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EVOLUTIONS OF THE MULTIPLE-RESOURCE THEORY OF ATTENTION: AN ACADEMIC OVERVIEW

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ABSTRACT

The Multiple-Resource Theory (MRT) of Attention has significantly advanced our understanding of cognitive processing by proposing that humans allocate attentional resources across multiple modalities and processors. Since its origin, the theory has undergone numerous adaptations and expansions, aligning with emerging empirical evidence and technological advancements. This overview therefore traces the evolution of the MRT, highlights key developments, critiques, and contemporary perspectives, and underscores the importance of ergonomic considerations in optimizing human performance across various settings.

KEYWORDS: Multiple-Resource Theory, Attention Allocation, Cognitive Processing, Human Factors, Ergonomics, Modality-Specific Resources.

INTRODUCTION

Attention is described as the primary modality for cognition. As such, other cognitive skills such as working memory, abstract reasoning, and executive functions, including problem-solving are premised on attention (Arif et al., 2020; Posada et al., 2012). Various models exist to explain the neuroscience of attention, including (Broadbent, 1958) and the Feature Integration Model of attention, proposed by (Treisman, 1964). Posner and Petersen's (1990), Attention Network Model continue to be one of the most widely used models to explain attention. According to the model, attention is divided into three networks: the alerting network, the orienting network, and executive network (Posner & Petersen, 1990a).

The alerting network is involved in maintaining a state of vigilance to sustain attention for a long period of time. The orienting network accounts for the human ability to select certain stimuli, from multiple sensory stimuli, and to ignore irrelevant stimuli.

Lastly, the executive network monitors and resolves conflicts in planning and dividing attention (Posner & Posner, 1990). Anatomically, the frontostriatal, and thalamic regions are implicated in the alerting network (Morris et al., 2016). The superior parietal lobes, and the temporal parietal junction are thought to regulate the orienting network of attention (Petersen & Posner, 2012a).

Lastly, the anterior cingulate and lateral prefrontal cortical regions are thought be essential for regulating the executive network of attention (Petersen & Posner, 2012a). However, evident multitasking capabilities prompted the development of more complex frameworks, including the Multiple-Resource Theory (MRT) proposed by Wickens (1984). MRT posits that several pools of attentional resources exist, distributed across modalities and processors, thereby facilitating simultaneous task performance under certain conditions(Wickens et al., 2016a).

Recognizing that human performance is also influenced by physical and environmental factors, integrating ergonomic principles into MRT enriches understanding by accounting for how workspace design, equipment layout, and interface interactions modulate attentional resource demands. This intersection holds critical implications for designing safer, more efficient work environments, especially in high-stakes domains such as aviation, manufacturing, and healthcare.

Historical Development of Multiple-Resource Theory

Multitasking is prevalent in our society. For instance, texting while driving, or being on a call while cooking call for understanding the extent to which such dual-task performance will lead to decreases in time-sharing ability. Multiple resource theory is one approach to this understanding. Wickens (1984) introduced the MRT as a response to limitations of earlier single-resource models. While the MRT is generally accepted, it has yet to be systematically tested and the cognitive resource structure thoroughly understood. For example, two tasks that do not seem to overlap on any of Wickens' dimensions can still interfere with each other.

This interference cannot be fully explained by his model, unless one considers a general resource overload or executive processing bottleneck. Dual-task experiments that hold one task constant among a variety of secondary tasks provide a useful framework for exploring the MRT and the effects of different specific resource demands (Chen & Bailey, 2021). Many dual-task psychology studies have used simple activities such as finger tapping or verbal suppression while doing various other tasks simultaneously, but less research has been done on more realistic and complex physically demanding tasks that might be expected in high-risk operations (Chen & Bailey, 2021). The exercise science community has also extensively explored the interaction between many physical and cognitive tasks, providing an additional body of work to that of laboratory cognitive psychology (Kalakoski et al., 2020; Oluwaseun & Regina, 2020; Robertson et al., 2009).

Mental fatigue has been shown to impair physical performance (Mahdavi et al., 2024) physical fatigue can impair certain types of mental performance (Van Cutsem et al., 2017; Mortimer et al., 2024), and there have also been beneficial cognitive effects found (e.g., a review by Lambourne et al. (2010), found that simple choice and discriminant reaction time task performance generally improved during steady-state aerobic exercise). Unfortunately, most of the exercise science experiments use rather artificial tasks such as treadmill running, walking, and stationary cycling, which require minimal cognitive resources.

A gap therefore exists between the available research and reality. Both the exercise science and basic cognitive psychology experiments generally fail to look at how the resource theories apply to real-world problems, where the demands of both the physical and mental activities will likely require greater and more diverse resources. For example, it is much harder, both mentally and physically, to run on a trail with obstacles and uneven terrain or through an urban environment with traffic, like an army scout or police officer might have to do, than on a treadmill (Donnelly et al., 2016; Lambourne & Tomporowski, 2010; Mortimer et al., 2024), the person performing the physical task often must simultaneously self-pace, navigate, calculate, or communicate with remote team members.

In these situations, greater interference is expected, and it is important to understand whether it is due to physical demand, spatial demand, other resources, or perhaps a drain on the general resource pool and/or a processing bottleneck.

Ergonomic factors intersect with MRT by influencing the demand on specific resource channels. For instance, ergonomic workspace design can reduce the cognitive load associated with physical discomfort or inefficient task presentation, thereby freeing attentional resources (John & John, 2024; Zadem & Chettouh, 2024).

Proper ergonomics minimizes unnecessary attentional diversion caused by discomfort, awkward postures, or poorly designed interfaces, ultimately enhancing multitasking capacity.

The Integration of Attention and Memory

Attention and memory are fundamental cognitive processes that interact intricately to facilitate perception, learning, problem-solving, and decision- making(Sridhar et al., 2023). Historically, these functions have been studied as distinct domains; however, contemporary cognitive science emphasizes their deep interconnection (Snow, 2016). Understanding how attention influences memory encoding, storage, and retrieval, and vice versa, provides comprehensive insights into human cognition and informs applications in education, clinical intervention, and human- computer interaction (Călinescu, 2024; Zielonka et al., 2024).

The human brain exhibits remarkable efficiency, yet the mechanisms underlying its processing capabilities are not fully understood. Ranking cognitive models objectively remains difficult because most models explain specific phenomena without offering comprehensive accounts (Wang et al., 2023; Wang & Wang, 2006). When evaluating models of human cognitive processing, it is essential to acknowledge the intrinsic relationship between cognitive resources, such as attention, and memory (Petersen & Posner, 2012b; Posner & Petersen, 1990b).

Theories of memory often debate the modular organization of information processing in the brain. For instance, Baddeley's working memory model and Wickens' Multiple Resource Theory (MRT) propose that the brain consists of distinct regions or processes that manage different cognitive demands and can process simultaneous inputs if these inputs utilize separate cognitive stores (Baddeley, 2012). While most memory research extends beyond the scope of this review, it is necessary to address current perspectives on the division of memory, particularly as they relate to the structure of cognitive resources.

Memory is generally conceptualized as comprising distinct components: sensory memory, working memory, and long-term memory. Immediate perception and processing occur in the first two systems, while long-term memory stores a more permanent collection of knowledge and experiences (Wade et al., 2019). The information processing model of memory replaced the widely known multistore model, which was a unitary, structural model consisting of a sensory register, short-term memory, and long-term memory (Atkinson & Shiffrin, 1968).

Although this theory inspired significant research, its limitations prevented it from remaining the dominant model. Craik and Lockhart (1972), introduced the levels of processing model, positing that memory depends on the depth of processing (shallow or perceptual versus deep or semantic) rather than on structural components or distinctions between short- and long-term memory.

In contrast, Baddeley and Hitch (1974), argued for a specifically structured memory system, suggesting the existence of working memory rather than short-term memory. proposed an influential re-conceptualization of working memory, arguing that it is not a separate and independent system but is instead embedded within short-term and long-term memory. In his embedded-processes model, Cowan suggested that working memory reflects the temporary activation of information within long-term memory (LTM) combined with a limited-capacity focus of attention that allows for the manipulation and conscious use of that information.

According to this view, memory is organized hierarchically: at the broadest level lies the entirety of LTM, from which a subset becomes temporarily activated and therefore more accessible for ongoing tasks. Within this activated subset exists an even smaller focus of attention, typically limited to about four chunks of information, that can be directly accessed for immediate cognitive processing (Cowan, 1988, 1999, 2001). This model thus redefines short-term memory (STM) as a state of activation and attentional focus rather than a distinct storage system.

Cowan's approach contrasts sharply with the multicomponent model proposed by Baddeley and Hitch (1974), which posited that working memory consists of separate stores, such as the phonological loop and the visuospatial sketchpad, supervised by a central executive. While the Baddeley model treats working memory as an independent system specialized for temporary storage, Cowan argued that no such separate structure is necessary. Instead, temporary memory is simply the activated portion of long-term representations. The critical factor distinguishing active memory from passive storage is the role of attention**:** items in the focus of attention are immediately available for processing, while other activated items remain accessible but require retrieval mechanisms to be brought into awareness (Cowan, 2005, 2019).

Empirical evidence supports Cowan's embedded-processes model in several ways. Behavioral studies demonstrate a capacity limit of around four items in working memory tasks, consistent with the proposed limits of the focus of attention (Cowan et al., 2020). Reaction-time and interference experiments reveal that information currently in the focus of attention is accessed more rapidly and is less susceptible to proactive interference than information merely in the activated state (Cowan et al., 2020).

Neuroscientific research using neuroimaging and electrophysiological techniques also aligns with this model: it shows that a small set of neural representations is strongly active when items are in conscious focus, whereas other recently encountered items exhibit weaker, distributed activation (Cowan et al., 2020; Nyberg et al., 2012) patterns characteristic of activated LTM (Cowan et al., 2020, 2024). Developmental and aging studies further support this framework, showing that age-related changes in working memory performance are more closely linked to variations in attentional control and activation maintenance rather than to declines in a separate memory store (Mavhu et al., 2020; Oberauer, 2019).

The embedded-processes model offers several advantages. It provides a parsimonious explanation of memory by integrating working and long-term memory into a single system differentiated by activation and attention rather than by structural separations (Cowan et al., 2020). It also highlights the essential role of attention and executive control in determining which information remains active, thereby linking working memory performance to attentional capacity and control mechanisms (Holmes et al., 2020; Karyotaki et al., 2017; Martella et al., 2011).

Moreover, the model accounts for the effects of expertise and prior knowledge: because working memory relies on activated long-term memory, individuals with well-organized knowledge structures can hold and process more meaningful information by chunking related elements (Breckel et al., 2013; Unsal et al., 2021). Nonetheless, some limitations and debates remain. Critics argue that Cowan's model does not fully explain certain short-term memory phenomena, such as detailed serial position effects or rapid forgetting, unless the mechanisms of activation are precisely defined (Baddeley, 2012).

Additionally, while the concept of "activation" provides a useful theoretical bridge between STM and LTM, its exact neural and temporal boundaries are still under investigation. Despite these challenges, Cowan's embedded-processes model has become one of the most influential frameworks in contemporary cognitive psychology, shaping current understandings of attention, memory capacity, and cognitive control.

In summary, Cowan's (1988), proposal that working memory is an embedded process rather than a distinct system has transformed how researchers conceptualize memory. It emphasizes that short-term retention arises from activated portions of long- term memory and that the focus of attention governs immediate cognitive operations. This integrative framework unites attention, memory, and learning into a single dynamic system, offering a more holistic understanding of human cognition and its limitations.

Ergonomics

According to the International Ergonomics Association (IEA, 2000), ergonomics is the scientific field that studies how people interact with various socio-technical system components. According to this definition, the field of ergonomics is the application of theory, concepts, data, and design techniques to maximize system performance as well as human well-being (Bailey et al., 2023). It is specifically in charge of designing and assessing jobs, tasks, environments, products, and systems to ensure that they are appropriate for people's requirements, abilities, and limits (Bailey et al., 2023). To promote worker health and safety, ergonomics is essential. Musculoskeletal illnesses (MSDs) like tendinitis, carpal tunnel syndrome, and back discomfort can be brought on by poorly designed equipment and workstations (Jones & Manager, 2022).

The majority of occupational diseases and injuries, which cause pain, impairment, and decreased productivity, are caused by multiple stress disorders (MSDs), according to the Occupational Safety and Health Administration (OSHA) (By, 2018). Ergonomics can increase productivity by optimizing the relationship between employees and their surroundings. Effective and comfortable workstations help employees stay focused and complete activities more successfully by reducing fatigue and discomfort (Bailey et al., 2023; Tompa et al., 2010). This can therefore result in decreased absenteeism and turnover rates as well as increased job satisfaction.

Cognitive Ergonomics

The word cognitive comes from the Latin cognoscere "to get to know" and refers to the ability of the brain to think and reason as opposed to feel (Li-Wang et al., 2023a). From a cognitive neuroscience perspective, cognition encompasses the internal mental activities that enable individuals to perceive, attend to, remember, reason, and make decisions (Banich & Compton, 2018). In occupational contexts, employees' cognitive development can therefore be understood as the progressive enhancement of their ability to think, process information, solve problems, and apply knowledge effectively.

This includes higher-order mental functions such as awareness, perception, interpretation of information, and the purposeful use of that information to guide action and performance. Despite its centrality to psychology and human factors research, the construct of "cognition" does not lend itself to a single, fixed, or universally accepted definition. Several scholars, including Bayne (2019) and Jan, Yvonne, and Barnes (2016), have argued that cognition is a multifaceted and theoretically complex concept.

Bayne (2019), contends that while some definitions of cognition may be more useful or explanatory than others, no single definition can adequately capture all legitimate uses of the term. As such, any attempt to define cognition necessarily involves a degree of theoretical stipulation. Nonetheless, Bayne emphasizes that the pursuit of a definition remains valuable, as it helps to illuminate the core and theoretically significant features that underlie cognitive phenomena, rather than forcing an overly narrow or reductionist account of cognition.

Jan et al. (2016), further highlighted the pivotal role of cognition in contemporary psychology and empirical clinical research, noting that different theoretical traditions conceptualize cognition in distinct but complementary ways. Within cognitive psychology, cognition is primarily explained in terms of information-processing mechanisms, focusing on how information is encoded, stored, transformed, and retrieved. In contrast, functional psychology conceptualizes cognition in relation to observable behaviour, emphasizing how mental processes serve adaptive functions in response to environmental demands.

Importantly, these perspectives are not mutually exclusive. Instead, they can be integrated within a functional-cognitive framework that recognizes two interdependent levels of explanation: a functional level, which seeks to explain behaviour in terms of environmental contingencies, and a cognitive level, which aims to understand the internal mental mechanisms through which environmental factors influence behaviour.

In alignment with this integrative view, Soman (2018), drawing on the work of Uma, defined cognition as the systematic study of how human beings receive, process, integrate, and respond to information. This definition captures the dynamic and interactive nature of cognitive processes and aligns closely with the objectives of cognitive ergonomics, which seeks to design tasks, systems, and work environments that are compatible with human cognitive capabilities and limitations. By accounting for attention, memory, decision-making, and mental workload, cognitive ergonomics plays a critical role in enhancing performance, safety, and well-being in complex work settings.

Cognitive Load Theory

Cognitive load theory is an instructional framework grounded in established principles of human cognition (Paas & van Merriënboer, 2020; Sweller, 1988). Since its development in the 1980s (e.g., Sweller, 1988), the theory has applied elements of human cognitive architecture to produce experimentally validated instructional effects. These effects are identified when novel instructional procedures are evaluated against traditional methods in randomized controlled experiments. When a novel procedure enhances learning, as measured by test performance, a new effect attributable to cognitive principles may be established (Sweller, 1988).

Cognitive Architecture

The cognitive architecture underpinning Cognitive Load Theory (CLT) has developed progressively over several decades and is grounded in an evolutionary perspective on human cognition (Paas & Sweller, 2012; Sweller & Sweller, 2006). At its core, this architecture assumes a biologically constrained human cognitive system composed of a limited capacity working memory and an effectively unlimited long-term memory, with learning conceptualized as the construction and automation of schemas stored in long-term memory (Sweller, Ayres, & Kalyuga, 2011). This framework draws explicit analogies to evolutionary processes, proposing that cognitive structures and learning mechanisms have been shaped by evolutionary pressures to efficiently solve recurrent problems in the environment.

Contemporary theoretical and empirical research continues to refine this cognitive architecture by extending CLT beyond its original focus on instructional materials and information presentation. Notably, recent work has emphasized the role of the physical and social environment in shaping cognitive load and learning outcomes.

For example, Paas et al. (2020), highlighted how embodied and situated learning contexts influence cognitive processing, demonstrating that learning is not solely an internal mental activity but is dynamically coupled with environmental affordances.

Similarly, emerging research has incorporated human movement and physical activity into CLT showing that motor actions can reduce cognitive load or support schema acquisition when appropriately aligned with learning objectives (Sepp et al., 2019). These developments reflect a broader shift toward viewing cognition as a distributed, interactive system rather than a purely internal process. A central feature of CLT's cognitive architecture is its application of evolutionary theory to distinguish between biologically primary and biologically secondary knowledge (Geary, 2007, 2008).

Biologically primary knowledge refers to cognitive skills that humans have evolved to acquire naturally because they were essential for survival and reproduction across evolutionary history. Such knowledge includes abilities like face recognition, spoken language acquisition, basic social cognition, and intuitive understanding of physical and social environments. These skills are typically acquired unconsciously, rapidly, and with minimal cognitive effort, driven largely by intrinsic motivation and exposure rather than formal instruction.

In contrast, biologically secondary knowledge consists of culturally specific skills that have emerged relatively recently in human history, such as reading, writing, mathematics, and formal scientific reasoning (Geary, 2008; Sweller et al., 2011).

Because these skills did not evolve directly through natural selection, humans are not biologically predisposed to acquire them effortlessly. Consequently, learning biologically secondary knowledge places substantial demands on working memory and requires explicit instruction, deliberate practice, and sustained conscious effort. Cognitive Load Theory is primarily concerned with optimizing the instructional conditions under which biologically secondary knowledge is acquired, with the goal of managing intrinsic, extraneous, and germane cognitive load.

Importantly, CLT does not treat biologically primary and secondary knowledge as independent systems. Rather, it emphasizes how biologically primary knowledge can be leveraged to support the acquisition of secondary knowledge. Paas and Sweller (2012) argued that primary skills such as human movement, social interaction, imitation, and collaboration can function as cognitive resources that facilitate learning when integrated appropriately into instructional design. For instance, collaborative learning can exploit evolved social cognition mechanisms, while embodied actions can offload cognitive processing demands from working memory. In this way, the evolving cognitive architecture of CLT provides a theoretically coherent framework for understanding how instruction can align with fundamental properties of human cognition shaped by evolution.

Empirical Evidence, Ergonomic Considerations, and Refinements

Empirical research in human performance and cognition consistently highlights the critical role of ergonomics and task design in optimizing multitasking and workload management. Wickens et al. (1684) provided foundational evidence through their studies on Multiple Resource Theory (MRT), demonstrating that tasks utilizing separate input modalities, such as visual and auditory channels can be executed concurrently with greater efficiency compared to tasks that rely on overlapping modalities. This is because the cognitive system can allocate attention across distinct perceptual and cognitive resources, thereby minimizing interference and cognitive overload.

However, these performance benefits are contingent upon ergonomic factors such as display positioning, control accessibility, and interface clarity, which directly affect perceptual processing and motor coordination. Poorly designed control systems, such as cluttered panels, non-intuitive button layouts, or excessive information density can negate the advantages of multimodal tasking by increasing cognitive demands and the likelihood of errors (Wickens et al., 1984).

Building on the foundational principles of Multiple Resource Theory (MRT), Malec and Wickens (2007) refined the model by incorporating the principle of dynamic resource allocation, which acknowledges that cognitive resources are not fixed but are flexibly distributed in response to task demands, environmental conditions, and operator expertise. This refinement emphasizes that human performance is shaped by continuous interactions between the operator and the system, rather than by static capacity limits alone.

Consequently, it highlights the importance of adaptive ergonomic design approaches that can support real-time adjustments in human performance. For example, interfaces that dynamically adjust visual density, auditory alerts, or automation levels in response to workload fluctuations can help prevent cognitive saturation and preserve situational awareness, particularly in high-risk domains such as aviation, healthcare, and complex control systems (Endsley, 2018).

Furthermore, empirical evidence from applied ergonomics research demonstrates that improvements in environmental and interface design significantly influence both perceived and objective cognitive resource demands. Hooijmans et al. (2010), reported that ergonomic interventions, including adjustable workstations, optimized display configurations, and improved environmental controls such as lighting, temperature regulation, and noise reduction, not only reduce musculoskeletal strain but also enhance cognitive efficiency, task performance, and user satisfaction.

These findings are consistent with the core principles of cognitive ergonomics, which advocate for system designs that are aligned with human perceptual, attentional, and cognitive capabilities. In cognitively demanding environments, including healthcare settings and human–AI collaborative systems, ergonomically optimized designs can thus function as cognitive aids, supporting mental resilience, accuracy, and effective multitasking under high workload conditions (Parasuraman & Wickens, 2008).

Summarily, empirical and theoretical advancements demonstrate that optimizing ergonomic design is not merely a matter of physical comfort it is a cognitive strategy that enhances attentional distribution, minimizes interference, and enables more effective multitasking. As human, machine systems become increasingly complex and automated, integrating ergonomic principles into interface design and task structuring remains vital for sustaining optimal human performance.

Integrations, Extensions, and Ergonomic Applications

Recent theoretical and empirical advancements have extended Multiple Resource Theory (MRT) by integrating it with cognitive systems theory and ergonomic design principles**,** thereby creating a more comprehensive framework for understanding human performance in complex socio-technical environments These integrated approaches emphasize that cognitive resource allocation is not merely a function of internal mental processes, but is also shaped by external, environmental, and ergonomic conditions.

John G John (2024), proposed hybrid cognitive-ergonomic models that account for the interplay between operator workload, environmental stressors, and system design features. Their research highlighted that environmental factors, such as lighting, temperature, and workspace noise, affect attentional control and can either facilitate or hinder optimal resource allocation (John & John, 2024) This integration underscores the importance of viewing cognition as a distributed process that emerges through continuous interaction between humans, technology, and the surrounding environment. Emerging evidence from neuroimaging research supports the biological basis of ergonomic effects on cognition.

Neuroimaging studies indicate that neural systems underlying attention, executive control, and working memory are sensitive to ergonomic conditions, including visual load, posture, and task configuration (Zhang et al., 2015; Wickens, McCarley, & Thomas, 2020). Zhang et al. (2015) demonstrated that increased visual complexity and non-neutral physical postures activate overlapping neural networks associated with cognitive control and attentional regulation, suggesting that perceptual demands and physical strain compete for shared cognitive resources.

This neural overlap provides a mechanistic explanation for observed decrements in performance under poor ergonomic conditions, as limited cognitive resources are diverted toward managing physical discomfort and sensory overload. Conversely, ergonomically optimized task environments reduce unnecessary neural load, thereby supporting attentional stability, lowering cognitive fatigue, and enhancing task efficiency and overall human performance.

In applied settings, these theoretical insights translate into tangible ergonomic innovations that improve human-system interaction and reduce cognitive burden. In aviation, for example, ergonomic refinements in cockpit design, including the spatial arrangement of instruments, standardization of control panels, and the use of multimodal feedback systems, significantly decrease the cognitive effort required for information monitoring and decision-making.

Such designs adhere to MRT's principle of resource channel separation, enabling pilots to process auditory alerts while visually attending to flight instruments without cross-modal interference (Huk et al., 2014). Similarly, in healthcare environments, ergonomic redesigns of nurse workstations and control rooms have shown measurable benefits in reducing mental fatigue, improving multitasking efficiency, and minimizing medical errors (Carayon et al., 2014; Patterson et al., 2020). These improvements demonstrate the power of ergonomically informed cognitive systems design in enhancing performance reliability and well-being in safety-critical domains.

Overall, the integration of MRT with ergonomic and cognitive systems frameworks represents a significant step toward a holistic understanding of human performance. It bridges the gap between cognitive theory, biological evidence, and practical design applications, supporting the creation of adaptive systems that are both cognitively efficient and ergonomically sustainable. Future research in this area is likely to focus on human–AI collaboration contexts, where adaptive interfaces and smart environments dynamically adjust task demands to match human cognitive and ergonomic capacities.

Critiques, Limitations, and the Role of Ergonomics

Although Multiple Resource Theory (MRT) has significantly advanced the understanding of human performance and cognitive workload, it is not without limitations. The theory's strength lies in its structured conceptualization of human attentional resources across multiple modalities, visual, auditory, cognitive, and motor (Wickens, 2008). However, this same compartmentalization has been criticized for oversimplifying the complex and dynamic nature of human cognition. Brown G Smith (2014), argue that the traditional MRT framework assumes a degree of independence between these resource pools that rarely exists in real-world settings.

In practice, cognitive and physical processes interact continuously and reciprocally, meaning that changes in one domain, such as physical posture or environmental noise, can substantially influence cognitive workload and attentional capacity (Brown & Smith, 2014). One of the central critiques of MRT is its limited ecological validity. Most MRT experiments have been conducted in controlled laboratory environments, which may not accurately capture the variability, unpredictability, and contextual pressures of real-world systems (Young et al., 2014). In complex socio- technical environments such as aviation, healthcare, and nuclear power, cognitive resources are constantly redistributed in response to fluctuating demands, social interactions, and environmental stimuli (Holden et al., 2013). As a result, MRT's static model of resource allocation may fail to account for the dynamic and adaptive nature of human performance in these contexts. Salvendy (2012) emphasizes that human performance cannot be understood in isolation from its physical and organizational context, and theories like MRT must evolve to incorporate broader ergonomic and systems-based variables that shape behavior under pressure.

Furthermore, MRT has been critiqued for its inadequate integration of physical and physiological dimensions of performance. Ergonomics research has consistently shown that physical strain, fatigue, and poor workstation design can interfere with cognitive processing and attentional control (Wilson, 2014). For instance, prolonged exposure to uncomfortable postures, glare, or noise increases both physical discomfort and mental workload, demonstrating that the cognitive system does not operate independently of the body. Fogelberg et al. (2025), describe this interaction through the concept of "energetic resources," emphasizing that both physiological and cognitive energy reserves deplete under high-stress or poorly designed ergonomic conditions (Fogelberg et al., 2025). This interplay challenges MRT's assumption that attentional capacity is a purely cognitive construct, highlighting the need for integrated models that consider the embodied and environmental dimensions of performance.

Another limitation concerns the static nature of MRT's resource allocation mechanisms. In many operational environments, attention is fluidly distributed across modalities based on experience, automation levels, and environmental feedback.

Recent findings in cognitive neuroscience suggest that attentional networks in the brain exhibit remarkable plasticity, adapting dynamically to changing task structures and sensory inputs (Sridhar et al., 2023; Stevens & Bavelier, 2012). MRT's relatively rigid resource structure thus fails to capture how learning, fatigue, stress, and environmental design alter neural efficiency and task prioritization over time(Mahdavi et al., 2024).

Incorporating findings from neuroergonomics, which is described as a field that examines brain activity in real-world task contexts and could significantly enhance MRT's explanatory and predictive power (Parasuraman, 2011).

Ergonomic design principles provide an essential framework for addressing these limitations (Parker, 2022).Ergonomics emphasizes fit between human capabilities and task demands, integrating physical, cognitive, and environmental considerations to optimize performance and reduce error (Wilson, 2014). Poor ergonomic design, such as cluttered interfaces, poorly illuminated workspaces, or non-intuitive control layouts, has been shown to increase attentional demands and error risk, especially in high-stakes or time- pressured situations For example, in aviation and healthcare, suboptimal interface layouts can cause attentional tunneling, where operators focus excessively on one task at the expense of situational awareness (Guo et al., 2025; Hasegawa et al., 2024; Syiem et al., 2024).Conversely, ergonomically optimized systems distribute cognitive and perceptual loads across multiple modalities in alignment with MRT's principles, thereby improving multitasking efficiency and resilience (Wickens et al., 2016).

In healthcare environments, the ergonomic perspective has proven particularly valuable for extending MRT's applicability. Carayon et al. (2014) found that ergonomic redesigns of nurse workstations and electronic health record interfaces led to measurable reductions in mental fatigue, improved situational awareness, and fewer patient safety incidents. These findings reinforce the argument that physical environment design can directly shape cognitive workload**,** supporting the call for a more integrated cognitive-ergonomic model of human performance. Similarly, in industrial and military domains, adaptive ergonomic systems that respond to real-time workload indicators, such as physiological stress measures, eye-tracking data, and performance metrics, have demonstrated significant potential to dynamically regulate cognitive resource demands (Parasuraman, Sheridan, & Wickens, 2000; Wilson & Russell, 2003).

These systems adjust information presentation, task allocation, or levels of automation based on the operator's current cognitive state, thereby helping to prevent overload and sustain performance under high-demand conditions. Such findings highlight a limitation of Multiple Resource Theory (MRT) when applied in isolation: while MRT effectively predicts patterns of resource competition across modalities, it does not account for temporal fluctuations in workload or adaptive system responses.

Consequently, adaptive ergonomics and cognitive state–based system design extend MRT by incorporating real-time human variability, enabling more resilient and context- sensitive human–system interaction (Parasuraman & Wickens, 2008).

To address its critiques, modern extensions of MRT increasingly adopt a systems-oriented and ecological approach that situates human performance within broader ergonomic, social, and technological contexts. By combining the structural clarity of MRT with the holistic insights of ergonomics, researchers can develop more realistic models of attention and workload that account for environmental complexity, physical embodiment, and human adaptability (Ozder, 2025). This integrated approach aligns with contemporary views in cognitive systems engineering and One Health domains, where human performance is understood as an emergent property of the interaction between people, tools, and their environments.

Ultimately, the critique of MRT does not diminish its theoretical value but underscores the need for refinement and integration. Future models must bridge cognitive and ergonomic sciences, incorporating physiological measures, environmental variability, and real-time adaptation mechanisms to represent human performance more faithfully. In this way, ergonomics is not simply a supportive discipline to cognitive theory, it is a core determinant of cognitive performance itself, shaping how humans think, perceive, and act within complex systems.

Contemporary Perspectives and Ergonomic Focus

The contemporary study of human performance has evolved significantly beyond the traditional parameters of Multiple Resource Theory (MRT**)**. While Multiple Resource Theory (MRT) laid a vital foundation for understanding how cognitive resources are distributed across modalities such as visual, auditory, cognitive, and motor channels, contemporary research emphasizes that these resources operate within a dynamic, interactive, and context-sensitive system rather than as fixed, independent pools (Wickens, 2002; Wickens et al., 2016). In recent years, the integration of MRT with ergonomic principles and cognitive systems engineering has reshaped how researchers and practitioners conceptualize human performance, particularly in complex, technology-mediated environments such as healthcare, aviation, and industrial automation (Blaga et al., 2025; Iyer et al., 2025; Mouhib et al., 2025).

This integrated perspective recognizes that human performance cannot be optimized through cognitive models alone; instead, it requires a nuanced understanding of how physical, technological, organizational, and environmental factors jointly influence attention, workload, and decision-making (Carayon et al., 2014). Ergonomics, as both a scientific discipline and a design philosophy, plays a pivotal role in this transformation by aligning system design with human cognitive and physical capabilities to enhance safety, efficiency, and resilience in complex sociotechnical systems (Dul et al., 2012).

The Shift Toward Adaptive and Cognitive-Ecological Systems

In contemporary contexts, the integration of MRT and ergonomics is increasingly informed by adaptive system theory, which conceptualizes human-machine interaction as a reciprocal relationship. In these systems, both human and technological components adapt to maintain balance and efficiency under variable conditions(Ioniță et al., 2025). For example, Basnet & Zahabi (2025), propose that the future of workload management lies in systems that can dynamically monitor user stress, workload, and attention through physiological indicators, such as heart rate variability, pupil dilation, and EEG signals, and adjust interface complexity or automation levels accordingly.

This represents a fundamental departure from static ergonomic principles of the past. Instead of designing systems solely for average performance, designers now aim for context-aware optimization, where the interface and environment evolve with the user. For instance, neuroadaptive interfaces can automatically reduce visual clutter, suppress redundant alerts, or adjust display brightness in response to measured cognitive strain. These innovations are rooted in the principles of MRT, specifically, the need to separate resource channels and prevent cognitive overload, yet they are actualized through ergonomic feedback loops that bridge cognitive theory and design practice (Wickens et al., 2016).

The cognitive-ecological perspective further expands this framework by viewing cognition as an emergent property of the interaction between individuals, tools, and environments. Rather than treating attention as an internal and limited commodity, cognitive-ecological ergonomics posits that performance depends on how well external artifacts, such as displays, layouts, and communication systems, support internal cognitive mechanisms. Thus, effective ergonomic design extends the boundaries of cognition itself, allowing humans to offload memory, perception, or computation onto well-designed systems (Hollnagel, 2017).

Ergonomic Design in Human-Machine Systems

The practical application of MRT within ergonomic frameworks is most evident in human–machine interface (HMI) design (Trstenjak et al., 2025). HMIs are the point of convergence between cognitive science and ergonomics, translating theoretical principles into real-world performance outcomes (Oviatt et al., 2006). The design goal is to reduce unnecessary attentional load and prevent cognitive interference by organizing visual, auditory, and tactile information according to human perceptual limitations.

For example, in aviation, cockpit interfaces are engineered to ensure that critical information is presented through distinct channels, following MRT's guidance that different modalities, such as auditory alarms and visual displays, an operate simultaneously with minimal interference (Wickens et al., 2007). However, ergonomic insights refine this approach by emphasizing layout coherence, perceptual grouping, and ease of motor response, ensuring that information is not only segregated by modality but also intuitively accessible under stress (Taufik, 2025).

In healthcare, the same principles apply to the design of electronic health record (EHR) systems, operating rooms, and nurse station layouts. Poorly designed interfaces can overload working memory and attention, leading to diagnostic errors and delays.

Conversely, ergonomically optimized systems, such as context-sensitive displays and adaptive alarms, help clinicians maintain situational awareness while reducing cognitive fatigue (Carayon et al., 2014). These improvements demonstrate that ergonomic refinement is not merely aesthetic; it is cognitively strategic, enhancing resource allocation efficiency and multitasking capacity in environments where errors carry significant human and economic costs.

Similarly, in industrial and military domains, human–machine collaboration increasingly relies on automation transparency, where ergonomic principles ensure that operators understand and trust automated decisions (Ioniță et al., 2025). When automation becomes opaque or unpredictable, humans must expend additional cognitive effort to interpret system behavior, creating what researchers call "automation- induced workload(Rogers, 2011)

Ergonomics as a Mediator of Cognitive Load and Performance

A central tenet of modern ergonomics is its capacity to mediate cognitive load, to balance task demands with available attentional and perceptual resources. Ergonomic interventions can either alleviate or amplify mental workload depending on their design. For instance, research in neuroergonomics, which is a discipline combining neuroscience and ergonomics, shows that environmental conditions such as lighting, noise, and temperature directly influence neural activation in regions associated with attention and decision-making (Cassioli & Balconi, 2022).

When work environments are ergonomically optimized, physiological indicators of stress and fatigue decrease, while measures of attention stability and decision accuracy improve. Conversely, suboptimal ergonomics, such as glare, excessive noise, or poorly placed displays, elevate cognitive strain and activate compensatory neural mechanisms that deplete attentional resources (Young et al., 2015) These findings confirm that cognitive efficiency is inseparable from ergonomic quality, supporting the argument that ergonomics is not peripheral but integral to cognitive system design.

In this light, MRT can be reconceptualized as part of a broader, embodied cognitive framework where mental and physical processes are co-dependent. The rigid distinction between "mental workload" and "physical ergonomics" no longer holds; instead, cognitive performance is seen as the outcome of an ongoing negotiation between the brain, body, and environment. Ergonomically supportive systems minimize friction in this relationship, allowing the operator to maintain performance with minimal cognitive expenditure.

Human-AI Collaboration and Adaptive Ergonomics

The increasing integration of artificial intelligence (AI) and automation introduces new dimensions to the ergonomic application of MRT(Trstenjak et al., 2025).In modern socio-technical systems, humans and AI agents operate as collaborative partners, sharing cognitive and perceptual tasks(Ioniță et al., 2025; Trstenjak et al., 2025). This collaboration presents unique ergonomic challenges: designing interfaces and workflows that balance automation assistance with human oversight.

Adaptive ergonomic design is now being used to enhance human–AI collaboration by dynamically distributing cognitive workload (Ioniță et al., 2025). For example, intelligent cockpit systems in aviation can predict pilot workload and automatically delegate monitoring tasks to AI during high-demand phases, while returning control to the human operator during low-demand periods (Wickens et al., 2016a).Similarly, in healthcare, AI-based decision-support systems are being ergonomically tuned to match clinicians' attentional patterns, providing information at the right time and in the right format to avoid cognitive overload(Wickens et al., 2016b).

These adaptive systems exemplify the next generation of cognitive ergonomics, where design is proactive rather than reactive. Instead of accommodating static human limitations, the goal is to amplify human cognitive capacity through responsive and intelligent environments. The MRT framework remains valuable here, offering a theoretical basis for understanding how multiple modalities and tasks compete for resources, but its utility is expanded through ergonomic adaptation that makes systems responsive to human variability.

Multitasking, Resilience, and Human Performance Sustainability

Multitasking capacity and performance resilience are central concerns in modern ergonomics and cognitive engineering. While MRT helps explain why certain multitasking combinations are more efficient than others, based on resource independence (Brüning et al., 2025). Ergonomic design determines whether this potential can be realized in practice. For example, well-designed control rooms, healthcare workspaces, or virtual environments can enhance task-switching efficiency, reduce mental fatigue, and sustain attention over long periods(Wilson, 2014).

However, when ergonomic principles are neglected, such as through poor spatial layout, excessive visual clutter, or ambiguous controls, the same multitasking demands lead to cognitive fragmentation, stress, and performance errors (Carayon et al., 2014; Haims & Carayon, 1998). In high-pressure environments like air-traffic control or surgical operations, this can have critical consequences. As Carayon et al. (2014) demonstrate, ergonomic interventions that restructure spatial organization and streamline information flow can significantly reduce cognitive interference, leading to safer, more resilient performance.

Contemporary perspectives also emphasize the sustainability of human performance (Thatcher, 2014). Ergonomic design is now evaluated not only for its short-term effects on efficiency but also for its long-term contribution to health, well-being, and mental resilience (Africa et al., 2024; Goggins et al., 2008; John & John, 2024; Li-Wang et al., 2023b; Robertson et al., 2009). Chronic exposure to poorly designed systems contributes to cognitive fatigue, burnout, and decreased situational awareness, all of which degrade system reliability(Dale et al., 2021; Salmon et al., 2017; Wilson, 2014).

Therefore, the ergonomic integration of MRT supports a sustainable human–system equilibrium, ensuring that performance can be maintained safely and effectively over time.

Toward a Holistic Ergonomic Paradigm

The success of adaptive, ergonomically informed systems underscores the importance of viewing human performance through a holistic lens. The integration of MRT and ergonomics demonstrates that attentional resource utilization and multitasking capacity depend not only on individual cognitive limits but also on environmental affordances, the possibilities for action and perception offered by the system.

Contemporary ergonomic research thus seeks to develop intelligent environments that sense, interpret, and respond to human cognitive states in real time. These systems extend MRT's logic of resource management to include feedback-driven ergonomics, where interfaces continuously evolve to maintain optimal cognitive equilibrium. Such environments represent the culmination of decades of interdisciplinary research, uniting psychology, engineering, and neuroscience to build systems that are cognitively aligned, physically supportive, and environmentally adaptive.

Ultimately, the convergence of MRT and ergonomics has redefined how human performance is understood and optimized. Ergonomic design is no longer seen as a supplemental consideration but as a core determinant of cognitive effectiveness in modern systems. As automation, AI, and digital transformation continue to reshape the human–machine relationship, this integration provides the conceptual and practical foundation for a new era of adaptive, human-centered system design.

CONCLUSION

In conclusion, the convergence of Multiple Resource Theory (MRT) and ergonomic science marks a pivotal advancement in understanding and optimizing human performance within complex socio-technical environments. Contemporary perspectives emphasize that human cognition and attention cannot be fully comprehended in isolation from the physical and environmental contexts in which they operate. By integrating ergonomic principles, such as optimal interface layout, adaptive feedback mechanisms, and user-centered design, modern systems can dynamically regulate cognitive load, promote attentional balance, and enhance multitasking efficiency.

The development of adaptive and intelligent human–machine interfaces exemplify this integration in practice. These systems are increasingly capable of sensing operator workload, adjusting information displays, and modulating automation levels in real time. Such adaptability not only mitigates cognitive overload but also ensures sustained human engagement, safety, and situational awareness. Empirical evidence from fields such as aviation, healthcare, and industrial operations consistently supports the view that ergonomically designed interfaces lead to improved accuracy, faster decision- making, and reduced mental fatigue, thereby validating the applied relevance of MRT in the modern era.

Furthermore, the evolution toward cognitive-ergonomic models underscores a shift from static to dynamic conceptions of resource allocation**.** Human attention is now understood as fluid, context-sensitive, and influenced by environmental affordances.

Consequently, future systems must move beyond traditional compartmentalized theories of cognition and embrace models that reflect the reciprocal relationship between mind, body, and environment**.** Ergonomic interventions thus serve not merely as supportive enhancements but as foundational components of cognitive performance architecture.

Ultimately, the success of these integrated approaches demonstrates that ergonomic design is a cognitive enabler, it transforms abstract theories of attention and workload into tangible improvements in system usability, safety, and human well-being.

As automation and artificial intelligence continue to reshape work environments, the fusion of MRT and ergonomic principles provides a scientifically grounded pathway toward creating adaptive, human-centered systems that preserve the essential role of human cognition within complex technological ecosystems.

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