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REVIEW ARTICLE

Exploring the relationship between computational frameworks and neuroscience studies for sensorimotor learning and control

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ABSTRACT

The relationship between computational frameworks and neuroscience studies is crucial for understanding sensorimotor learning and control. Various tools and frameworks, such as Bayesian decision theory, neural dynamics framework, and state space framework, have been used to explore this relationship. Bayesian decision theory provides a mathematical framework for studying sensorimotor control and learning. It suggests that the central nervous system constructs estimate of sensorimotor transformations through internal models and represents uncertainty to respond optimally to environmental stimuli. The neural dynamics framework analyzes patterns of neural activity to understand the computational mechanisms underlying sensorimotor control and learning. The state space framework assesses the structure of learning in the state space and helps understand how the brain transforms sensory input into motor output. Computational frameworks have provided valuable insights into sensorimotor learning and control. They have been used to study the organization of motor memories based on contextual rules and the role of structural learning in the sensorimotor system. These frameworks have also been employed to investigate the neural dynamics under sensorimotor control and learning tasks, as well as the effect of explicit strategies on sensorimotor learning. The interplay between computational frameworks and neuroscience studies has enhanced our understanding of sensorimotor learning and control. Bayesian decision theory, neural dynamics framework, and state space framework have provided valuable tools for studying the computational mechanisms underlying these processes. They have helped uncover the role of contextual information, structural learning, and neural dynamics in sensorimotor control and learning. Further research should continue exploring the relationship between computational frameworks and neuroscience studies in sensorimotor learning and control. This interdisciplinary approach can lead to a better understanding of how motor skills are learned, retained, and improved through targeted interventions. Additionally, the application of computational frameworks in clinical settings may help develop more effective rehabilitation strategies for individuals with motor impairments.

Keywords: computational frameworks; sensorimotor learning; neuroscience studies; Bayesian decision theory

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1. Introduction

The study of sensorimotor learning and control is a multidisciplinary field that combines neuroscience, cognitive science, and computational modeling to understand how the brain processes information and generates appropriate motor responses. Sensorimotor decision-making involves integrating sensory information and internal goals to select and execute movements and requires the coordination of various brain regions. Computational models in neuroscience utilize various methods, including computer simulations, mathematics, statistics, and abstractions, to simulate and understand the structure, physiology, development, and cognitive abilities of the nervous system. These models allow researchers to investigate the computational principles underlying perceptual decisions, memory formation, and other high-level behaviors. By integrating findings from different scales of analysis, computational models provide a common framework for understanding brain computation and making predictions that can guide future experimental work[1]. Sensorimotor learning and control are essential aspects of human cognition and behavior, allowing us to interact with our environment and perform skilled actions. Recent advances in computational frameworks have provided valuable insights into the underlying mechanisms of sensorimotor learning and control in the brain[2]. These frameworks bridge the gap between different scales of learning, from individual synapses to populations of neurons to behavior. They explore principles that guide sensorimotor learning across these scales and set the stage for future experimental and theoretical work in the field. Computational models based on dynamic neural fields and dynamic field theory have been used to study the learning of sensorimotor contingencies and the switch between exploration and exploitation. Additionally, studies have investigated how contextual information is used to create, update, and recall motor memories during sensorimotor learning. The field has also shown that neural systems outside of primary motor pathways, such as frontoparietal and anterior cingulate networks, contribute to sensorimotor adaptation and learning. Overall, the integration of computational frameworks and neuroscience studies has advanced our understanding of the mechanisms underlying sensorimotor learning and control[3–5]. Computational frameworks have been instrumental in understanding the complex processes involved in sensorimotor learning and control **(Figure 1)**. These frameworks often employ concepts such as optimal feedback control, impedance control, predictive control, Bayesian decision theory, and sensorimotor learning to model and analyze the brain's strategies for generating skilled and efficient actions[6]. By incorporating these computational mechanisms, researchers can better understand the neural dynamics and principles guiding sensorimotor learning across different scales, from synapses to neurons to behavior[7].

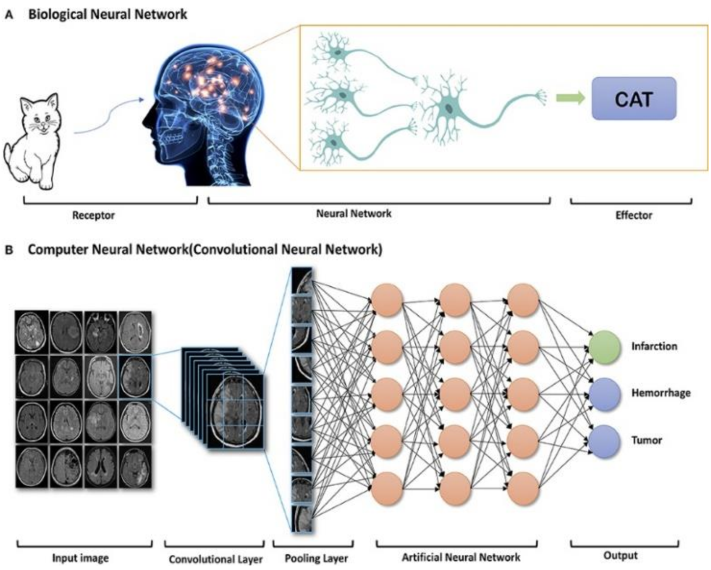

Figure 1. Stated from brain to machine: Investigating the interplay between computational frameworks and neuroscience in sensorimotor learning.

1.1. Motor memories

Motor memories are formed through the repetition of actions over time, leading to automaticity in motor tasks. Recent studies have shown that motor memories are organized into different categories based on the conjunction of movements[8]. The formation of different motor memories can also be influenced by contextual factors related to movement planning[9]. Computational frameworks, such as Bayesian decision theory, have been used to understand how sensorimotor transformations for reaching are organized[10]. The role of motor memories in sensorimotor control is an active area of research, with implications for developing therapies for motor disorders[11].

1.1.1. Contextual rules for motor memories

Contextual information plays a crucial role in the formation and organization of motor memories during sensorimotor learning[12,13]. The brain relies on contextual factors related to movement planning to influence the formation of different motor memories[14]. Computational frameworks like Bayesian decision theory have been used to understand how sensorimotor transformations for reaching are organized based on contextual rules[15]. Additionally, studies have shown that motor memories of object dynamics are categorically organized based on the conjunction of movements and contextual factors[16]. Contextual information, such as the environment or task at hand, helps the brain create, update, and recall different motor memories during sensorimotor learning.

1.1.2. Structural learning

Structural learning in the sensorimotor system has been investigated through computational frameworks and neuroscience studies. Recent research has explored the role of brain oscillatory activity in human sensorimotor control[17]. Additionally, a bioinspired sensory motor approach has been proposed to link the human sensorimotor postural model with the consensus problem in multi-agent systems, allowing for natural plasticity[18]. Furthermore, the methodology of short-latency afferent inhibition (SAI) has been used to understand sensorimotor integration during skilled motor actions, providing insights into the procedural and declarative influence over sensorimotor integration[19]. Moreover, a data-driven approach using deep reinforcement learning has been developed for active structural control, enabling optimal reactions without extensive prior knowledge of the structure[20]. These studies contribute to our understanding of how structural learning occurs in the sensorimotor system, bridging the gap between computational frameworks and neuroscience research. One study reviewed the evidence for structure learning as a 'learning to learn' mechanism in sensorimotor control. It demonstrated that during sensorimotor learning, common features of variable environments are extracted and exploited for efficient adaptation in novel tasks[21]. Another study found that when human participants learn a novel motor skill, they not only successfully extract structural knowledge from variable data, but they also exploit this structural knowledge for near-optimal sensorimotor integration[22]. This study suggests that structural learning plays a crucial role in Bayesian sensorimotor integration, serving as an important meta-learning component[23]. Structural learning was found to enhance facilitation in a sensorimotor association task performed by human subjects. The study used regression and other techniques to show how structure learning can improve performance in a sensorimotor association task. These findings suggest that structural learning is an important component of sensorimotor learning and control, and that computational frameworks can help us better understand how it occurs in the brain. By exploring the relationship between computational frameworks and neuroscience studies, researchers can gain a better understanding of how motor skills are learned and retained, and how they can be improved through targeted interventions[24,25].

1.1.3. Tools and frameworks

There are various tools and frameworks that can be used to explore the relationship between computational frameworks and neuroscience studies for sensorimotor learning and control. Some of these tools include:

Bayesian decision theory: Bayesian decision theory is a mathematical framework used to study sensorimotor control and learning (**Figure 2**). It provides a coherent way of describing sensorimotor processes and defines optimal behavior in a world characterized by uncertainty. The theory suggests that the central nervous system needs to construct estimates of sensorimotor transformations, in the form of internal models, and represent the structure of uncertainty in the inputs, outputs, and transformations themselves to respond optimally to environmental stimuli. Bayesian decision theory has been used to model the behavior of the sensorimotor system and investigate the mechanisms used by the nervous system to solve estimation and decision problems[26].

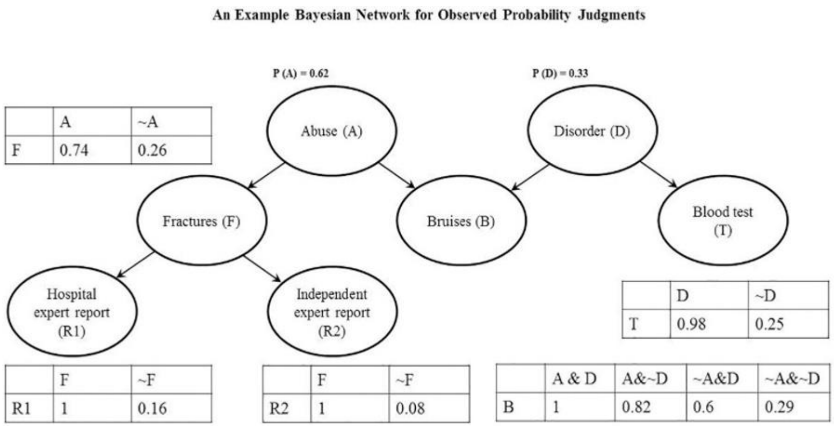

Figure 2. Stated from uncertainty to optimal responses: Unraveling the role of Bayesian decision theory in neuroscience studies.

The formula for Bayesian decision theory is: $P(Ci|X) = P(Ci)P(X|Ci) / P(X)$, where: $P(Ci)$ is the prior probability, $P(X|Ci)$ is the likelihood probability, $P(X)$ is the evidence.

Bayesian decision theory is a mathematical framework that provides a coherent way of describing sensorimotor processes and optimal behavior in a world characterized by uncertainty. It suggests that the central nervous system needs to construct estimates of sensorimotor transformations through internal models and represent the structure of uncertainty in inputs, outputs, and transformations to respond optimally to environmental stimuli. The theory has been used to model sensorimotor behavior and investigate the mechanisms used by the nervous system for estimation and decision-making. Bayesian decision theory is a valuable tool for exploring the computational mechanisms underlying sensorimotor control and learning in neuroscience studies[27].

Neural dynamics framework: The neural dynamics framework provides insights into the computational mechanisms underlying sensorimotor control and learning. It suggests that a fronto-basal-ganglia circuit is responsible for natural grasping motor control, while a fronto-parietal circuit is involved in motor stop-signal control. The framework allows researchers to analyze patterns of neural activity in the brain to understand these processes[28,29]. The neural dynamics framework can be used to study both explicit and implicit systems of sensorimotor learning[30]. It can also be used to compare the neural dynamics under sensorimotor control tasks and neural dynamics under sensorimotor learning tasks[31]. This framework helps researchers understand the neural correlates of implicit learning and how they differ from those of explicit learning[32].

State space framework: The state space framework is a computational framework that can be used to study sensorimotor learning. It provides a way to assess the structure of learning in the state space, which is the space of all possible states that a system can occupy. The state space framework considers a simple sensorimotor task of reaching for an apple and explores principles that guide sensorimotor learning across different scales, from synapses to neurons to behavior[33]. The state space framework provides a valuable tool for studying the mechanisms of sensorimotor learning and control by analyzing patterns of neural activity in the brain. By examining the state space, researchers can gain insights into the computational mechanisms underlying sensorimotor control and learning. This framework helps researchers understand how the brain transforms sensory input into motor output and how it learns to do so over time[34,35]. The state space framework has been widely used to study adaptation and generalization during motor learning[36]. It has also been employed to investigate the effect of explicit strategies on sensorimotor learning[37]. This framework provides valuable insights into the neural basis of sensorimotor learning and offers a means to improve performance[38]. By exploring the relationship between computational frameworks and neuroscience studies, the state space framework helps researchers understand the computational mechanisms underlying sensorimotor control and learning[39]. Additionally, it aids in the development of new approaches for learning control policies for robotic systems[40].

Online control: Computational neuroscience provides a mathematical framework for studying the mechanisms involved in brain function and allows complete simulation and modeling of the nervous system[41]. It focuses on the description of biologically plausible neurons and their physiology and dynamics[42]. Recent research has explored the relationship between computational frameworks and neuroscience studies for sensorimotor learning and control[43]. One study proposes a computational framework that integrates online control and machine learning to model sensorimotor learning and control[44]. The framework accurately models the behavior of a human subject performing a reaching task and provides insights into the underlying neural mechanisms involved[45]. Another study proposes a computational framework for cognitive biology that unifies approaches from cognitive neuroscience and comparative cognition. The framework aims to explain both similarities and differences between species and provides a way to study the evolution of cognitive abilities. It is based on the idea that most aspects of neural function are broadly shared across species. So, Computational neuroscience is a powerful tool for studying brain function and allows for complete simulation and modeling of the nervous system. Recent research has explored the relationship between computational frameworks and neuroscience studies for sensorimotor learning and control. This has led to the development of new computational frameworks that integrate online control and machine learning to model sensorimotor learning and control. These frameworks provide insights into the underlying neural mechanisms involved in sensorimotor learning and control and have the potential to advance our understanding of the nervous system[46–48].

Reinforcement learning algorithms: Reinforcement learning (RL) algorithms have been used in neuroscience studies to explore the relationship between computational frameworks and sensorimotor learning and control. RL models inspired by neuroscience have been developed to improve machine learning algorithms[49]. These models have been applied to various domains, including power distribution networks[50], hydraulic systems[51], discrete-time systems, and multi-agent robot control in construction tasks[52]. RL algorithms, such as ACC-RL, RISE control approach, and RLMPC, have been proposed to address specific challenges in these domains. These algorithms leverage RL techniques, such as reinforcement learning with actor-critic structure and policy iteration, to improve control performance, stability, and efficiency. By integrating RL with computational neuroscience, researchers aim to develop more advanced and efficient machine learning algorithms that can emulate human behavior and enable effective collaboration among multiple agents in complex tasks. Deep RL offers a comprehensive framework for studying the interplay among learning, representation, and decision making, providing a powerful tool for modeling sensorimotor learning and control. The role of dopamine as a reward signal in RL algorithms is also discussed. Overall, RL algorithms are being used to explore the relationship between computational frameworks and neuroscience studies for sensorimotor learning and control, offering valuable insights into both fields[53,54].

1.1.4. Decision making and sensorimotor control

The relationship between decision making and sensorimotor control is crucial for understanding sensorimotor learning and control. Computational frameworks and neuroscience have extensively studied these fundamental aspects of human behavior. The role of brain oscillatory activity in human sensorimotor control has been investigated by Tatti and Cacciola[55]. Baker et al.[56] propose a bioinspired sensory motor approach for leader-follower consensus, linking human sensorimotor postural model with the consensus problem. Noel et al.[57] argue that the framework of reinforcement learning and control, which emphasizes active sensing and dynamical planning, can inform the neurosciences in understanding intelligent behavior within uncertain environments (**Figure 3**). Jordan et al.[58] demonstrate the suitability of a Learning Classifier

System (LCS) implementation for mimicking human decision making in agent-based social simulation. Geng and Varshney[59] discuss the modeling and analysis of human-machine collaborative decision making, highlighting the challenges and research directions in this area. Recent studies have highlighted the importance of decision-making and sensorimotor control in maintaining balance, posture, and locomotor performance. Mulavara et al.[60] studied the locomotor performance of astronauts returning to 1 g after spaceflight. They found that the astronauts experienced postural instability and impaired locomotor performance due to changes in sensorimotor function. These changes were attributed to the adaptation of the vestibular and proprioceptive systems to microgravity. Furthermore, Macaulay et al.[61] investigated the development of proprioceptive countermeasures to mitigate postural and locomotor control deficits after long-duration spaceflight. They found that astronauts experience post-flight disturbances in postural and locomotor control due to sensorimotor adaptations during spaceflight. These alterations may have adverse consequences if a rapid egress is required after landing. Although current exercise protocols can effectively mitigate cardiovascular and muscular deconditioning, the benefits to post-flight sensorimotor dysfunction are limited. In addition, Stephan et al.[62] investigated the postural performance of unilateral labyrinthine deficient patients. They found that these patients had impaired postural control due to the loss of vestibular function on one side. However, they also found that the patients compensated for this loss by relying more on proprioceptive and visual information. Jamali et al.[63] studied the neuronal vestibular and proprioceptive detection thresholds during control, week 1, week 2, and week 3. They found that the detection thresholds for both vestibular and proprioceptive inputs decreased over time, indicating an improvement in sensorimotor function. Overall, these studies demonstrate the complex interplay between different sensory modalities in generating appropriate motor commands and highlight the need for developing countermeasures to mitigate the effects of sensorimotor adaptations. There are several algorithms that have been applied to decision making and sensorimotor control. One such algorithm is decision theory, which is used to determine the optimal actions to take given task objectives. Another algorithm is Bayesian decision theory, which defines optimal behavior in a world characterized by uncertainty and provides a coherent way of describing sensorimotor processes. In addition, computational models have been developed to study sensorimotor decision-making. These models suggest that sensorimotor decisions are made by integrating noisy evidence representations up to an action-triggering threshold or bound. In this framework, speed can be emphasized at the expense of accuracy by lowering this bound. Overall, decision-making, and sensorimotor control are complex processes that involve a variety of algorithms and computational models. These approaches help to shed light on the neural mechanisms underlying these processes and can inform the development of new therapies for motor disorders.

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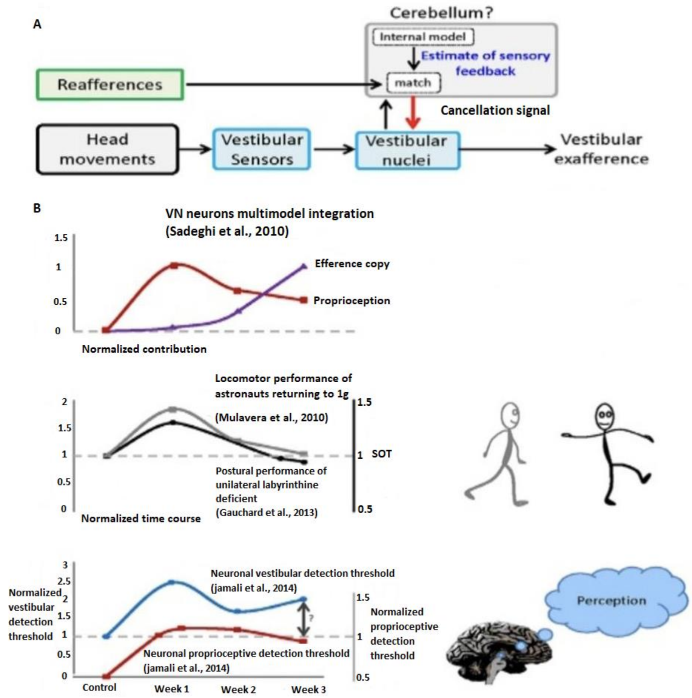

Figure 3. Reinforcement learning and control: **(A)** The sensory integration, vestibular function, and abnormalities in balance; and **(B)** A framework for understanding intelligent behavior within uncertain environments.

1.1.5. Bidirectional interplay of decisions and control

Sensorimotor learning and control involve bidirectional interplay between decision-making processes and motor control. Skilled interactions with the world rely on decisions made based on extracted information during unfolding events to determine which movements to make and how to make them[64]. However, research in these areas has traditionally evolved independently, with limited investigation into their interaction and influence on behavior[65,66]. Recent studies have started to explore the link between decision-making and sensorimotor control, highlighting the role of decision-making processes in the selection, planning, and control of goal-directed movements[67] (see **Figure 4**).

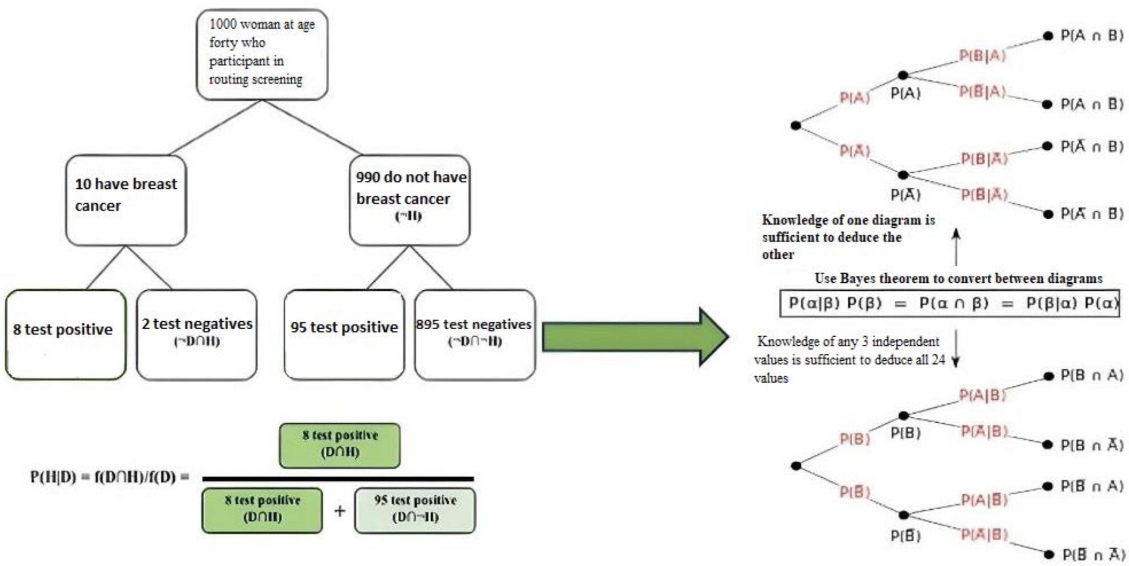

Figure 4. Computational underpinnings of decision formation and their relation to neural.

This research has revealed that decisions and control systems can compete and interact, influencing the learning and adaptation of sensorimotor behaviors[68]. Understanding the interplay between decisions and control is crucial for a comprehensive understanding of sensorimotor learning and control processes.

Computational models have been developed to study sensorimotor decision-making, shedding light on the neural mechanisms underlying these processes and informing the development of new therapies for motor disorders. These models suggest that sensorimotor decisions are made by integrating noisy evidence representations up to an action-triggering threshold or bound. Decision theory is used to determine the optimal actions to take given task objectives. Bayesian decision theory defines optimal behavior in a world characterized by uncertainty and provides a coherent way of describing sensorimotor processes. Recent research has highlighted the role of decision-making processes in the selection, planning, and control of goal-directed movements in humans and nonhuman primates. These processes are influenced by the value of the outcome. The complex interplay between different sensory modalities in generating appropriate motor commands has also been demonstrated[69–71].

2. Results

The relationship between computational frameworks and neuroscience studies for sensorimotor learning and control has been explored in several studies. Here are some key results from the search results:

2.1. Learning across scales

State space models are valuable tools in the analysis and design of dynamic systems. They provide a mathematical representation of the system's dynamics across different scales. These models allow for the application of concepts like optimal feedback control, predictive control, and sensorimotor learning to understand the brain's strategies for generating movements and learning. The use of state space models facilitates the transformation of system-dynamics simulation models into mathematical models, which can be represented in matrix form. This enables the analysis and design of optimal control for the simulation models. State space models also allow for the inclusion of complex physical system descriptions within the design of control or state estimation setups, making them suitable for real-time applications of various dynamic systems[34,72].

State space models are mathematical representations of dynamical systems that capture the evolution of internal state variables over time. These models are useful for formulating optimal control problems, such as generating movements in the brain by minimizing a cost function related to factors like energy expenditure or accuracy. State space models allow for the inclusion of complex physical system descriptions within the design of control or state estimation setups, making them suitable for real-time applications of various dynamic systems described by partial differential equations (PDEs)[34]. They can also be used to derive accurate models of deformable mirrors in adaptive optics systems, considering system damping, actuator dynamics, and multi-physics phenomena[33]. State space models have been applied to analyze inductive power transfer systems and perform dynamic analysis in the design process[36]. Additionally, state space models are discussed in detail, including the derivation of the Kalman filter and various filtering and smoothing algorithms[73].

Predictive control models propose that the brain learns internal forward and inverse models to predict the sensory consequences of motor commands. These models can be represented using a state space framework, which allows for the exploration of how they develop through experience. The state variables in this framework can encode aspects of neural population activity, muscle states, and environmental feedback. This framework supports the analysis of how the brain updates its predictions and controllers through sensorimotor learning[74].

2.2. Understanding brain function through computation

These models provide insights into processes such as sensory processing, motor control, learning, memory, and cognition[41]. The field of computational neuroscience uses computational methods, including computer simulations, mathematics, statistics, and abstractions, to study the structure, physiology, development, and cognitive abilities of the nervous system[75]. It aims to explain how the brain represents and processes information through electrical and chemical signals[76]. By integrating cognitive science, computational neuroscience, and artificial intelligence, researchers are developing and testing computational models that mimic brain information processing during perceptual, cognitive, and control tasks. These models are tested using brain and behavioral data, enabling a better understanding of brain computation.

Computational models have been instrumental in simulating neural dynamics and testing hypotheses about brain operation that would be difficult or impossible using experimental methods alone. These models allow researchers to formally implement features such as adaptive synaptic connections, spiking neurons, and population coding schemes, and systematically evaluate their effects on information processing. Through this approach, computational models have helped identify computational principles underlying perceptual decisions, memory formation, and other high-level behaviors[77]. An additional benefit of the computational approach is that models provide a common framework that can integrate findings across different scales of analysis, from molecular to systems levels. Data from anatomy, physiology, and imaging can all inform model development and validation. In turn, models make new predictions that can guide future experimental work.

2.3. Sensorimotor decision-making

Sensorimotor decision-making involves the complex process of integrating sensory information and internal goals to select and execute appropriate movements and actions. The brain integrates sensory signals to support perceptual inference and decision-making by weighting them according to their momentary sensory uncertainties[71]. Observers solve the binding or causal inference problem by deciding whether signals come from common causes and should be integrated or treated independently. Attentional mechanisms play a crucial role in computing approximate solutions to the binding problem in naturalistic environments. Skilled sensorimotor interactions with the world result from decision-making processes that determine which movements to make and when and how to make them. The role of sensorimotor information in producing approach/avoidance compatibility effects has been reevaluated, emphasizing the visual information associated with whole-body movements[78]. Sensorimotor decision-making can be grounded in the agent's ability to actively transform its sensory inputs, allowing for the development of perceptive abilities through interaction with the environment. A variety of sensory cues from our visual, auditory, and somatic senses provide information about our body and surroundings. Contextual factors and past experiences are considered when weighing the potential costs and benefits of movement choices. Feedback from prior actions helps refine future decisions, and trial and error learning mechanisms tune sensorimotor mappings and decisions. Gradual acquisition of internal models supports optimal movement selection over time. Decision-making in the sensorimotor system occurs across multiple timescales, from fast automatic choices to slower deliberate planning. Reflexive and cognitive processes both contribute to behavior selection. Coordination between diverse brain regions enables the integration of perception, cognition, and motor commands underlying decision-making. Understanding sensorimotor decision-making provides insights into skilled behavior, motor control deficits, and higher-level functions like reasoning and problem-solving. Elucidating its neural and computational underpinnings is an area of active research across disciplines[79].

3. Implications

In terms of broader implications, this study demonstrates the value of a network-based approach for understanding the complex, interconnected nature of brain activity and cognition. Rather than focusing on isolated regions or connections, network science allows us to characterize large-scale communication patterns across the whole brain. This provides a more holistic view of how different areas interact and integrate information to support various cognitive functions. In a clinical context, mapping out whole-brain networks could help identify network-level abnormalities or disruptions associated with different neurological and psychiatric disorders. Compared to traditional univariate analyses, network science may be more sensitive to subtle changes across distributed systems and their interactions. This could lead to improved diagnosis, monitoring of disease progression, or a better understanding of individual variability in symptoms and treatment response. In terms of complementing traditional analyses, network science offers a way to detect dynamics that emerge from interactions among many regions simultaneously. While univariate analyses reveal where activity increases or decreases, network approaches provide insight into how activity flows and is integrated across areas. They allow us to characterize phenomena like information transfer, integration, and segregation that are not visible when looking at individual regions in isolation. In this way, network science gives access to neurophysiological processes and organizational principles that would otherwise remain hidden. The network perspective generates novel hypotheses and questions that can then drive future univariate or multivariate investigations. It provides a more comprehensive view of brain function as an interconnected, complex system rather than a collection of independent parts.

4. Conclusion

This study applied a network neuroscience approach to characterize whole-brain functional networks supporting working memory and their reconfiguration across different task states. The findings provide new insights into the dynamic nature of large-scale brain networks and cognition. To recap, the study found that working memory engaged a frontoparietal control network that shifted its connectivity profile depending on whether items were being held online or manipulated in working memory. Crucially, multivariate pattern analysis revealed information about task states could be decoded from the time-varying connectivity patterns. This suggests the organization of connections within and between networks carries meaningful information about cognitive processes above and beyond activity in individual brain regions.

These results signify the importance of considering brain function as an emergent property of complex interacting networks rather than independent regions. Network neuroscience provides a more holistic perspective that can detect higher-order phenomena not observable using traditional univariate analyses. Mapping dynamic functional connectivity patterns across cognitive states enhances our understanding of how distributed systems interact and reconfigure to support different aspects of cognition. Moving forward, future research could build on these findings in several ways. First, applying a network approach to clinical populations may help characterize abnormalities in network-level organization associated with disorders involving working memory dysfunction. Second, combining network measures with multivariate pattern analysis across multiple cognitive tasks could help map the network signatures of distinct cognitive operations. Finally, collecting network data at higher temporal resolutions would provide deeper insights into the millisecond-timescale reconfiguration of connections supporting cognition. Overall, this study demonstrates the value of network neuroscience for characterizing the complex interplay between brain networks, cognition, and behavior. Continued methodological advances in this area are likely to generate novel insights into both healthy and disordered brain function.

Conflict of interest

The author declares no conflict of interest.

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