, Information Overload, AI Assistant, Cognitive Load, Consumer Behavior, and Decision Support Systems: A Survey

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Abstract

This survey paper explores the intricate interplay among decision fatigue, information overload, AI assistants, cognitive load, consumer behavior, and decision support systems, highlighting their collective impact on modern decision-making processes. Decision fatigue and information overload diminish decision quality by overwhelming individuals with excessive choices and data. AI assistants, by optimizing information processing, play a crucial role in alleviating cognitive load, thus counteracting these adverse effects. The paper examines how these phenomena influence consumer behavior, shaping purchasing patterns and preferences. It emphasizes the importance of AI-driven decision support systems in enhancing decision quality and efficiency by providing data-driven insights. The survey underscores the necessity for transparent and reliable AI systems to foster user trust, particularly in sensitive domains like healthcare. It also highlights the need for effective visualization and interface design to manage cognitive load and improve decision-making outcomes. The paper calls for further research into conversational agents, gamification strategies, and the integration of AI in project management to enhance cognitive load management and decision-making efficacy. By addressing these challenges, the survey aims to contribute to the development of strategies that enhance decision quality and user satisfaction across various domains.

1 Introduction

1.1 Interconnectedness of Key Concepts

The interplay among decision fatigue, information overload, AI assistants, cognitive load, consumer behavior, and decision support systems is essential for understanding contemporary decision-making. Decision fatigue occurs when individuals face excessive choices, resulting in diminished decision quality, particularly in critical sectors like healthcare [1]. Concurrently, the relentless influx of digital information exacerbates information overload, impairing cognitive processing and intensifying decision fatigue. Web search engines and conversational agents serve as intermediaries that can alleviate these challenges by streamlining user interactions and reducing cognitive demands [2].

AI assistants significantly reduce cognitive load by enhancing information processing and decision-making, counteracting the negative impacts of decision fatigue and information overload. In clinical settings, AI systems improve decision support by integrating patient-generated data, thereby enabling personalized healthcare strategies [3]. However, the introduction of AI into decision-making processes raises concerns regarding transparency and trust, especially in sensitive areas such as medical decision-making, where algorithm reliability is crucial for user trust and decision outcomes [3].

Consumer behavior is intricately linked to these concepts, as cognitive load and decision fatigue heavily influence purchasing patterns and preferences. The effect of decision support systems on consumer decision-making is evident in how online reviews are processed, with decision support

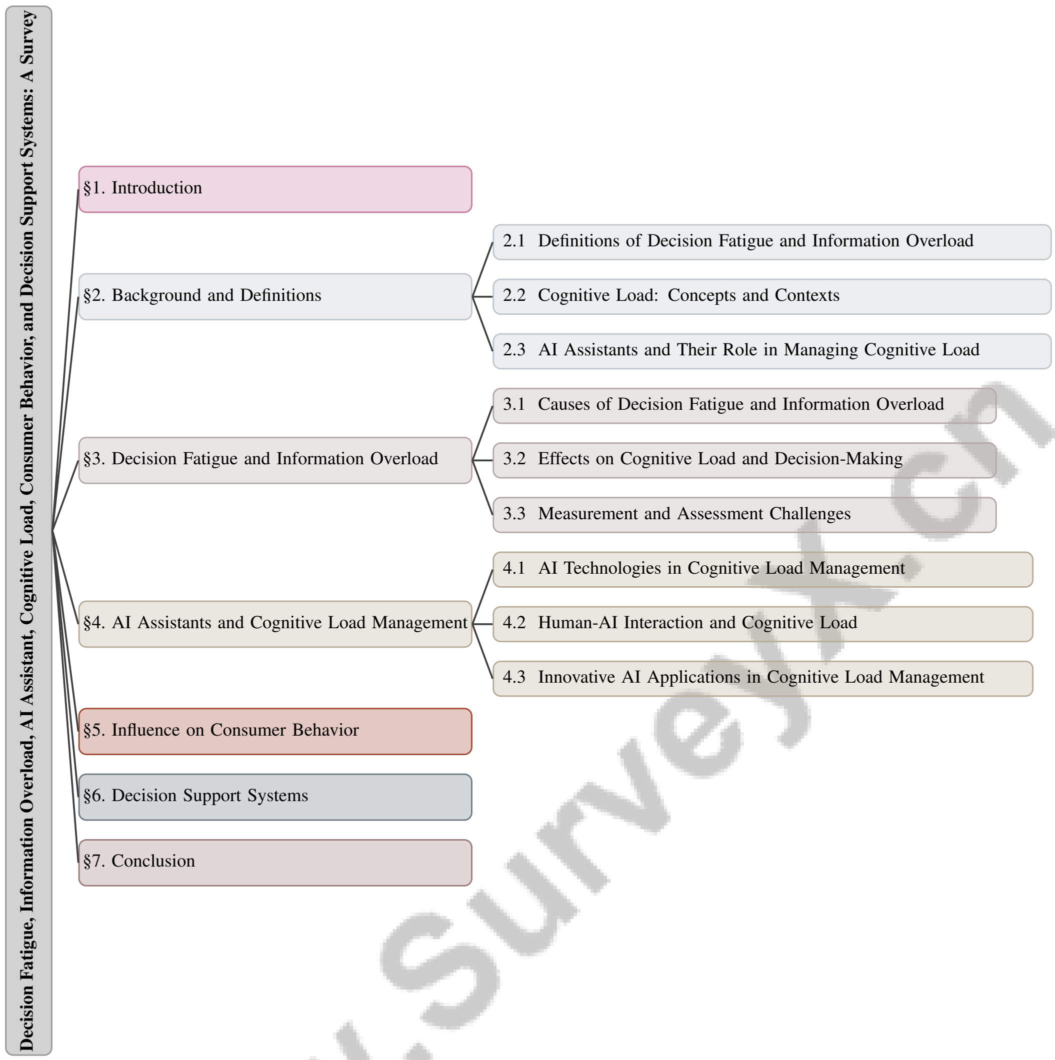

Figure 1: chapter structure

information having the potential to either mitigate or exacerbate information overload, thus affecting decision satisfaction [4]. Additionally, effective visualization in decision-making tasks underscores the importance of well-designed decision support systems in managing cognitive load [2].

Decision support systems, often enhanced by AI, aim to improve decision quality and efficiency through data-driven insights and recommendations. These systems leverage the synergy between human cognition and machine capabilities to optimize decision-making, addressing challenges posed by cognitive and data biases [3]. Understanding the interconnectedness of these concepts is vital for developing strategies that effectively manage cognitive load, enhance decision-making, and improve consumer satisfaction across various domains. Exploring these dynamics is crucial in rapidly evolving environments, where integrating situational awareness and information fusion can significantly enhance decision-making processes [1].

1.2 Significance in Modern Decision-Making

The contemporary decision-making landscape increasingly emphasizes the integration of decision fatigue, information overload, AI assistants, cognitive load, consumer behavior, and decision support systems. The vast availability of information, particularly through user-generated content, intensifies information overload, complicating users' abilities to process data and make informed decisions [5]. This issue is exacerbated by the abundance of online reviews, where both the volume and quality of information can lead to decision difficulties and reduced satisfaction [6].

While AI technologies present potential solutions to these challenges, they also introduce complexities. The effectiveness of AI in enhancing decision-making relies on the alignment of AI outputs with human intentions, a relationship often characterized by misalignment issues [2]. This misalignment highlights the necessity for a deeper understanding of human-AI interactions to optimize decision-making processes.

The cognitive load imposed by technological tools, such as chatbots and voice assistants, significantly impacts productivity and decision-making efficacy. The capacity of these tools to manage cognitive load effectively is crucial, as is the development of decision support systems that users trust and adopt widely. This necessitates advanced learning algorithms capable of navigating complex environments and providing clear, actionable insights [2].

Moreover, the rapid spread of misinformation, or infodemics, calls for a multidisciplinary approach to tackle these challenges effectively. Combating misinformation and enhancing decision-making quality require integrating insights from various fields, including computer science—especially in developing recommender systems and AI-assisted data analysis—linguistics for understanding language nuances, and cognitive psychology to inform how users process and verify information. This multidisciplinary perspective leverages advancements in AI technology and cognitive strategies to improve the reliability of information and user interactions with AI systems, ultimately fostering better decision outcomes [7, 8, 9].

In high-stakes environments, such as power grid management and healthcare, the challenges of information overload and the need for rapid decision-making are particularly acute. The interplay between algorithmic transparency, reliability, and user confidence is essential for the successful implementation of AI-driven decision support systems [2]. Understanding these dynamics is critical for ensuring that decision-making processes are efficient, accurate, and aligned with user needs and expectations.

1.3 Structure of the Survey

This survey is systematically organized to investigate the multifaceted relationships among decision fatigue, information overload, AI assistants, cognitive load, consumer behavior, and decision support systems. The paper opens with a detailed introduction that clarifies the intricate relationships among key concepts such as artificial intelligence, decision-making, and information systems, emphasizing their vital role in navigating the complexities of modern decision-making environments, particularly concerning information overload and the integration of advanced technologies like recommender systems and big data analytics [10, 11, 12, 13, 7]. Following the introduction, the survey provides background and definitions, ensuring a comprehensive understanding of decision fatigue, information overload, cognitive load theory, and the role of AI assistants in alleviating cognitive challenges.

Subsequent sections examine the causes and effects of decision fatigue and information overload, detailing their impact on cognitive load and decision-making capabilities. The survey also addresses challenges associated with measuring and assessing these phenomena. It then transitions to the role of AI technologies in managing cognitive load, highlighting the dynamics of human-AI interaction and innovative applications that enhance decision-making processes.

A dedicated section analyzes how these psychological and technological phenomena influence consumer behavior, detailing the ways cognitive load, information overload, and decision fatigue shape consumer decision-making, preferences, and purchasing behaviors. The paper further investigates the development and application of decision support systems, particularly those driven by AI, emphasizing their integration with cognitive load management strategies.

The conclusion synthesizes key findings and insights, underscoring the importance of addressing these phenomena to enhance decision-making processes and systems. This structured approach facilitates a comprehensive examination of the topics, promoting a deeper understanding of the complexities involved in decision-making within contemporary environments, akin to the design and implementation strategies discussed in AI assistant applications for power grid operations [14].The following sections are organized as shown in Figure 1.

AI-generated, for reference only.

2 Background and Definitions

2.1 Definitions of Decision Fatigue and Information Overload

Decision fatigue describes the deterioration in decision quality following extensive decision-making, often resulting in suboptimal outcomes and diminished cognitive performance. This phenomenon is particularly pronounced in environments demanding continuous decision-making, such as power grid operations, where operators handle complex systems [15]. In healthcare, the manual input of patient data into decision support systems exacerbates decision fatigue, contributing to physician burnout [16]. Novice users of intelligent decision support systems (IDS) also face challenges in distinguishing between optimal and suboptimal recommendations, highlighting the cognitive strain associated with decision fatigue [17].

Information overload occurs when users confront an overwhelming amount of information, particularly from user-generated media (UGM) [5]. This is prevalent in digital and social media, where the sheer volume of data exceeds users' cognitive processing capabilities [6]. In investment, the vast data availability complicates decision-making [4]. The rise of generative AI has intensified this issue by increasing content supply, potentially leading to information saturation and reduced user satisfaction [18]. In healthcare, accurately interpreting symptoms from video data can overwhelm decision-making, necessitating decision support systems to manage cognitive load effectively [19].

The interplay between decision fatigue and information overload is evident across domains like consumer markets, where unstructured digital data challenges traditional econometric methods, complicating user behavior analysis [1]. This complexity is amplified by incomplete observations of diffusion networks, underscoring the significant impact of information overload on decision-making [20]. Understanding these dynamics is crucial for developing strategies to manage cognitive load and enhance decision-making in sectors such as healthcare and consumer behavior analysis [21].

2.2 Cognitive Load: Concepts and Contexts

Cognitive Load Theory (CLT) offers a vital framework for understanding cognitive resource allocation during complex tasks, particularly in instructional design and decision-making. CLT divides cognitive load into intrinsic, extraneous, and germane categories. Intrinsic load pertains to the material's inherent complexity, extraneous load to information presentation, and germane load to the mental resources for processing and understanding [22].

CLT's implications extend across fields like mobile health and economic theory. In mobile health, cognitive load affects user engagement and self-reporting effectiveness, underscoring the need for designs that minimize cognitive load to enhance interaction and data accuracy [23]. In economics, critiques of rational expectations highlight human cognitive limitations, advocating for models that consider bounded rationality and cognitive constraints [4].

In education, managing cognitive load is crucial for optimizing learning and enabling practitioners to use complex AI models without overload. In programming education, understanding cognitive load aids in designing instructional tools that support learning and problem-solving [24]. Similarly, in digital health, clinicians must navigate intricate AI-driven decision support systems [3].

CLT is relevant to large-scale projects and complex data environments, where effective cognitive load management is essential for decision-making and information processing [25]. Reducing cognitive load can enhance performance and comprehension, as shown in complex reasoning tasks where integrating visualization and text-based data improves understanding [26]. Innovative methods like EEG and pupil dilation offer ways to assess cognitive load [27].

As technology progresses, integrating CLT with adaptive strategies and advanced measurement techniques will be crucial for navigating modern information complexities. This integration can enhance user experience by personalizing learning support, improving information retrieval, and utilizing tools like recommender systems and conversational agents. Such approaches will facilitate better access to scholarly literature and optimize educational technology design, fostering improved learning outcomes and engagement [28, 29, 7, 30]. This ensures effective cognitive load management across applications, from educational technology to smart home systems.

2.3 AI Assistants and Their Role in Managing Cognitive Load

AI assistants play a crucial role in reducing cognitive load and enhancing decision-making across various domains through advanced data analytics and machine learning techniques that streamline information processing. These systems significantly lower the mental effort needed for effective decision-making, particularly in complex environments. For instance, the dual dialogue system proposed in [1] demonstrates how AI can assist therapists by reducing cognitive load, thereby improving decision-making during client interactions.

Innovative methodologies, such as EEG-based cognitive load classification using advanced transformer architectures [31], employ self-supervised masked autoencoding for pre-training on emotion datasets, followed by transfer learning for cognitive load classification. These methods enable AI systems to adapt to users' cognitive states, optimizing interaction and reducing cognitive strain.

In user engagement contexts, integrating gamified elements into mobile surveys, as proposed in [23], illustrates AI's role in cognitive load management by enhancing engagement and alleviating the burden of self-reporting, thereby improving data quality and reliability.

Empirical studies on human-AI interactions in decision-making tasks highlight the importance of these interactions in managing cognitive load [2]. These studies emphasize the need for AI systems that are efficient, intuitive, and user-friendly, with the ability to deliver context-aware recommendations and insights essential for a more interactive decision-making environment.

AI assistants are vital in managing cognitive load by providing personalized, context-aware insights that enhance decision-making across domains. By leveraging advanced AI and Natural Language Processing techniques, these assistants facilitate tailored learning experiences, improve collaboration in decision-making tasks, and assist analysts in validating AI-generated data analyses. By offering easy access to information, generating interactive learning materials, and translating natural language instructions into actionable code, AI assistants reduce cognitive burdens while enhancing engagement, accuracy, and satisfaction across applications such as education, healthcare, and data analysis [29, 8, 32]. These systems not only streamline information processing but also foster a more interactive and comprehensible decision-making environment, ultimately enhancing user satisfaction and decision quality.

In examining the multifaceted phenomena of decision fatigue and information overload, it is essential to understand their hierarchical structure and the various factors that contribute to these challenges. Figure 2 illustrates this structure, categorizing the causes and effects on cognitive load and decision-making processes. The figure emphasizes not only the cognitive and contextual factors involved but also their implications in both digital and clinical settings. Furthermore, it underscores the necessity for innovative methodologies to effectively address these complex issues, thereby enhancing our comprehension of how decision fatigue and information overload manifest in different environments. This visual representation serves to clarify the intricate relationships between these variables, reinforcing the theoretical framework discussed in this review.

3 Decision Fatigue and Information Overload

3.1 Causes of Decision Fatigue and Information Overload

Decision fatigue and information overload stem from cognitive and contextual factors impacting decision-making in various domains. Digital platform interactions, especially on social media, intensify information overload due to diverse user behaviors and constant data flow [5]. In financial markets, individuals face decision fatigue as they struggle to process vast information volumes [4]. Healthcare professionals experience decision fatigue from traditional clinical pathways and opaque machine learning models, which hinder adaptation to patient needs and algorithmic trust [1]. Algorithm transparency and reliability are essential for user trust, yet current benchmarks often fall short, exacerbating decision fatigue [19].

User-generated content and online reviews contribute to information overload, reducing decision satisfaction [6]. Simplistic AI collaboration paradigms limit their support for human decision-making, adding to cognitive strain [2]. Extensive self-reporting in health applications deters user engagement, heightening cognitive overload [23]. Emerging fields often lack established frameworks, complicating effective decision support system design and increasing cognitive strain [33]. Generative AI's content

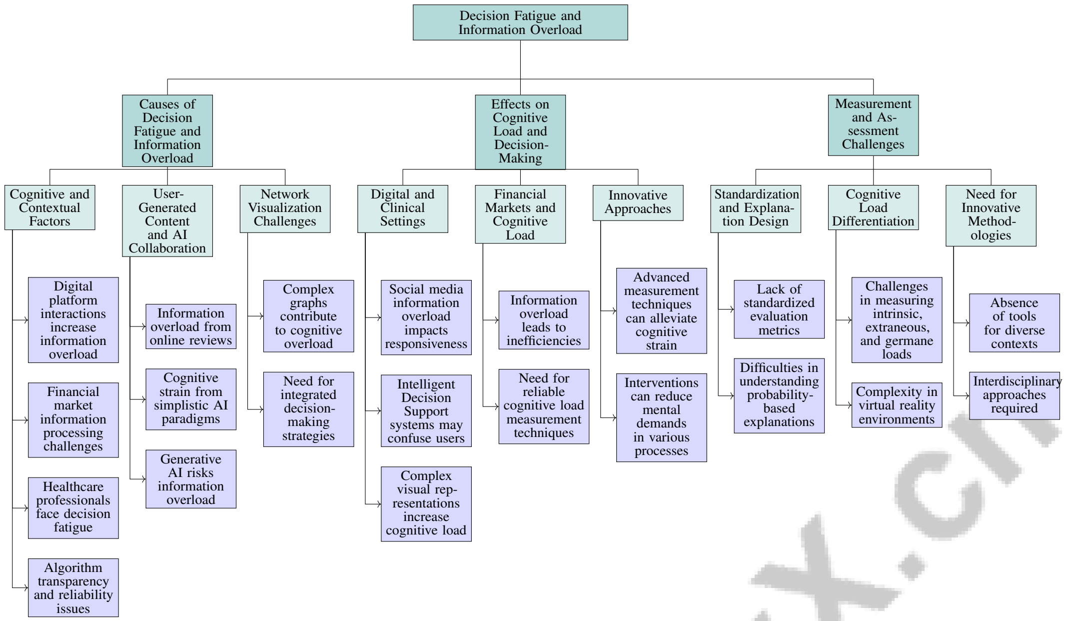

Figure 2: This figure illustrates the hierarchical structure of decision fatigue and information overload, categorizing the causes, effects on cognitive load and decision-making, and challenges in measurement and assessment. It highlights cognitive and contextual factors, the impact on digital and clinical settings, and the necessity for innovative methodologies in addressing these complex issues.

diversity offers benefits but also risks information overload and market disruption [18]. Network visualization challenges, especially with complex graphs, indicate structural factors contributing to decision fatigue and information overload [27].

Addressing decision-making challenges requires integrated strategies that consider cognitive factors like user intuition and contextual elements such as information dynamics and evolving preferences. Combining Large Language Models (LLMs) with Constraint Programming shows promise in adaptive decision support systems for complex tasks like meeting scheduling. Understanding how users reconcile intuition with AI predictions is crucial for optimizing AI reliance, fostering collaboration between human decision-makers and AI technologies for informed and effective decision-making [10, 34, 35, 36, 37].

3.2 Effects on Cognitive Load and Decision-Making

Decision fatigue and information overload significantly impact cognitive load and decision-making abilities across domains, from digital interactions to clinical settings. Information overload in social media hampers user responsiveness and conversation dynamics, as mathematical models and simulations demonstrate [38]. Users are less likely to retweet information as incoming information rates rise, indicating diminishing returns on information processing [39]. This cognitive strain highlights the need for systems that manage information influx to maintain user engagement and decision quality.

In clinical environments, assuming Intelligent Decision Support (IDS) systems always provide optimal recommendations can confuse users and lead to poor decision-making [17]. Tools like the Clinical Evidence Engine (CEE) can alleviate cognitive load by enhancing clinical trial information retrieval, aiding informed clinical decisions [40]. Visual representation complexity, such as node-link diagrams, increases cognitive load, with effectiveness declining as complexity rises [27]. This finding aligns with user concerns on platforms like Twitter, where information overload adversely affects cognitive load and decision-making [5].

In financial markets, information overload leads to inefficiencies, as even knowledgeable investors struggle to process all available information, resulting in suboptimal decisions [4]. Variability in cognitive load estimation across visualizations exacerbates inefficiencies, highlighting the need for generalized benchmarks and reliable measurement techniques to enhance cognitive load management strategies [22].

The interplay between decision fatigue, information overload, and cognitive load necessitates innovative approaches to improve decision-making processes. As illustrated in Figure 3, the categorization of cognitive load and decision-making challenges across social media, clinical decision support systems, and financial markets highlights key studies and findings in each domain. Advanced measurement techniques, such as physiological signal analysis and eye-tracking, alongside strategies to enhance user engagement, can alleviate cognitive strain and improve decision-making outcomes across applications, including information seeking and technical interviews. Research indicates cognitive load varies significantly across different stages of these processes, with interventions—such as providing semantic information during web searches—demonstrating potential to reduce mental demands and foster a more effective user experience [41, 42, 43, 44].

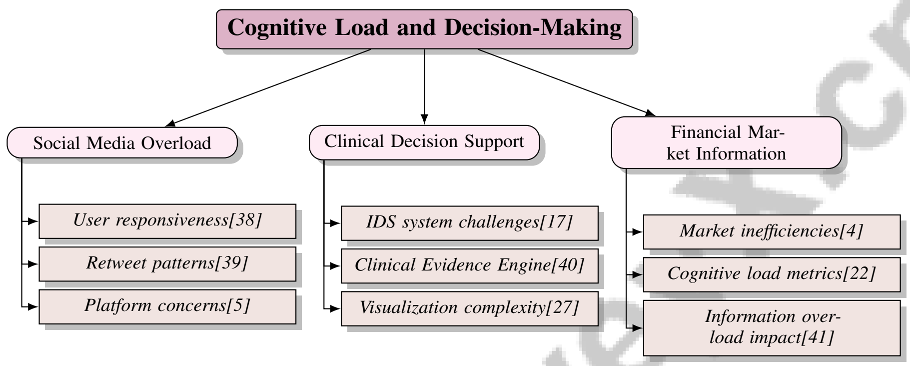

Figure 3: This figure illustrates the categorization of cognitive load and decision-making challenges across social media, clinical decision support systems, and financial markets, highlighting key studies and findings in each domain.

3.3 Measurement and Assessment Challenges

Benchmark	Size	Domain	Task Format	Metric
AI-Debias[45]	12,000	Visualization	Ensemble Average Estimation	Response Time, Estimation Error
ThreatCluster[46]	2,462	Cybersecurity	Clustering	V-measure, Homogeneity
AI-DRL-HMI[47]	1,000	Process Safety	Decision Support	Accuracy, SART
AVCAffe[48]	108,000	Cognitive Load Assessment	Collaborative Task Completion	F1-score, Weighted F1-score
EP-Fatigue[49]	2,065	Emergency Medicine	CT Scan Requests And Inpatient Referrals Analysis	p-value, frequency of requests
CLE-Benchmark[50]	4,536	Cognitive Load Estimation	N-back Task	F1-score
DSS-Benchmark[51]	1,305	Human-AI Interaction	Decision-making Simulation	Score, Time to Completion
AI-CDSS[52]	780	Breast Cancer Diagnosis	Image Classification	Accuracy, Trust

Table 1: The table presents a comparative overview of various benchmarks utilized in the assessment of cognitive load, decision support, and related domains. It includes detailed information on the size, domain, task format, and evaluation metrics associated with each benchmark, highlighting the diversity and specificity of approaches in addressing measurement and assessment challenges.

Accurately measuring and assessing decision fatigue and information overload presents challenges due to their multifaceted nature and the intricacies of cognitive load dynamics. A primary obstacle is the lack of standardized evaluation metrics for explanations in decision support systems, hindering intuitive explanation design for non-expert users [53]. Understanding probability-based explanations is difficult, leading to low user acceptance of automated normative reasoning techniques [54].

Measuring cognitive load itself is challenging, requiring differentiation between intrinsic, extraneous, and germane cognitive loads and understanding their interactions with learner characteristics and instructional materials [22]. This complexity is pronounced in virtual reality (VR) environments, where assessing cognitive load necessitates subjective and objective measurement tools to capture nuanced effects of immersive tasks on cognitive processing [55].

Moreover, the absence of accessible tools for measuring cognitive load across diverse contexts, including VR, limits the development of comprehensive strategies for managing decision fatigue and information overload [55]. These challenges underscore the need for innovative methodologies and interdisciplinary approaches to enhance cognitive load measurement and assessment, improving decision-making processes and system design. Table 1 provides an illustrative comparison of benchmarks employed in the study of cognitive load and decision support systems, emphasizing the varied methodologies and metrics used to tackle the complexities of measurement and assessment in these fields.

4 AI Assistants and Cognitive Load Management

4.1 AI Technologies in Cognitive Load Management

AI technologies play a pivotal role in managing cognitive load by employing advanced algorithms and user-centric designs to optimize information retrieval and enhance user interaction. These systems are tailored to accommodate various user behaviors, such as single query, multi-document, and iterative query users, thereby streamlining information flow and alleviating cognitive strain [2]. In clinical environments, AI frameworks enhance clinician-AI communication through structured interpretability approaches, which include pre-processing, interpretable modeling, and post-processing, facilitating the integration of AI-generated insights into clinical decision-making and reducing cognitive load [3].

Machine learning models, such as cognitive load detectors using photoplethysmography (PPG) signals, exemplify the use of physiological data to estimate cognitive load during surveys, minimizing self-reporting burdens [23]. This capability allows AI systems to dynamically adapt to users' cognitive states, optimizing interactions and reducing mental effort. In finance, models addressing information overload highlight the cognitive load's impact on decision-making, underscoring the necessity for AI systems to manage cognitive strain in complex data environments [4]. EEG-based cognitive load classification, utilizing advanced transformer architectures, assesses cognitive load and enables adaptive support for users in high-demand contexts [31].

AI technologies significantly enhance decision-making by providing personalized, context-aware insights. Explainable AI (XAI) positively affects cognitive load and task performance in medical decision-making, emphasizing the need for tailored explanations. In collaborative environments, AI recommendations' effectiveness varies with user expertise; novice users benefit more from AI assistance compared to proficient users, who discern when to rely on AI suggestions. Furthermore, managing AI-generated content quality is crucial, as inaccuracies can undermine user reliance and data quality. In complex project management, AI improves cognitive capacity by enhancing access to relevant information, aiding project managers in navigating intricate data landscapes. These insights illustrate AI's multifaceted role in optimizing cognitive load management and decision-making across diverse fields [29, 25, 32, 9, 56].

4.2 Human-AI Interaction and Cognitive Load

Human-AI interaction dynamics are crucial for managing cognitive load, especially as these technologies integrate into decision-making processes across sectors. Clinical Decision Support Systems (CDSS) exemplify how AI can ease cognitive load by providing timely alerts and recommendations based on patient data, enhancing clinical decision-making [57]. However, the complexity of AI systems can breed mistrust, presenting challenges for effective human-AI interaction, necessitating improved communication among clinicians [58]. Specialized large language models (LLMs) address shortcomings in existing models, enhancing trust and usability in clinical settings, which are crucial for effective human-AI collaboration [59]. Adapting AI-CDSS to local contexts, particularly in rural healthcare, emphasizes incorporating social and cultural factors into design, significantly influencing cognitive load and decision efficacy [60].

To further illustrate these concepts, Figure 4 presents a hierarchical categorization of key concepts in Human-AI Interaction and Cognitive Load. This figure focuses on AI applications in clinical settings, decision support tools, and interaction strategies, highlighting the diverse approaches to managing cognitive load and enhancing decision-making through AI technologies.

Tools like the X-Selector, which predicts user behavior to tailor explanations, enhance decision-making by aligning insights with human cognitive strategies [61]. AI driving coaches provide structured explanations that facilitate learning without overwhelming novice drivers, demonstrating the efficacy of multimodal explanations in reducing cognitive load [62]. Real-time cognitive load data, obtained through eye-tracking technology, offers immediate feedback on instructional design, allowing adaptive systems to adjust interactions based on users' cognitive states [30]. The influence of token noise in LLMs on decision-making underscores the importance of comprehending AI-generated insights to mitigate cognitive load effectively [63].

AI-first assistance may lead to over-reliance, while AI-follow assistance can help mitigate this bias, highlighting the need for balanced human-AI interaction strategies [2]. Subgoal-based explanations leverage cognitive strategies to simplify complex tasks, enhancing user understanding and decision-making performance [17]. In healthcare, adaptive questionnaires reduce cognitive load by minimizing unnecessary clinician input, improving data entry efficiency and human-AI interaction [16]. The dynamics of human-AI interaction necessitate a comprehensive approach that includes user behavior analysis, physiological monitoring, and the development of intuitive AI systems to enhance decision-making efficacy. Advanced technologies and methodologies enable AI systems to effectively manage cognitive load, alleviate cognitive strain, and enhance user satisfaction across diverse applications. In scholarly information systems, these technologies help users navigate the growing volume of literature by recommending relevant articles, streamlining information discovery, and mitigating information overload. AI-driven chatbots in enterprise contexts reduce cognitive load during human-technology interactions, increasing productivity and improving task quality in complex collaborative scenarios. These advancements exemplify AI's potential to foster a synergistic relationship between human cognitive abilities and machine capabilities, enhancing user experience and performance [7, 64].

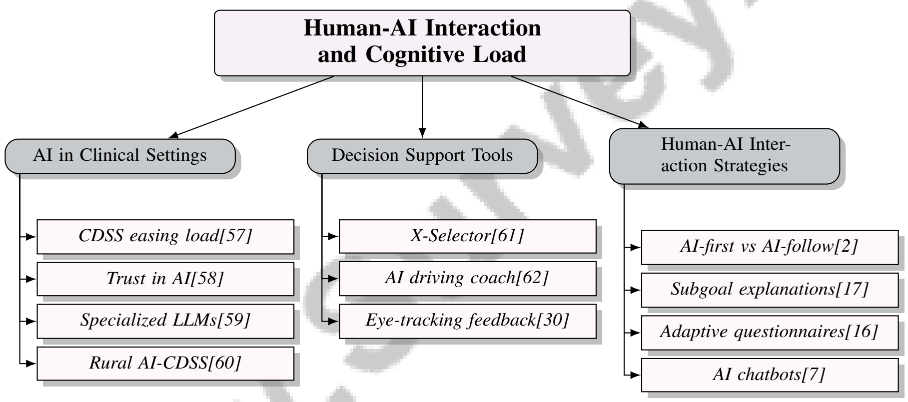

Figure 4: This figure illustrates the hierarchical categorization of key concepts in Human-AI Interaction and Cognitive Load, focusing on AI applications in clinical settings, decision support tools, and interaction strategies. It highlights the diverse approaches to managing cognitive load and enhancing decision-making through AI technologies.

4.3 Innovative AI Applications in Cognitive Load Management

Method Name	Application Domains	Technological Integration	Outcome Enhancement
CP[65]	Clinical Settings	Deep Learning	Decision-making
XAI-CDSS[66]	Clinical Settings	Xai Techniques	Personalized Interventions
ICLAM[67]	Modern Education	Eeg Signals	Effective Educational Content
MM[34]	Decision Support Systems	Large Language Models	Enhance Decision-making
CLDF[68]	Automation, Robotics	Machine Learning	User Experience
EBRA[69]	Human-computer Interaction	Machine Learning Techniques	Mental Workload Classification
HDPA[70]	Big Data Analytics	Distributed Computing	Decision-making
M			
	M[71]	Education, Design, Health	Multimodal-multitask Framework
Improving Engagement			
RMCDSS[72]	Decision Support Systems	Content Monitoring Methodologies	Conflict Modeling Accuracy
Res-TCN[73]	Disease Detection	Skeleton Data	Decision-making

Table 2: Overview of AI-based methods across various domains, highlighting their application areas, technological integrations, and outcomes. This table summarizes the innovative approaches in cognitive load management, showcasing the role of AI in enhancing decision-making, educational content, user experience, and mental workload classification.

Innovative AI applications are increasingly crucial for managing cognitive load, providing transformative solutions across various domains. Table 2 presents a comprehensive summary of innovative AI applications in cognitive load management, detailing the methods, their respective domains, technological integrations, and the enhancements they provide. In clinical settings, integrating advanced deep learning models with interactive visualizations, such as those in the CarePre system, enhances clinical decision-making by delivering accurate predictions and user-friendly interpretations, reducing cognitive load for healthcare professionals [65]. XAI techniques improve CDSS transparency, assisting clinicians in managing cognitive load through multidimensional analytical insights [66]. In education, combining EEG data with machine learning enables real-time classification of cognitive load levels, providing immediate feedback to instructional designers and enhancing personalized learning experiences [67]. This approach allows educators to tailor materials to individual cognitive states, improving engagement and learning outcomes. LLMs translate natural language inputs into structured constraints, streamlining complex decision-making processes [34].

In software engineering, applying cognitive load theory to predict usability outcomes in programming language design emphasizes AI's role in managing cognitive load [24]. Future research should focus on real-time integration of psychophysiological data into Integrated Development Environments (IDEs) to enhance understanding of developer behavior and productivity [74]. Categorization patterns clarify the strategic and operational roles of information in decision support systems, facilitating effective decision-making by providing structured insights [12]. Exploring interactions among robot autonomy, cognitive load, and trust highlights the significance of shared autonomy in managing cognitive load and enhancing user experience [75].

The framework proposed by [68] demonstrates the potential of physiological data in cognitive load assessment, achieving over 90% accuracy in classifying cognitive load. This underscores the promise of physiological measures for innovative cognitive load management applications. Empirical validation of EEG band ratios as reliable indicators of mental workload further enriches the understanding of cognitive load assessment [69]. The CLARE dataset's potential for real-time cognitive load assessment emphasizes the importance of frequent self-reports in improving model accuracy [76]. Innovative applications like the HDPA system represent significant advancements in cognitive load management by reducing computation time while maintaining high accuracy in processing large datasets [70]. The RCC approach, incorporating reasons, counterfactuals, and confidence, showcases innovative AI applications in managing cognitive load [53]. Effective interface and assistance function design support operators in decision-making within power grid operations, exemplifying another dimension of AI's role in cognitive load management [14].

The cross-modality multihead attention mechanism of the M&M model enhances cognitive load assessment by synchronizing audio and video data processing [71]. Applying a second-order rank reflexive model to create design patterns for knowledge bases in decision support systems improves modeling of complex interactions in information operations [72]. Integrating risk and trust measures into decision support systems enhances interpretability and reliability of machine learning outputs, relevant to AI applications in cognitive load management [73]. These innovations illustrate AI's transformative potential in managing cognitive load, offering tailored solutions that enhance decision-making and user satisfaction across diverse applications. By leveraging advanced technologies and methodologies, such as Natural Language Processing and recommender systems, AI can significantly alleviate cognitive strain on users and improve outcomes across various domains, including education and scholarly research. These systems facilitate personalized learning experiences and efficient information discovery, enabling users to access relevant literature and tailored support that aligns with their needs and learning styles. This human-machine synergy enhances engagement and satisfaction while addressing challenges posed by information overload in an increasingly complex digital landscape [29, 7].

5 Influence on Consumer Behavior

5.1 Impact of Cognitive Load on Consumer Decision-Making

Cognitive load profoundly affects consumer decision-making, influencing both the speed and accuracy of choices. In investment scenarios, excessive cognitive load, often due to information overload, impairs decision-making, leading to suboptimal choices as investors struggle with data processing [4]. Effective cognitive load management is essential for improving decision efficiency and accuracy.

In digital environments, the effects of cognitive load are nuanced. Users with extensive social media connections report less information overload, suggesting that well-managed cognitive load facilitates better decision-making [5]. Conversely, complex visual data representations, such as dense graphs, can cause cognitive overload, adversely affecting consumer interaction with information [27]. Individual characteristics, such as product knowledge, significantly influence cognitive load, with knowledgeable consumers experiencing less cognitive strain [6].

This is further illustrated in Figure 5, which categorizes the impact of cognitive load on decision-making into three main areas: cognitive load effects, AI influences, and management strategies. The figure highlights specific scenarios, such as investment decisions and healthcare AI applications, alongside the critical role of consumer empowerment in managing cognitive load.

AI tools highlight the importance of cognitive load management in decision-making. In healthcare, the lack of interpretability in AI systems can increase cognitive load, negatively impacting clinician decision-making [3]. Advanced AI models, including transformer architectures, show promise in capturing cognitive load characteristics through EEG signals, potentially improving decision-making by providing insights into cognitive states [31]. Despite the potential benefits of gamification in reducing cognitive load, studies suggest it does not significantly alleviate cognitive burden during survey completion, indicating the complexity of cognitive load dynamics in decision-making [23].

Managing cognitive load effectively is crucial for optimizing decision-making processes, as excessive demands can lead to information overload, increased decision difficulty, and lower satisfaction. Research shows that the quality and quantity of decision support information, such as online reviews, significantly affect cognitive load and outcomes. Individual differences, such as product knowledge, further influence how consumers process information, emphasizing the need for tailored approaches to enhance consumer empowerment and satisfaction in the digital marketplace [77, 6, 42, 43]. By leveraging AI technologies and strategic interventions to mitigate cognitive strain, decision efficiency and consumer satisfaction can be enhanced across various contexts.

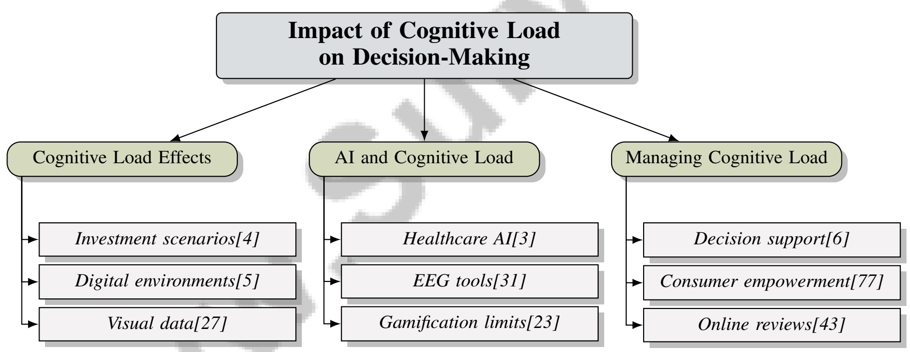

Figure 5: This figure illustrates the impact of cognitive load on decision-making, categorizing the effects into cognitive load effects, AI influences, and management strategies. It highlights specific scenarios such as investment decisions, healthcare AI applications, and the role of consumer empowerment in managing cognitive load.

5.2 Effects of Information Overload on Consumer Preferences

Information overload significantly impacts consumer preferences by overwhelming individuals with excessive data, impairing optimal decision-making. In digital environments, particularly on social media platforms like Twitter, the constant influx of information affects conversation dynamics and user engagement. There are optimal thresholds for user responsiveness; beyond these, information overload leads to decreased interaction [38]. This is evident among active Twitter users, where the rate of information receipt inversely correlates with susceptibility to social contagions, illustrating the cognitive strain of excessive information [39].

Generative AI complicates this landscape by introducing an infinite supply of content, disrupting traditional economic models and affecting user utility through information overload [18]. The overwhelming availability of AI-generated content may lead consumers to prioritize superficial characteristics, such as prominence or novelty, over substantive quality, skewing preferences and encouraging heuristic processing strategies to cope with cognitive demands.

The distinction between raw information and synthesized knowledge is critical, as consumers often base decisions on incomplete or misleading data, affecting their preferences. The growing volume of scholarly literature, increasing at approximately 3.5 percent annually, contributes to a gap between information availability and meaningful knowledge synthesis. This overload can hinder effective decision-making, underscoring the need for strategic interventions that enhance information processing capabilities, such as advanced recommender systems that leverage machine memory and human cognition [12, 7].

Mitigating the negative effects of information overload on decision-making requires enhancing information dissemination strategies and user interface designs, facilitating a tailored and manageable flow of information that aligns with users' needs in an increasingly complex digital landscape [38, 7]. Digital environments must support effective information management to help consumers navigate data deluge, fostering informed decision-making and enhancing satisfaction. By leveraging technological advancements and implementing strategic measures, addressing the challenges of information overload becomes feasible, aligning consumer preferences with their true interests and values.

5.3 Decision Fatigue and Its Influence on Purchasing Patterns

Decision fatigue significantly affects consumer purchasing patterns by impairing decision quality, particularly after prolonged deliberation. This results in a tendency for default selections or risk-averse behaviors as individuals may lack the cognitive resources to thoroughly evaluate alternatives. The uncertainty in AI service environments exacerbates this issue, prompting increased variety-seeking behaviors among consumers, complicating purchasing decisions [78].

Decision support systems are crucial in alleviating decision fatigue, enhancing customer service efficiency, and reducing cognitive strain on service employees, which indirectly influences consumer satisfaction and purchasing behavior [79]. However, the absence of regulatory frameworks to manage the implicit steering of consumer preferences by conversational AI presents challenges in effectively addressing decision fatigue [80]. This necessitates ethical guidelines and transparency in AI applications to prevent undue influence on consumer choices due to algorithmic biases.

Research indicates that user interface design, such as engaging information buttons, does not significantly alter behavior, suggesting that interface design alone may not suffice to mitigate decision fatigue's impact on purchasing patterns [81]. Instead, improving data quality and user interfaces in AI systems could enhance decision-making processes, reducing cognitive burden and influencing purchasing decisions [13].

In healthcare, decision fatigue has been observed in inpatient referral patterns, although it did not significantly affect CT scan decision-making, highlighting variability in decision fatigue effects across contexts [49]. This variability suggests that consumer purchasing behavior may similarly be influenced by context-specific factors, necessitating tailored strategies to address decision fatigue in diverse environments.

While decision fatigue is recognized, its direct effects on clinical decision quality and patient safety remain uncertain, warranting further investigation [82]. This uncertainty implies that the impact of decision fatigue on consumer purchasing patterns may also require additional exploration to fully understand its implications across various domains.

Understanding decision fatigue's effects on purchasing patterns is essential for developing strategies that enhance consumer decision-making. By leveraging interdisciplinary research and prioritizing ethical AI implementation, it is possible to mitigate the adverse effects of decision fatigue and improve consumer satisfaction across diverse sectors [83].

6 Decision Support Systems

Decision Support Systems (DSS) are integral to modern decision-making processes, providing structured methodologies that enhance decision quality and efficiency across numerous domains. These systems synthesize data from various sources to offer actionable insights, particularly in complex and uncertain environments, facilitating informed choices. The integration of DSS with contemporary information systems and AI-assisted tools presents challenges for analysts in data analysis and decision-making [15, 7, 8]. This exploration underscores the multifaceted roles of DSS in improving decision-making outcomes.

6.1 Decision Support Systems: Definitions and Applications

DSS are sophisticated frameworks designed to enhance decision-making by providing actionable insights from diverse data sources, crucial in complex and uncertain environments. In spreadsheet modeling, DSS are pivotal in error management, equipping users with tools to identify and rectify errors, thereby enhancing the reliability of decisions [15]. In healthcare, DSS have significantly improved clinical decision-making by integrating AI-based medical devices and digital health technologies to deliver patient-specific recommendations [3]. The adaptive questionnaire method optimizes question order and visibility, enhancing data entry efficiency and reducing cognitive load on clinicians [16].

DSS applications extend to mobile monitoring systems, employing certainty theory to model inexact reasoning, thus improving the detection of respiratory distress triggers [84]. Visualization tools within DSS are evaluated for their completeness and utility, highlighting their significance in supporting decision-making tasks [20]. In low-theoretical domains, methods like the SCOA leverage experience and expertise to create effective decision support solutions [33]. Algorithm reliability and transparency influence user trust in DSS design, emphasizing the need for systems that are both reliable and transparent [19].

The development of improved filtering tools to manage information consumption drives DSS advancements, particularly in social media contexts [5]. Addressing these challenges allows DSS to assist users in navigating complex information environments, enhancing decision quality and user satisfaction across various domains.

6.2 AI-Driven Decision Support Systems

AI-driven DSS enhance decision-making processes by utilizing advanced algorithms and machine learning to provide data-driven insights and improve decision accuracy. In digital environments, AI-driven DSS mitigate challenges such as information overload, especially through online reviews, enhancing market efficiency [6, 4]. The SCOA method exemplifies AI-driven DSS applications, addressing unique challenges through informed decision-making grounded in real-world experience [33]. In healthcare, AI-driven DSS utilize EEG-based cognitive load classification to capture real-time physiological signals, enhancing user engagement and decision-making processes.

Generative AI impacts market dynamics, necessitating effective policy interventions, highlighting AI-driven DSS's role in navigating complex decision-making landscapes [18]. Human-AI collaboration patterns emphasize the need for AI systems that facilitate effective user engagement and decision quality [2]. AI-driven DSS advance cognitive load management and decision accuracy through Explainable AI (XAI) technologies, providing tailored explanations to users. These systems assist in processing large volumes of data, strategically aligning AI suggestions with user decisions, minimizing discrepancies and enhancing overall task performance [10, 61]. By addressing information overload and market inefficiencies, AI-driven DSS improve decision-making processes, enhancing user satisfaction across various domains.

6.3 Integration of AI and Cognitive Load Management

Integrating AI-driven DSS with cognitive load management strategies is crucial for enhancing decision-making across various domains. These systems optimize information processing, reducing cognitive strain and addressing information overload challenges in complex environments. In healthcare, AI-driven DSS improve clinician workflows and decision-making efficiency by incorporating interpretability strategies, bolstering trust and communication between AI tools and providers [3]. Visualization design plays a critical role in cognitive load management, significantly alleviating cognitive strain and enhancing user experience [26]. Tools like the X-Selector predict explanation combinations' effects on user decisions, allowing strategic selection that minimizes discrepancies between user and AI decisions [1].

Incorporating risk and trust measures into DSS further enhances cognitive load management, improving decision quality by ensuring informed decisions with confidence. This approach is particularly relevant in healthcare, where AI integration must address ethical and practical challenges to fully realize machine learning's potential [21]. Future research should focus on developing user-friendly interfaces, integrating AI-CDSS with existing healthcare systems, and fostering collaborative human-AI interactions that respect clinician autonomy [2]. By leveraging advanced technologies and methodologies, AI systems effectively manage cognitive load, enhance user satisfaction, and ensure ethical and transparent decision-making across diverse applications.

7 Conclusion

This survey delves into the intricate relationships among decision fatigue, information overload, AI assistants, cognitive load, consumer behavior, and decision support systems, highlighting their collective influence on contemporary decision-making frameworks. A key finding is the capacity of AI systems to alleviate cognitive load, thereby enhancing decision-making efficiency and quality across various sectors. The integration of AI within decision support systems not only improves user interactions by ensuring transparency and reliability but also builds trust in algorithmic decisions. This underscores the necessity for incorporating user feedback in developing interpretable systems, which is crucial for mitigating information overload and refining decision-making processes.

The survey also emphasizes the importance of understanding user interactions with decision support tools, validated through a comprehensive typology for decision-making tasks in visualization. This framework is instrumental in clarifying complex decision processes and improving the design of decision-support tools. Additionally, the exploration of consumer empowerment reveals the advantages of informed decision-making experiences, suggesting the need to reassess economic models to include considerations of bounded rationality and the impacts of information overload.

Future research should prioritize the development of conversational agents that effectively aid users in diverse search tasks, addressing emerging trends in user interaction with search technologies. Moreover, investigating various gamification strategies and conducting real-world studies could further substantiate findings related to cognitive load management. The integration of AI in project management also holds promise for enhancing cognitive load management, improving project outcomes, and reducing failure rates.

Confronting the challenges associated with decision fatigue, information overload, and cognitive load is essential for advancing decision-making processes and systems. By leveraging advanced technologies, fostering interdisciplinary collaboration, and integrating evidence-based design, decision quality and user satisfaction can be significantly enhanced across diverse applications.

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