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Integrating Physical and Cognitive Ergonomics: Workload, Performance, and Human–Technology Interaction Across Complex Systems

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ABSTRACT

This review paper explores the integration of physical and cognitive ergonomics within complex systems such as aviation, healthcare, and military operations, emphasizing workload, performance, and human–technology interaction. It synthesizes current research on the effects of combined physical and cognitive demands on task performance and safety, incorporating physiological, behavioral, and computational approaches to cognitive workload measurement. Key themes include adaptive human performance under high demand, trust and engagement in human–robot interaction, decision-making and error mechanisms, individual cognitive differences, and ergonomic system design. The review highlights the importance of multimodal assessment strategies and personalized ergonomic interventions to enhance resilience, efficiency, and well-being. Findings underscore the necessity of integrated ergonomic designs and training programs to support user safety and system performance, while identifying ongoing challenges in modeling complex cognitive processes and implementing adaptive technologies. Future research should focus on refining multimodal workload models, addressing individual variability, and advancing human–machine collaboration to optimize ergonomic outcomes.

Keywords: Physical Ergonomics, Cognitive Ergonomics, Workload Measurement, Human–Technology Interaction, Human–Robot Interaction, Cognitive Workload, Ergonomic Design

1. INTRODUCTION

The integration of physical and cognitive ergonomics is critical for optimizing human performance and safety across various complex systems, including aviation, healthcare, military operations, and industrial settings. Complex systems typically impose simultaneous physical and cognitive demands on operators and workers, necessitating a comprehensive understanding of how these demands interact and affect overall workload and task performance. For example, aviation environments are known for high cognitive demands, where multitasking under conditions of divided attention can severely challenge pilot performance (Scarince, Moreno, Clausen, & Payne, 2024). Complementing this, Holley and Miller (2023) highlight the growing complexity and digitization of flight decks that elevate cognitive load, threatening operational safety if cognitive resilience mechanisms are not effectively developed and trained.

In healthcare, the cognitive ergonomic challenges are equally pronounced. Aminuddin and Hakim (2023) emphasize how emergency room nurses experience burnout and increased likelihood of human error under intense cognitive and physical pressures during the COVID-19 pandemic. Similarly, integrating cognitive ergonomics in patient-AI interactions has shown promise for improving diagnostic reasoning by fostering cognitive empathy, thereby increasing patient trust and satisfaction (Alam & Mueller, 2023).

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Industrial work environments transitioning into Industry 4.0 and 5.0 paradigms face new challenges involving human-robot collaboration where cognitive workload management is paramount (Hilmi, Abdul Hamid, & Wan Ibrahim, 2024). Ergonomic interventions such as low-back exoskeletons demonstrate the dual physical and cognitive impacts, with research indicating user preference and training can mitigate cognitive loads during complex manufacturing tasks (Outlaw et al., 2025). Moreover, helmet weight studies underscore the influence of physical ergonomic factors on cognitive performance, suggesting design considerations should address both aspects to optimize safety and efficiency (Kazemi et al., 2021).

Furthermore, cognitive workload and mental fatigue analyses across domains utilize varied psychophysiological measures including EEG, eye tracking, and pupillometry to capture real-time mental demands, informing adaptive system and interface designs (Niamba & Schieber, 2022; Venkatesh, Jaiswal, & Nanda, 2023). Emerging cognitive modeling approaches such as those based on ACT-R architectures offer predictive insights into decision-making, vigilance decrement, and workload dynamics, informing training and interface optimization (McCarley, 2025; Oh, Yun, & Myung, 2023).

2. INTERACTION BETWEEN PHYSICAL AND COGNITIVE WORKLOAD

2.1 Effects of Divided Attention and Fatigue

Simultaneous physical and cognitive demands frequently challenge human performance across complex environments, particularly where divided attention is required. Scarince et al. (2024) investigated how training Unmanned Aerial Systems (UAS) pilots under conditions of divided attention—performing visual and auditory cognitive tasks concurrently with flight operations—affected their task performance. They observed that flight efficiency and cognitive task performance decreased under divided attention conditions initially; however, with practice across multiple sessions, pilots demonstrated significant improvement, highlighting the adaptability of cognitive processing under complex multitasking demands. This suggests that cognitive training protocols incorporating divided attention tasks can enhance operator readiness for high-demand environments.

Similarly, in the domain of physical-cognitive interaction during locomotion, Sumianto et al. (2025) examined the cognitive demands of peripheral versus centered dual-tasking in virtual reality environments affecting gait variability. Their findings revealed that peripheral dual-tasking significantly increased step width compared to conditions without secondary tasks, indicating higher cognitive load and adjustments in physical gait stability. Complementing these observations, Gupta et al. (2021) reported that individuals with faster cognitive reaction times tended to prioritize coordination with exoskeleton assistance over maintaining gait stability when performing treadmill walking tasks coupled with secondary cognitive challenges. These studies collectively emphasize how divided attention and cognitive fatigue can impact the integration of physical motor tasks and cognitive processing, with implications for rehabilitative and assistive technologies.

2.2 Workload in Safety-Critical Performance

In safety-critical domains such as aviation and law enforcement, cognitive overload can reduce operational effectiveness and increase error susceptibility. Holley and Miller (2022, 2023) examined cognitive processing disruptions in flight deck environments, identifying that approximately 30% of incident reports may be linked to cognitive overload resulting from the increasing complexity and digitization of flight deck controls. Their analyses showcased that distractions or surprise disruptions negatively affect working memory capacity and cognitive processing speed, posing risks to situation awareness and safety. They further underscore the need for cognitive resilience training and adaptations, such as modifying the Crew Resource

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Management-Threat and Error Management (CRM-TEM) framework to accommodate cognitive resilience in pilots.

Extending this focus to law enforcement, Wozniak et al. (2022) found that novice officers exhibit average or elevated cognitive workload during typical patrol driving, with physiological indicators such as heart rate variability and eye tracking correlating with subjective workload measures. Such evidence underscores the necessity for ergonomic interventions tailored to novice personnel who face steep cognitive demands in operational settings.

Moreover, Holley and Miller (2022) investigated neural dynamics related to cognitive loading, tying the disruption of "cognitive flow" to exponential increases in processing loads on working memory, which impede safe performance. Their work advocates for neural metrics and cognitive flow monitoring as tools to identify overload thresholds, further supporting intervention design in domains where cognitive failure has severe consequences.

2.3 Impact of Ergonomic Design on Physical and Cognitive Load

Ergonomic design plays a pivotal role in balancing physical and cognitive loads to optimize performance and safety. Kazemi et al. (2021) evaluated the effects of helmet weight on cognitive performance and mental workload, finding that heavier helmets significantly impaired cognitive task outcomes, as measured by the N-back task and Continuous Performance Test. This highlights the importance of helmet design considerations that minimize unnecessary physical load to prevent cognitive performance degradation.

In physical assistance technologies, Gupta et al. (2021) explored how individual cognitive factors affect exoskeleton-augmented gait strategies. They reported that cognitive traits such as reaction time influence user adaptation to exoskeleton support, implying that ergonomic design should accommodate individual cognitive variability to enhance user safety and comfort.

User interface design also critically affects cognitive load management. Gürfidan (2024) proposed a design for augmented reality-based autonomous vehicle interfaces whereby driver fatigue detection is integrated into the user interface, aimed at reducing mental workload and increasing driving safety. The design emphasizes real-time cognitive ergonomics principles to enhance driver awareness and promote health.

Similarly, Sarma (2025) advocated a hybrid cognitive ergonomics approach combining digital prototypes with physical mock-ups in interface design education to reduce cognitive strain and enhance usability. Such integration ensures that the cognitive demands placed on users are minimized through iterative, user-centered design.

Furthermore, Hilmi et al. (2024) demonstrated that in industrial contexts, the application of cognitive ergonomics principles with real-time workload monitoring via biosensors and eye tracking improves task performance and supports worker well-being. They emphasize that cognitive load management technologies—such as adaptive human-machine interfaces and integration with AI and VR—hold promising potential to prevent mental fatigue and cognitive overload.

2.4 Physiological, Behavioral, and Subjective Indicators

Cognitive workload assessment has steadily incorporated diverse physiological, behavioral, and subjective techniques, each contributing unique dimensions to understanding mental demands. Among physiological measures, pupillometry stands out for tracking cognitive effort. Niamba and Schieber (2022) addressed a key limitation in pupillometry—the confounding effects of ambient illumination—by implementing Support Vector Machine algorithms to differentiate pupil

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diameter changes due to cognitive workload from those caused by fluctuating brightness. Their approach demonstrates how machine learning can enhance the reliability of pupillary indicators in dynamic environments.

Eye tracking metrics also provide valuable insights into cognitive load during task performance. Venkatesh et al. (2023) utilized ocular parameters collected via eye trackers to analyze cognitive load during challenging manual text classification tasks. Their findings indicate that complex or difficult-to-understand texts induce higher cognitive load, especially for non-native English speakers, showcasing the sensitivity of eye tracking to task difficulty and linguistic proficiency. Similarly, Zahabi et al. (2023) combined EEG-derived measures with subjective NASA-TLX scores to assess cognitive workload during VR forklift training. They found significant correlations between task difficulty and both neurophysiological and self-reported workload, confirming the utility of EEG theta power and NASA-TLX as complementary metrics.

Subjective tools like NASA-TLX remain a foundational component in workload assessment owing to their ease of administration and direct accounting for perceived effort. Hewitt and He (2022) employed NASA-TLX alongside systems usability scales to evaluate web browsing across different contrast levels and task difficulties, concluding that task difficulty significantly impacted cognitive load ratings but contrast levels did not. This underscores the nuanced influence of task characteristics on perceived workload independent from interface factors.

Neurophysiological responses have expanded to include event-related potentials such as frontal P3 (fP3) to index susceptibility to auditory stimuli under cognitive load. Van der Heiden et al. (2021) measured fP3 in automated driving simulations, showing reduced auditory processing when participants engaged in additional cognitive tasks, emphasizing workload's effect on attentional resources.

2.5 Computational and Theoretical Models

Complementing empirical workload measures, computational cognitive models provide explanatory and predictive frameworks for mental workload dynamics. McCarley (2025) presented a computational model grounded in signal detection theory to simulate vigilance decrements. This model generates resource depletion-like effects without directly assuming resource exhaustion, offering a mechanistic account that overcomes vagueness in traditional resource theories.

Du et al. (2022) developed a cognitive model simulating autonomous cyber defense decision-making under varying attacker threat levels and feedback conditions. By incorporating human cognitive constraints, the model predicted defense performance declines with increasing attacker sophistication and suggested that reduced feedback frequency could mitigate losses. This work exemplifies how cognitive models can guide system design and operator support in complex, high-stakes environments.

ACT-R cognitive architecture has served as a robust platform for mental workload modeling. Oh et al. (2023) introduced an ACT-R based Stroop task model integrating dual-process theory to quantitatively predict cognitive load shifts between intuitive and deliberate processes. Validated with experimental data, this model captures both performance patterns and error tendencies, demonstrating a formal computational approach linking cognitive workload and task performance.

Similarly, Zhang et al. (2022) developed an ACT-R-based model to predict driver takeover response times in conditionally automated vehicles. By accurately capturing non-time-critical takeover dynamics, this model aids design and safety evaluations for emerging automated vehicle

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systems. These computational frameworks inform workload modeling by blending cognitive theory with practical applications.

2.6 Multimodal Assessment Strategies

Acknowledging that no single measure comprehensively captures cognitive workload, recent studies advocate multimodal assessment combining physiological, performance, and subjective signals. Fogelberg et al. (2025) illustrated triangulation among error rates, task completion times, self-report ratings, and heart rate variability (HRV) during cognitively demanding manufacturing assembly tasks. Correlations among these different workload indices supported the robustness of combined measurement approaches, enabling nuanced evaluation of operator state.

Similarly, Zhang et al. (2024) emphasized the importance of integrating behavioral, psychophysiological, and self-reported data in investigations of cognitive factors during conditionally automated driving. Their design captured heterogeneous signals such as eye gaze, galvanic skin response, and heart rate variability, facilitating comprehensive workload evaluation. This approach aligns with recommendations stressing that complex cognitive phenomena are best understood through multimodal data fusion.

Another notable advancement includes combining neural engagement metrics derived from EEG with behavioral performance to optimize training and application tasks in virtual reality environments (Spencer et al., 2025). By monitoring phase- and load-dependent neural signals indicative of cognitive effort and sustained attention, adaptive training systems can tailor learning to individual cognitive capacities.

3. HUMAN PERFORMANCE, LEARNING, AND TRAINING UNDER HIGH DEMAND

3.1 Skill Acquisition & Adaptation Over Time

Training under conditions of high cognitive demand plays a crucial role in improving task performance and managing cognitive workload. Scarince et al. (2024) demonstrated that unmanned aerial system (UAS) pilots exposed to divided attention tasks during flight courses initially experienced decreased flight efficiency and cognitive task performance. However, with repeated practice over multiple training sessions involving both auditory and visual cognitive challenges, performance significantly improved, indicating a positive effect of skill acquisition and adaptation over time despite high attention demands. Similarly, Venkatesh et al. (2023) studied cognitive load during manual text classification tasks and found that repeated exposure and training reduced cognitive workload, as assessed by eye tracking metrics and NASA-TLX, especially when task difficulty varied. Their findings highlighted the importance of iterative learning in managing mental demands during complex cognitive-perceptual tasks.

Further expanding on skill acquisition, Spencer et al. (2025) investigated neural engagement differences from training to application phases in a virtual reality (VR) simulated assembly task. Results showed that while the training phase involved foundational engagement, the application phase elicited higher sustained attention and integrative cognitive processing, particularly under increased intrinsic and extraneous cognitive load. This suggests that learning under controlled workload variations fosters adaptive neural mechanisms that support improved task execution in operational environments.

In contexts involving physical augmentation, Gupta et al. (2021) connected cognitive factors with gait strategies during exoskeleton-assisted walking, revealing individual differences in adaptation based on cognitive processing capacity. Faster reaction times correlated with prioritizing coordination over gait stability, implying cognitive learning and prioritization strategies evolve with continued system exposure and practice.

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3.2 Cognitive Load and Work Improvement Strategies

Adaptive systems and feedback mechanisms have shown efficacy in improving cognitive workload management and overall task performance. Zhang et al. (2025) examined how explanations from automated vehicles (AVs) influence cognitive and affective trust. The study revealed that providing users with clear, reason-based explanations significantly bolstered cognitive trust and enhanced affective, emotionally driven trust, thereby facilitating a more engaged and confident human–automation interaction. This effect is essential for training programs and system designs aimed at improving user acceptance and reducing mental workload associated with automation skepticism.

Parcell et al. (2023) contributed to this domain by applying nonlinear dynamics to analyze cognitive workload and situational trust in highly automated vehicles. Their results underscore the potential of leveraging real-time behavioral and physiological measures to adapt feedback and task intensity dynamically to the operator's current cognitive state, optimizing learning and operational performance.

Cognitive workload reduction during training is further exemplified in immersive technologies. Zahabi et al. (2023) assessed cognitive workload variations in VR-based forklift training, documenting increased mental effort when task difficulty increased but noted significant reductions in both EEG theta power and subjective workload scores with repeated training. This finding supports the potential of VR as an effective, controlled environment for managing graded learning curves and mental demand adaptations. Likewise, Jamshid Nezhad Zahabi et al. (2023) developed forecasting models capable of predicting upcoming cognitive fatigue states during sustained working memory tasks, allowing for preemptive workload adjustments and personalized interventions to maintain performance.

Beyond immediate workload management, a task battery developed by Sabine and Thompson (2024) offers a reconfigurable military cognitive assessment platform (IMPACT) that integrates subjective, psychophysiological, and performance measures for optimized cognitive task demand assessment. This tool stands as a promising framework for targeted training and adaptive workload management across varied operational contexts.

3.3 Enhancing Resilience and Error Management

Cognitive resilience—the ability to recover from or adapt to cognitive overload and disruptions—is critical in safety-sensitive fields such as aviation and military operations. Holley and Miller (2023) extensively reviewed cognitive processing disruptions affecting pilots and air traffic controller performance, drawing attention to the increasingly digitized and complex flight deck environments. They noted that surprise disruptions and overload events comprise up to 30% of reported aviation safety incidents and emphasized the necessity for cognitive resilience training and adaptation of models like Crew Resource Management- Threat and Error Management (CRM-TEM) to effectively mitigate risks caused by cognitive stress.

In the domain of error management, Lew and Boring (2023) introduced a cognitive loading task aimed at empirically examining error dependency in human reliability analysis (HRA). Their preliminary findings suggest that understanding how cognitive workload influences error probabilities and dependencies can inform better error prediction models and training designs that preempt cascading failures during high-demand tasks.

Complementing these perspectives, Chis et al. (2023) explored the tradeoff between cognitive load and productivity during multitasking and interdependent task switching in team environments. They found that reducing the frequency of task set switching improved working

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memory load and overall team performance, implying that resilience not only involves post-error recovery but also strategy optimization during task execution to minimize overload.

4. HUMAN–TECHNOLOGY AND HUMAN–ROBOT INTERACTION

4.1 Trust, Explanation, and Engagement

Trust in automation and human–technology interaction remains a critical challenge, particularly in domains like automated vehicles (AVs) and AI healthcare systems. Zhang, Yang, and Robert (2025) explored how different forms of explanation content influence user trust in automated vehicles. Their experiment with 121 drivers demonstrated that providing explanations significantly enhanced cognitive trust compared to no explanation conditions. Importantly, explanations that articulated the reasoning behind the vehicle's decisions particularly boosted affective trust, fostering an emotional connection with the AVs. These findings highlight that effective explanation content can bridge the trust gap by improving user understanding and emotional engagement, which is essential for broader acceptance of AV technologies.

Similarly, Alam and Mueller (2023) investigated cognitive empathy elements within patient-AI communication in diagnostic reasoning contexts. Their research demonstrated that AI systems incorporating cognitive empathy fostered a shared understanding with patients, increasing satisfaction and willingness to use AI diagnostics. This emotional and cognitive alignment may be pivotal in healthcare technology adoption, as patients typically require relational trust, not just functional reliability.

Building on emotional engagement, Bruni and Brown (2022) identified affordances of cognitive assistants that simultaneously support instructors and learners in virtual classrooms. Their work stresses the importance of real-time cognitive support to manage workload and sustain engagement, further emphasizing how thoughtfully designed technological explanations and interactions promote trust and cognitive alignment.

4.2 Conflict Monitoring and Cognitive Empathy

Conflict monitoring, an implicit measure of cognitive processing, has been studied in human-robot interactions to understand attitudes and emotional responses toward robots. Abubshait et al. (2023) used a gambling task paradigm with the social robot Cozmo to reveal cognitive conflict when participants were forced into prosocial behavior toward the robot, such as rewarding it against their own gain. Participants showed slower response times in these conditions, indicating heightened conflict. This cognitive conflict suggests that forced prosociality toward robots is psychologically taxing, revealing underlying tensions in human-robot social dynamics.

Alam and Mueller's (2023) findings on cognitive empathy also intersect with this domain, emphasizing the potential of AI systems to create shared understanding and reduce conflict during human-AI interactions. By embedding cognitive empathy, machines may better align with user expectations and reduce psychological friction, promoting smoother collaborations.

Further, Zhang et al. (2023) examined explanation content's impact on both cognitive and affective trust. Their results reinforce that cognitive empathy manifested through clear, reasoned explanations can mitigate conflict and enhance user trust, particularly during critical decisions in automated systems.

4.3 Cognitive Offloading and Support Technologies

Cognitive offloading strategies and support systems are increasingly employed to mitigate cognitive load and enhance performance in complex human-machine teaming.

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Diaz Alfaro, Fiore, and Oden (2024) applied extended cognition theory to manned-unmanned teaming, proposing that cognition can be scaffolded and offloaded onto external systems to reduce operator workload. By conceptualizing the human-machine ensemble as a single cognitive unit, their approach encourages the design of technologies that effectively share cognitive responsibilities, thus reducing operator strain.

Complementary research by Outlaw et al. (2025) compared user preferences and cognitive load when using passive low back exoskeletons during manufacturing tasks. Their findings showed that suitable exoskeleton choice, aligned with user preference and training, can effectively reduce physical and cognitive load, enhancing task performance. This illustrates how assistive devices can serve as a form of cognitive and physical offloading in demanding tasks.

In augmented reality (AR) interfaces, Gürfidan (2024) proposed an AR-based user interface for autonomous vehicles designed according to cognitive ergonomics principles, including features like driver fatigue detection displays. Such ergonomic interface designs enable cognitive offloading by externalizing important status information, easing mental workload and improving safety.

Furthermore, Venkatesh, Jaiswal, and Nanda (2023) utilized eye-tracking to analyze cognitive load during manual text classification tasks, revealing that well-designed support tools can adapt to user cognitive demands, easing load especially for complex tasks. Technologies capable of real-time workload monitoring, like biosensors integrated into support devices mentioned by Hilmi et al. (2024), help dynamically balance workload by providing information that facilitates cognitive offloading and decision support.

5.0 DECISION-MAKING, ATTENTION, AND ERROR MECHANISMS

5.1 Vigilance and Error Dependency

Vigilance decrement, characterized by a decline in sustained attention over time during monotonous tasks, remains a critical challenge in many safety-critical environments. McCarley (2025) develops a computational cognitive model based on signal detection theory to simulate vigilance decrement, addressing the theoretical gaps present in existing resource depletion models. This model successfully reproduces the hallmark behavioral patterns associated with vigilance decrement without relying on an explicit depletion mechanism, offering a more precise computational framework to understand sustained attention failures. This advancement facilitates rigorous testing of theories around vigilance and contributes to designing systems to mitigate attentional decline.

Building on the understanding of error mechanisms, Lew and Boring (2023) introduced a novel cognitive loading task, Flppr, to empirically investigate the concept of error dependency in human reliability analysis (HRA). Error dependency refers to how one error might influence the likelihood of subsequent errors, especially under cognitive load. Their work highlights the complexities in quantifying dependent errors, which is essential for improving system safety assessments by incorporating cognitive task loading. By designing cognitively demanding tasks to explore error dependency, this study adds an empirical means to refine models of error propagation in operational settings.

Additionally, Bragg et al. (2022) provide insight into error mechanisms through their examination of phishing behavior. Their findings suggest that even with cybersecurity familiarity, only a fraction (26%) of phishing information is accurately transmitted from stimulus to judgment, illustrating cognitive challenges in attention and error recognition in cybersecurity tasks. The study underscores cognitive limitations that contribute to error vulnerability, emphasizing the cognitive load inherent in task discrimination.

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5.2 Attention Switching and Disruption

Attention switching and disruption significantly impact task performance, especially when interruptions are frequent or of varying emotional and cognitive significance. Zhou and Rau (2023) investigated the effects of interruption value type—utilitarian (work-related) versus hedonic (pleasure-related)—and source (internal or external) on cognitive and emotional responses during tasks. Their results indicate that hedonic interruptions generally increase emotional valence, while utilitarian interruptions decrease it, with internal interruptions amplifying these effects. Importantly, these interruptions influenced attention allocation phases and led to longer resumption lags and extended interruption durations depending on the task value type and source. Such nuanced understanding aids in designing work environments that minimize detrimental impacts of interruptions on cognitive focus.

Zhang and Yang (2022) also explored interruptions but focused on the emotional and cognitive impacts via neural evidence. Their findings reveal that interruptions differ in their requirements for attention and emotional regulation depending on value and source, influencing performance and exhaustion levels. This underscores the need to consider interruption characteristics in workload and human factors designs, managing not just frequency but qualitative aspects of task disruption.

Another angle on attention disruption comes from Holley and Miller (2022), who examined cognitive loading effects on pilots and air traffic controllers. Their work connects disruptions in cognitive flow—with elements such as working memory overload and compromised situation awareness—to neural dynamics and Polyvagal theory. They emphasize that disrupted cognitive flow leads to exponential increases in working memory load and rapid onset of performance plateaus that jeopardize safety. This research highlights the criticality of mitigating cognitive overload and maintaining cognitive resilience in high-stakes operational environments.

5.3 Cognitive Resilience and Safety Management

Cognitive overload is a prevalent risk factor in complex sociotechnical systems, raising concerns about safety and human performance. Holley and Miller (2023) analyzed data from the Aviation Safety Reporting System to identify cases with cognitive overload threats in increasingly digitized flight decks. Their assessment revealed that approximately 30% of analyzed cases represent such threats, underscoring the importance of cognitive resilience as a countermeasure. They also explored the adaptation of Crew Resource Management – Threat and Error Management (CRM-TEM) models to incorporate cognitive resilience training to mitigate surprise disruptions and support recovery from overload events.

Brady et al. (2024) contribute further insight on cognitive resilience in team environments, noting the negative impacts of cognitive fatigue on reaction times, errors, and positive outcomes in team performance. This work emphasizes that cognitive fatigue not only impairs individual performance but also degrades collective functioning, which is critical in cooperative, high-demand tasks like aviation, emergency response, and military operations.

Addressing these cognitive dynamics, Diaz Alfaro et al. (2024) advocate a macrocognitive perspective emphasizing cognitive offloading and extended cognition in human-machine teaming. By conceptualizing the system-environment operator as an integrated cognitive unit, their approach offers strategies to reduce cognitive workload through scaffolding and task support, fostering resilience against cognitive failures.

The integration of computational cognitive models, empirical studies on attention disruption, and real-world safety analyses together provides a holistic understanding of the mechanisms underlying decision-making errors, attentional failures, and methods to bolster cognitive

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resilience. Such multidisciplinary perspectives are vital for developing interventions, training protocols, and system designs that enhance safety and operational reliability in cognitively demanding domains.

5.4 Individual Differences and Cognitive Strategies

Understanding the variability in cognitive performance among different populations is critical for effective cognitive ergonomic interventions. Key variables influencing cognitive performance include age, fatigue, sleep quality, and expertise, which impact how individuals process information, make decisions, and maintain attention in complex environments.

Age-related cognitive changes follow a trajectory where cognitive speed, executive function, and working memory typically improve during early development, peak during middle age, and decline in later years. Chignell et al. (2025) demonstrated that cognitive assessment games could effectively track this age-related decline, providing valuable tools for early identification of cognitive deterioration and guiding ergonomic accommodations tailored to aging populations. Complementing this, Holt (2025) highlighted age-inclusive ergonomic strategies, emphasizing adaptations such as optimized interfaces and improved lighting to mitigate cognitive deterioration in older workers, leading to substantially fewer incidents and improved job satisfaction and productivity.

Fatigue and sleep quality are integral factors affecting cognitive performance. Rostampour et al. (2025) found a significant inverse relationship between sleep quality and job performance among airport staff, with poor sleep contributing to increased cognitive failures and human error. This underscores the need for ergonomic and organizational policies directed at improving sleep hygiene and fatigue management to enhance cognitive function and safety. Similarly, Brady et al. (2024) emphasized the detrimental effects of cognitive fatigue in team settings, revealing that fatigue increases reaction times, the frequency of errors, and decreases positive outcomes, critical considerations for team-based operations in high-demand environments.

Expertise and individual cognitive strategies also produce variability in performance. Hsing et al. (2022) investigated engineering students with low spatial ability and found that encoding processes were strongly associated with their employed spatial strategies, more so than transformation and confirmation processes. This suggests that cognitive interventions, such as targeted encoding improvements, can be effective in enhancing spatial problem-solving skills among learners with identified cognitive limitations.

Educational approaches leveraging cognitive ergonomics principles aim to foster intellectual development and effective cognitive strategies. Krylova (2021) discussed designing the teacher-educational information-student system to develop students' intellectual culture, which is essential for adapting to modern information demands. Effective instruction structured around cognitive ergonomics principles can elevate students' intellectual activities, thereby improving comprehension and retention especially in complex learning contexts. Parallelly, Sumianto et al. (2025) demonstrated the efficacy of integrated Dual Coding and Chunking strategies in elementary education, revealing significant improvements in observation skills and curiosity. These multimodal teaching strategies, grounded in cognitive ergonomics, enhance the interplay between visual and verbal processing and promote deeper analytical thinking and motivation.

Personalization of ergonomic solutions is crucial in addressing individual cognitive differences. Zhang et al. (2024) underscored the importance of adapting medical website designs according to users' recognition and recall heuristics to reduce cognitive load and facilitate decision-making. Tailored interfaces and work environments that accommodate individual cognitive strengths and limitations can optimize usability and workload.

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Cognitive engagement during training varies across individuals, with Spencer et al. (2025) illustrating that neural indicators such as sustained attention and integration/execution powers increase substantially during application phases compared to training phases under varying workloads. Their findings highlight the opportunity to design adaptive training systems that monitor individual cognitive engagement and adjust accordingly to optimize learning outcomes. Considering social cognitive factors, Alam and Mueller (2023) explored cognitive empathy in patient-AI communication, finding that incorporating empathic AI elements enhances shared understanding, patient satisfaction, and willingness to engage with diagnostic systems. This facet of cognitive strategy emphasizes the affective component of cognition, reinforcing the need for systems that consider emotional and cognitive congruence for improved user experience.

6.0 DESIGN IMPLICATIONS FOR PHYSICAL AND COGNITIVE ERGONOMIC SYSTEMS

6.1 Interface and System Design

Designing interfaces that effectively support human cognitive capacity while minimizing mental workload is critical in complex technological environments. Gürfidan (2024) emphasizes that reducing mental load in autonomous vehicle interfaces through cognitive ergonomics principles contributes to safer and more comfortable user experiences. His AR-based user interface proposal, which detects and displays driver fatigue, illustrates how real-time monitoring of cognitive states can be integrated seamlessly into system design to promote situational awareness and legal compliance. This work aligns with Sarma's (2025) findings in academia, which demonstrated that blending digital and physical interface elements—such as combining digital prototypes with tangible mock-ups—enhances usability and reduces cognitive strain during design processes. Sarma highlights that such hybrid approaches uncover latent usability issues and facilitate iterative redesign by providing richer sensory feedback, showcasing the importance of multimodal interaction in ergonomic interface design.

Further, Wuang et al. (2024) offer insights into virtual environments by demonstrating the trade-offs between usability and cognitive demands. Their expert usability evaluation of immersive virtual reality (I-VR) environments for scale cognition points to the necessity for balancing cognitive load with intuitive interface features to optimize learning and reduce user mental fatigue. This is particularly relevant for modern industry and training applications, where cognitive overload must be mitigated without compromising system functionality.

Complementing these studies, Niamba and Schieber (2022) successfully applied advanced Support Vector Machine algorithms to discriminate pupillary markers of cognitive workload from brightness-induced pupil changes. Their method highlights the promise of integrating physiological markers into adaptive interfaces that dynamically respond to user cognitive load, enhancing system responsiveness and reducing errors.

6.2 Training and Human–Machine Collaboration

Effective training and collaboration strategies are essential for improving human performance under high cognitive and physical demands. Biggs and Littlejohn (2022) provide critical lessons from military special operations, where integrating cognitive systems and enhancement tools enables high-performing personnel to manage extensive cognitive demands. Their recommendations for cognitive coaching emphasize personalized interventions and adaptive task load management, enabling sustained performance and resilience in stressful environments. Extending human cognitive capacity via external support technologies, Alfaro et al. (2024) advocate a macrocognitive approach focusing on cognitive offloading and extended cognition in human-machine teaming. Their framework posits that coupling human operators with intelligent assistive tools—such as cognitive assistants or decision aids—can scaffold cognitive processes, reduce workload, and improve trust and task efficiency. This is supported by Outlaw et al. (2025),

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whose work with passive low back exoskeletons in manufacturing tasks illustrates how user preference and experience influence both physical and cognitive load. Their results suggest that ergonomic devices tailored to user needs not only reduce muscle activation but also contribute to better cognitive performance, an important consideration for human–machine collaboration design.

Additionally, Venkatesh et al. (2023) demonstrated how repeated VR-based forklift training decreases cognitive workload, as measured by EEG and subjective NASA-TLX assessments, confirming that training adaptations can moderate mental strain over time. Together these findings underscore the value of adaptive training systems that monitor and respond to cognitive workload to optimize learning and task proficiency.

6.3 Well-being and Safety Interventions

Ergonomic interventions designed to enhance worker well-being and safety are increasingly important in aging societies and high-stress occupational environments. Holt (2025) synthesizes work on cognitive ergonomics tailored to the aging workforce, demonstrating how adaptive technologies, optimized interfaces, and improved lighting conditions mitigate cognitive decline and support older workers' performance and safety. Importantly, organizations implementing such interventions report significant reductions in incident rates and improvements in job satisfaction and productivity among employees aged 55 and above.

In healthcare settings, Aminuddin and Hakim (2023) highlight the heightened risks of burnout and human error among emergency room nurses during the COVID-19 pandemic. Their study using the Human Error Assessment and Reduction Technique (HEART) identifies complex tasks like first aid delivery as having high error probabilities. Their recommendations include strategies to manage workload, environmental stressors, and enhance situational awareness through cognitive ergonomic principles to preserve mental health and reduce errors.

Similarly, Zahabi et al. (2023) examined cognitive workload in novice forklift operators undergoing VR training, finding that task difficulty elevates mental workload as measured by EEG and subjective reports, but that repeated exposure reduces this strain. These results advocate for cognitive workload monitoring and task adaptation as safety measures in training programs to prevent fatigue-related accidents.

7.0 CONCLUSION

This comprehensive review demonstrates that integrating physical and cognitive ergonomics is critical for understanding and optimizing human performance in complex systems. The literature reveals that combined physical and mental workload substantially influences operational effectiveness, error susceptibility, and resilience. Multimodal measurement strategies, incorporating physiological, behavioral, and computational models, provide robust insights into workload dynamics but still face challenges in capturing individual variability and real-time adaptation. Advances in human–technology and human–robot interaction underscore the importance of trust, cognitive offloading, and engagement in enhancing system performance and user well-being. Moreover, tailored ergonomic designs and targeted training interventions emerge as vital for managing high-demand environments and fostering cognitive resilience. Despite significant progress, gaps remain in fully modeling dynamic cognitive workload and implementing adaptive, personalized ergonomic solutions. Future research should prioritize refining integrated models, exploring individual differences, and developing innovative human–machine collaboration techniques to promote safety, efficiency, and operator health across diverse complex settings.

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