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Centering cognitive neuroscience on task demands and generalization

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Cognitive neuroscience seeks generalizable theories explaining the relationship between behavioral, physiological and mental states. In pursuit of such theories, we propose a theoretical and empirical framework that centers on understanding task demands and the mutual constraints they impose on behavior and neural activity. Task demands emerge from the interaction between an agent's sensory impressions, goals and behavior, which jointly shape the activity and structure of the nervous system on multiple spatiotemporal scales. Understanding this interaction requires multitask studies that vary more than one experimental component (for example, stimuli and instructions) combined with dense behavioral and neural sampling and explicit testing for generalization across tasks and data modalities. By centering task demands rather than mental processes that tasks are assumed to engage, this framework paves the way for the discovery of new generalizable concepts unconstrained by existing taxonomies, and moves cognitive neuroscience toward an action-oriented, dynamic and integrated view of the brain.

Cognitive neuroscience seeks to understand physiological, mental and behavioral phenomena, articulating theories that jointly explain these domains. Central to this understanding is a foundational idea that has long been recognized but is often overlooked in empirical practice: we are agents, not observers of our environment[1]. We sample, move through and interact with the world in order to accomplish goals and satisfy innate drives. Sensory inputs are, therefore, not passively received by the nervous system, but a direct consequence of actions and the goals that drive them. Reciprocally, our goals, and the actions required to accomplish them, are constrained by the environment. For example, an animal may sniff while foraging for food, guided by smell, but may run in the presence of a predator, prioritizing hearing and sight to escape. The dynamic and interdependent nature of sensory impressions, goals and behavior implies that the demands imposed on an agent in any given moment are defined by the convergence of all of these factors, rather than by any single factor (Fig. 1). As the nervous system affords and is continuously shaped by such agent–environment interactions, the demands that emerge from this interplay ultimately determine the behavioral, mental and physiological states that persist. We argue that parsimonious, generalizable theories of these states can only be formulated by unpacking the constraints mutually imposed on them by such demands, which, in an experimental context, we refer to as 'task demands'.

In pursuit of generalizable theories, we propose a framework for cognitive neuroscience that centers on elucidating how task demands influence behavioral and physiological measures. Operationalizing task demands and determining their influence on empirical data comes with a critical challenge: Although task demands drive neural activity and behavior broadly with measurable effects, they themselves can be neither directly controlled nor observed by the experimenter. Rather, task demands are the product of the requirements and conditions an agent encounters during an experiment and emerge from the inherent (that is, unavoidable) interaction between experimental components (for example, stimuli and instructions). Therefore, they can only

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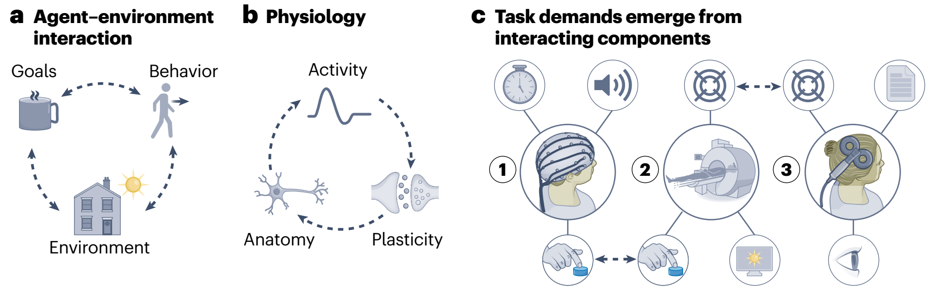

Fig. 1 | Centering task demands in our thinking. Interdependent factors collectively define agent–environment interactions, physiology and experimentation. **a**, Agent–environment interaction. Goals, behavior and sensory impressions of the environment are interdependent and need to be understood in terms of their constraints on each other, rather than individually. For example, the choice of instructions influences which aspects of the environment are relevant (for example, stimulus color versus motion), how the environment is sampled (for example, through eye movements) and the behavioral response given (for example, lever press). These factors jointly determine the demands on the agent in any given moment. **b**, Physiology. The nervous system adapts continuously to meet the demands on the agent. Activity drives plasticity, plasticity shapes anatomy, and anatomy constrains activity. **c**, Experimentation. In the experimental context, we attempt to control agent–environment interactions by manipulating experimental components (for example, stimuli, instructions and behavioral responses). Task demands emerge from the interaction between these components, constituting latent variables that determine the behavioral, physiological and mental states that occur during the experiment. Different experiments may have shared and unique experimental components, affecting their overlap in task demands (for example, experiments 1 and 2 feature button clicks but differ in stimuli and instructions; experiments 2 and 3 share instructions but differ in stimuli and prompted behaviors).

BOX 1

Outside-in versus inside-out: task demands bridge mental concepts and neural data

Cognitive neuroscience aims to formulate theories and models that jointly explain behavior, neural activity and mental states. The predominant approach relies on preexisting psychological concepts that guide the collection of physiological or behavioral evidence through experimentation and modeling, (for example, finding a mapping between neural activity and working memory). Although these types of experiments may be well suited to answer questions about specific putative concepts, they are not well suited for the empirical discovery of new concepts. This is because the psychological concepts and the tasks used to probe them are so tightly linked that any data acquired will necessarily lack the variability to avoid biases toward that concept. In fact, many tasks are even named according to the respective process they are assumed to engage (for example, a 'recognition task', 'working memory task'). This approach, often referred to as an 'outside-in approach', has been challenged[63], especially because psychological concepts do not provide a satisfying account for a growing body of neuroscientific data. More fundamentally, mapping preexisting concepts to the brain can only ever reify rather than redefine the century-old 'divisionist' taxonomy[64].

An alternative 'inside-out' approach instead prioritizes the biological substrate[63], conceptualizing the brain as a pattern generator that maps initially 'meaningless' activity patterns to environmental phenomena through actions, ultimately giving them their 'meaning'. Under this view, characterizing the neural patterns and establishing their meaning post hoc can lead to the discovery of new concepts. Although this approach is, therefore, free of the constraints imposed by existing taxonomies, it requires first discovering meaningful physiological patterns, and then finding the correct mapping between these patterns and an endless number of possible real-world phenomena and actions, probably without a unique mapping solution[65].

Importantly, neither outside-in nor inside-out approaches typically test the central assumption in neuroscience and psychology that inferences based on one task generalize to others, or even to the real world. This long-standing assumption of generalization is based on another: namely, that a task engages a specific mental process that operates beyond the specific experimental setting. These assumptions often lead to generalizations on the level of putative mental processes rather than the data. As a consequence, studies framed around the same process are often grouped together and distinguished from those examining other processes, and the task demands imposed by the experiments often receive less consideration. We suggest that by relying on such meta-level comparisons across studies on the level of mental processes, rather than explicitly testing for generalization across tasks on the level of the data, the predominant approaches have contributed to an unwarranted reification of existing taxonomies, and to an unnecessary fragmentation of the literature.

Our perspective is that regardless of which approach is taken, the link between the concept and the data is fundamentally the task demands of the specific experiment conducted. Thus, understanding the mutual constraints task demands impose on neural activity and behavior is key to formulating new concepts, theories and models that jointly explain these domains, alongside concomitant mental states. Understanding the constraints imposed by task demands requires formal quantifications of the generalization of results (or lack thereof) across tasks on the level of the data. Moreover, testing whether patterns generalize across neural and behavioral measures will allow the discovery of concepts that jointly explain data modalities. Such tests of generalization can reveal meaningful patterns in the data that can then be interpreted by linking them to the experimental components that were varied, ultimately fueling the creation of new empirically defined concepts.

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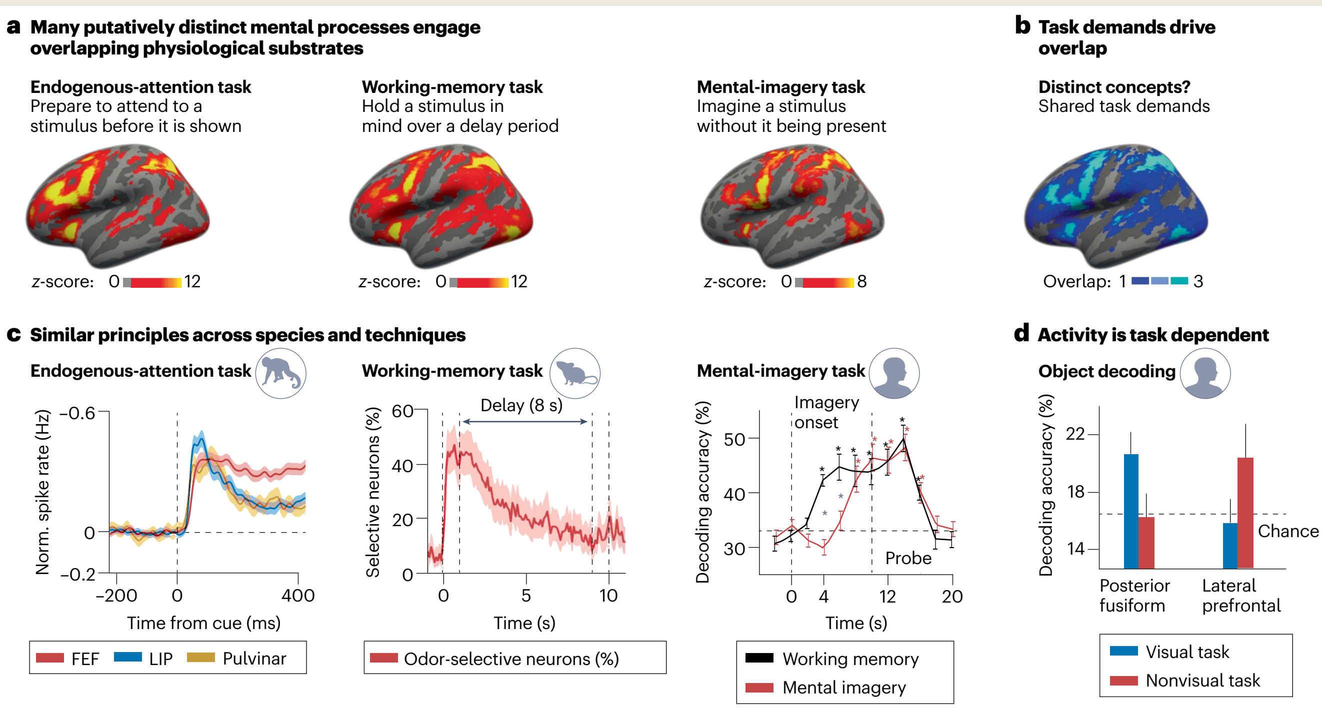
BOX 2

Shared task demands: the case of attention, working memory and mental imagery

To understand how task demands shape our empirical observations, consider the case of attention, mental imagery and working memory—three psychological concepts traditionally associated with separate mental processes. Although largely distinct literatures provide seemingly abundant behavioral and neurophysiological evidence for each one of these putative mental processes, much of this evidence overlaps across the three (Box 2 Fig.), calling into question the separability of the concepts themselves (see, for example, ref. 63).

In endogenous attention tasks, internally generated signals prepare one to attend to specific features of a stimulus, even in the physical absence of that stimulus. During such tasks, feature-specific modulations are observed in the neural response of many regions (for example, ref. 66). In working memory tasks, information needs to be maintained over time in the absence of a physical stimulus and often directly engages the same cortices that responded when the stimulus was present (for example, ref. 67). Such findings have been taken as support for a sensorimotor recruitment framework[68] and predict the behavioral pattern of interference between currently perceived and memorized stimuli[69,70]. In mental imagery tasks, specific stimulus features must be called to mind in the absence of a physical stimulus, with results suggesting a depictive representation mediated by common neural substrates for imagery and perception[71]. Converging evidence for shared neural substrates for imagery and perception has even prompted the question of how we are able to differentiate between the two[72].

Importantly, all three of these tasks engage neural substrates keyed to the stimulus content, which becomes especially apparent when directly compared within individuals[73]. In fact, the neural evidence taken as support for attention, working memory and imagery also overlaps with many other putative mental processes (for example, generating expectations), hinting at the possibility of formulating unified, more parsimonious concepts that explain these data (Box 1). Indeed, data-driven quantification of the relatedness



Box 2 Fig. Shared task demands drive similarities across domains. **a**, Putatively distinct mental processes engage overlapping physiological substrates. Example concepts that are typically probed with specialized tasks. Statistical maps show regions with strong association with the terms 'attention', 'working memory' and 'imagery' across hundreds of studies adapted from neurosynth[75]. Depicted are meta-analysis uniformity tests thresholded at $P<0.01$ (false discovery rate-corrected) overlaid on Freesurfer's FSaverage surface. Note that these maps may mask individual differences in activity strength and localization. **b**, Common task demands probably explain neural overlap observed across putatively distinct mental concepts. We depict a surface render of the overlap between the statistical maps in **a**. Bright blue shows areas that overlap across all three example concepts. **c**, Example studies reporting similar principles across species and techniques. Left, Neurons in the macaque show increased spiking during a cue–target delay period when the target is expected to appear in their receptive field (adapted from data in ref. 66). Middle, Neurons in the mouse show selectivity for specific odors during delay period (adapted from data in ref. 67). Right, Stimulus identity can be decoded from early visual areas during both working memory and mental imagery tasks (adapted from data in ref. 73). FEF, frontal eye field; LIP, lateral intraparietal area. **d**, Example study showing that neural activity is task dependent. Decoding of object identity in posterior fusiform cortex and lateral prefrontal cortex depends on the task used (adapted from data in ref. 70).

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of the most prominent concepts currently used in cognitive neuroscience shows that the boundaries between them are blurry at best[64]. We argue that neuroscientific evidence, such as the engagement of 'sensory' cortices by 'high-level cognitive processes' (for example, emotion schemas[74]), belies the distinction between even the most deeply rooted terms in our field such as perception and cognition. We suggest that rather than the psychological concepts themselves, the similarity in task demands across studies (for example, maintaining stimulus information over time) can explain the commonalities and differences in physiological responses they observe, and that many seemingly established distinctions between putative mental processes are unsubstantiated.

be manipulated indirectly through the choice of such experimental components. As the factors these components attempt to control interact, seemingly small changes in one component can produce large differences in task demands, making it difficult to disentangle the impact of individual experimental components on the level of behavioral and physiological measures. To address this challenge and uncover how task demands drive empirical measures, we argue that studies need to characterize the interactive influence of experimental components on the data. This quantification can be achieved by varying multiple components simultaneously, and formally testing the generalization of results across tasks and across neural and behavioral data. We contend that such an approach will enable the data-driven discovery of new concepts while remaining grounded in theory, combining the strengths of the established and predominant 'outside-in' and 'inside-out' approaches while simultaneously overcoming their limitations (Box 1).

The following sections describe the theoretical and practical implications of this framework based on a synthesis of perspectives, approaches and data from diverse literatures. We begin by discussing why all empirical measures are ultimately grounded in task demands, and how their influence can be understood through the interaction between experimental components. Next, we outline how agent–environment interactions, which underlie task demands, shape all aspects of physiology on multiple spatiotemporal scales, leading into three sections focusing on the dynamic, interconnected and multifunctional nature of neural circuits. We then highlight the fundamental importance of comprehensively analyzing behavior for any and all tasks, and why improvements in behavioral testing and study design are essential for advancing our understanding of the nervous system. We conclude by emphasizing the relevance of open science and large-scale interdisciplinary initiatives for accomplishing the long-term objectives of cognitive neuroscience, which includes the creation of a new and adaptive taxonomy that unifies neural, behavioral and mental states.

Behavioral and physiological measures are grounded in task demands

Traditionally, studies vary a single experimental component (for example, stimuli) while keeping others constant (for example, instructions), mapping variations in that component to variations in the recorded data (for example, neural spiking and behavioral responses). Although this approach has led to key discoveries, it has a central limitation: varying only one component renders us blind to interactions between components (Fig. 1). However, a large body of literature suggests that the choice of each experimental component can affect the influence of others, making it challenging to attribute results to a single component or variable. Further, most neurons exhibit mixed selectivity that is task dependent. The activity of subicular neurons, for instance, reflects an interaction between an animal's location, head direction and running speed, but the variance in activity accounted for by each depends on the animal's task[2]. Similarly, neural activity in putatively sensory cortices, such as early visual cortex, reflects not just stimulus-evoked responses but also task-related goals, behaviors[3] and physiological signals (such as arousal)[4]. Studies using multiple tasks have further shown a strong influence of experimental instructions or cues on widespread neural activity in humans (for example, ref. 5), monkeys (for example, ref. 6) and rodents (for example, ref. 7), and multitask designs offer improved parcellation and connectivity estimates when compared to traditional approaches (for example, ref. 8). Experimental instructions also have profound effects on behavior (for example, ref. 9). Finally, studies probing putatively distinct mental processes (for example, working memory, attention and mental imagery) often report similar or overlapping neural activity, which probably reflects similarities in their underlying task demands (Box 2). These results collectively suggest that behavioral and neural measures—and the mapping between them—are inherently task dependent.

In light of these findings, we propose that task demands emerging from interacting experimental components underlie any neural or behavioral result, making it crucial to formally unpack their influence. To this aim, studies need to vary multiple experimental components (for example, stimuli, instructions and, prompted behaviors) and quantify their interaction on the level of the data. Such multitask studies enable the identification of patterns of results that generalize across tasks and across data types, which can then be interpreted by linking them to the experimental components that were varied, as well as to other factors not explicitly manipulated (for example, time of day). Formal tests of generalization are essential for the broader applicability of research findings, as across-task generalization is a crucial prerequisite for generalization to the real world. To enhance ecological validity of experiments and, therefore, generalizability of their results, we agree with others in prioritizing naturalistic conditions (for example, ref. 10) or allowing free ambulatory behavior (for example, ref. 11). Notably, naturalistic conditions can be achieved while maintaining a high level of experimental control, for example, through photorealistic rendering[12] or the use of virtual reality[13]. Ultimately, by focusing on multitask studies, naturalistic conditions and the pursuit of across-task generalization, we believe that empirically grounded concepts can be derived from the data that jointly explain neural activity, behavior and mental states (Box 3).

Agent–environment interactions shape all aspects of physiology

Although task demands are specifically defined within experimental contexts, determining their influence on empirical measures can reveal general principles about the nervous system and its grounding in agent–environment interactions. Given that activity drives plasticity, plasticity shapes anatomy, and anatomy constrains activity (Fig. 1), the nervous system continuously adapts to meet demands on the agent. These adaptations range from immediate, local adaptations in protein synthesis and synaptic modifications (for example, ref. 14), to large-scale network changes on developmental[15] and evolutionary timescales[16]. As the history of behavioral successes and failures determines which neural circuits and dynamics persist[17], all aspects of the nervous system are ultimately yoked to the behavior it produces. This action-centric view accounts for a burgeoning literature showing that behavioral correlates can be found in activity throughout the brain[18], even in early sensory cortices[19], as well as for the widespread integration of motor outputs and sensory inputs (for example, efference copies[20]). Moreover, this perspective supports the idea that actions are an integral part of sensory processing[21], and suggests that the conjunction of

BOX 3

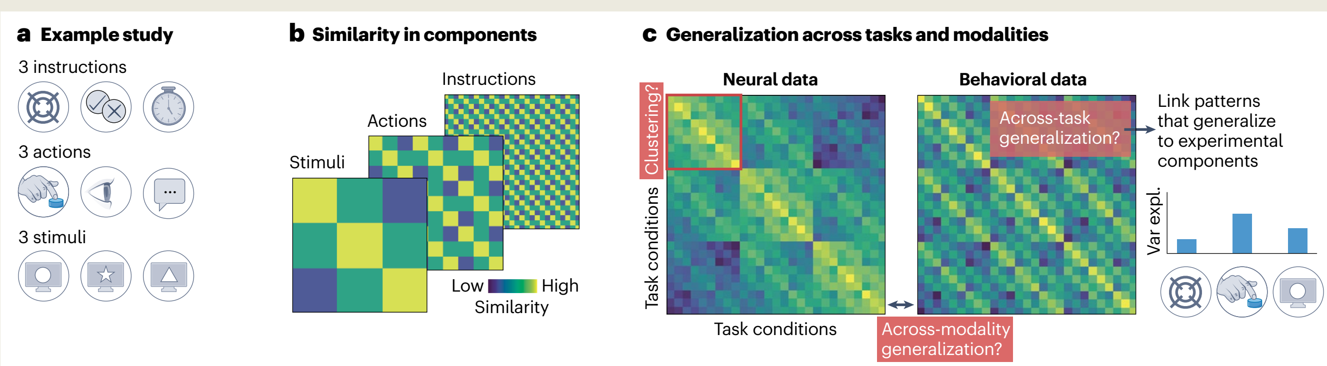
Empirical approaches for examining the constraints of task demands on physiology and behavior

Experiments yield a relationship between empirical measures (for example, neural responses) and a specific combination of experimental components (for example, stimuli, instructions and behavioral responses). To unpack task demands, experiments need to be designed to specifically characterize the interaction between these components, ideally within individuals, which can be achieved by implementing a multitude of task variations and empirical measures, yielding rich datasets that combine high experimental control with high data variability (Box 3 Fig.). When neural activity and behavior are densely sampled, such multitask designs are ideal for testing generalization of results across task conditions and across data modalities (Box 3 Fig.), leveraging the full richness of neural and behavioral dynamics to uncover their common constraints. Moreover, focusing on task demands and generalization through multitask studies will make studies more naturally extendable and comparable to later studies, especially when designed with open science and quantitative convergence as the goal (see section 'Transforming the culture of cognitive neuroscience').

Various analysis techniques can discover patterns that generalize across tasks and data modalities. For example, the behavioral or neural patterns that generalize across tasks can be identified through clustering analyses applied to across-task similarity matrices (Box 3 Fig.), via representational similarity analysis (for example, ref. 5), component modeling or factor analysis of all tasks together (similar to, for example, ref. 76), or training and testing encoding/decoding models across tasks (similar to, for example, ref. 77). Similar techniques could establish the mapping between neural and behavioral data, for example, by comparing principal components estimated for each measure[76], or through behavioral encoding models (for example, ref. 13). Alternatively, the mapping could be achieved by estimating joint low-dimensional embeddings for behavior and neural activity[59]. Not only do such techniques identify the general patterns that are shared across data types or tasks (Box 2), but they also yield those patterns that are unique to each one, which can then inform new hypotheses to be targeted in subsequent experiments (for example, ref. 78).

To interpret results, patterns that generalize across tasks and/or data types can be linked to the specific variations in the experimental components, for example, by computing how much variance each component explains in the across-task similarity matrices (Box 3 Fig.). Moreover, by considering the broader experimental context (for example, time of day), the component's contribution and their interaction can further be disentangled from factors that were not explicitly varied. Only by fitting all experimental components together, and by quantifying nonlinearities in their mapping to the empirical measures, can their interaction be directly characterized on the level of the data, which we argue is required to go beyond reification of existing taxonomies (for example, Box 2) and empirically derive new mental concepts that jointly explain behavioral, neural and mental states (Box 1).

Given resource constraints, one concern is whether multitask designs are practically feasible, especially at a larger scale. We believe that challenges associated with multitask designs are surmountable even for individual studies, and that multitask studies are ultimately efficient and cost-effective, as they balance the increase in the number of experimental components with the advantage of harnessing systematic variability within the data. For example, unlike single-task studies, multitask studies allow for new and numerous questions to be addressed within the same data, and pooling data across tasks still allows addressing individual questions with high statistical power. As characterizing behavior thoroughly can inform both the phenomena targeted and the design of physiological investigations, the efficiency of multitask designs can further be improved by diversifying our behavioral measures, which in turn probably decreases the amount of more costly neural data required. Fortunately, behavioral



Box 3 Fig. Example approach for quantifying the effects of task demands. a, Example study varying multiple experimental components (instructions, prompted actions and stimuli) with a total of 27 task conditions. Varying the experimental components indirectly manipulates task demands. **b**, Similarity between task conditions within experimental components. **c**, Generalization analysis. Matrices depict generalization scores for behavioral data (for example, similarity of whisker movements) or neural data (for example, neural pattern similarity in a region of interest) across task conditions. Arrows and boxes indicate example analyses toward quantifying the influence of task demands. First, clustering analyses can reveal which tasks elicit similar behaviors and neural activity. Second, meaningful patterns can be discovered by testing for across-task generalization (for example, decodability, encoding-model performance and representational similarity analysis). Third, brain–behavior relationships can be revealed by finding patterns that generalize across behavioral and neural data. Finally, data patterns that generalize form the basis for new concepts by linking them to the experimental components.

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tracking continues to become simpler and more affordable due to advances in machine learning[57]. In general, the number and extent of behavioral studies should be increased drastically[79] as they tend to be more affordable and practical than neural recordings (for example, crowd-sourced psychophysics[80]). Notably, as it is not feasible to test every possible variation in experimental components, the choice of what to vary must be informed by the research question and theory in general, the testing and refining of which should be both the starting point and the goal of experimentation.

sensory and action statistics is not just reflected in the activity of the nervous system, but also its structural organization.

These considerations underscore the need for theoretical and analytical approaches capable of linking conjunctive sensory and action statistics to physiological phenomena, while also uncovering common constraints on activity, plasticity and anatomy. We propose that centering the empirical approach on task demands can achieve these aims simultaneously, as it captures the interplay between sensory impressions, goals and behaviors that shape an agent's physiology broadly. As the very structure of the nervous system is a product of this interplay, characterizing the influence of task demands on empirical measures is critical for informing our interpretations beyond the specific experimental setting, even for studies involving self-generated experiences (for example, memory recall[22]), putative rest[23] or perturbation (for example, brain stimulation[24]). Further, activity patterns are fundamentally a function of the underlying anatomy and only in the context of that anatomy is it possible to reveal why one specific activity pattern emerged and not another. Synthesizing measurements of anatomy and activity obtained under varying task demands can, therefore, uncover important latent patterns that generalize across tasks and data modalities (for example, computational modeling of toroidal attractor dynamics in entorhinal grid cells[25]), and inform our understanding of neural activity, cell diversity, local architecture, connectivity and plasticity across spatiotemporal scales. Finally, because all aspects of behavior and physiology reflect an agent's unique history, we suggest that insights gained about the influence of task demands on our empirical measures can be leveraged for understanding individual differences in health and disease (Box 4).

Every brain state is unique

As neural activity is yoked to anatomy through plasticity, all of our experiences and behaviors leave structural traces throughout the nervous system. Thus, the global state of the nervous system never repeats. Indeed, many studies report substantial variability in neural activity across trials even for repeated conditions (for example, representational drift[26]). Although multiple potential mechanisms have been proposed, one commonality is that these variations appear to be systematic. For example, neural activity does not differ randomly across trials, but tends to drift in a task-dependent manner, with similarity in activity across trials diminishing with increased time between trials (for example, ref. 27). Such drift is paralleled in behavior, where performance in one trial depends on performance and experience in prior trials (for example, serial dependence[28]). Moreover, behavioral and neural activity drift often coincide (for example, ref. 29). Together, these findings demonstrate the non-static nature of behavior and neuronal firing patterns (Fig. 2) and suggest a possible common mechanism, such as accumulating plasticity-induced changes. An additional source of uncontrolled variability in neural and behavioral data stems from changes in the internal state of an agent, which fundamentally affects how a task is performed. For example, results can be affected by the duration that participants waited for the experiment to start[30].

The presence of such hysteresis and state-dependency effects suggests that variability in empirical measures across trials is as informative as any stable pattern observed. Rather than treating this variability as noise (for example, when computing test–retest reliability), it could be leveraged to understand the dynamics of and covariance between physiology and behavior. This can be achieved through multitask experiments that maximize variability in the measures while maintaining experimental control (Box 3). To take full advantage of the resulting datasets, analytical toolkits need be expanded beyond metrics of reproducibility and central tendency, toward developing new time-resolved, trial-wise and longitudinal analysis techniques (for example, manifold-learning techniques for time-series data[31]). Exploiting systematic variability in the data allows for a deeper understanding of the ongoing and inevitable changes in task demands and the physiological adaptations they induce over time. Notably, by considering broader temporal scales and the effect of often-overlooked contextual factors (for example, time of day), we can gain additional insights into dynamics extending beyond the scope of single experiments.

Neural circuits are both locally specific and globally constrained

Because all parts of the nervous system are collectively shaped by common demands, the activity and structure of any local neural circuit depends on its embedding in the wider network. No part of the nervous system is fully independent from the rest. This intrinsic network embedding conflicts with a long-standing focus on parcellating the neural substrate in search of dissociable contributions to mental states and behavior. Although parcellation efforts align with lesion studies that show that damage to one part of the brain can lead to selective deficits in the agent's experiences and abilities[32], such findings do not imply that activity in different circuits is independent. For example, neural signals linked with an animal's movements are tightly integrated with sensory inputs across the brain (for example, ref. 18), suggesting that 'sensory systems' and 'motor systems' are not cleanly separable. This notion extends to the brain as a whole, which cannot be fully understood separate from its embedding within a larger nervous system that spans the entire body. A consequence of the interconnected nature of circuits is that measuring changes in local activity between task conditions does not straightforwardly indicate a circuit's involvement in a task or lack thereof. In particular, finding similar activity across conditions does not necessarily reflect the lack of that circuit's contribution to task performance. The circuit may contribute equally, with similar activity across conditions reflecting shared task demands. Alternatively, there could be a differential effect across conditions of that circuit on other circuits, despite similar local activity[8], or local inactivity itself could inform the global state and behavior[33]. This complexity suggests that the nervous system's activity and structure are not strictly modular[34]; however, nor are computations homogeneously distributed. Instead, the contribution of any given circuit to task performance is influenced by the contribution of other circuits within the broader network (Fig. 2). Furthermore, localized activity and lesion effects should not be taken as evidence for one-to-one mappings between functions and neurons. Considering the interconnected and dynamic nature of neural circuits, viewing the nervous system as a heterarchical network without a clear start or apex may provide a more accurate framework than a strict hierarchical model[35].

The considerations above suggest that understanding the contributions of local neural circuits to task performance requires examining their embedding within the wider network. The network embedding of local neural circuits can be revealed through causal perturbations (for example, local cooling[36], ultrasound[37] or other techniques[24,38])

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BOX 4

Elucidating individual differences in health and disease

A primary objective in understanding health and disease is to link the unique characteristics and history of individuals to potential health risks, diagnoses and personalized treatment options. Recent years have seen the popularization of brain-wide association studies for elucidating individual differences based on the mapping between physiological and behavioral markers[81]. However, although brain-wide association studies promise an understanding of how the unique characteristics of individuals and their history (for example, lifestyle) relate to physiology, in practice, their utility for cognitive neuroscience and clinical research is limited. For example, inherent assumptions of localization and the stationarity of brain functions (for example, when relating optimized task measures or questionnaires to resting-state data[81]) necessitate large study sample sizes and high resulting costs. Given the history-dependent and task-dependent nature of behavioral and physiological measurements and the strong dependencies in activity between local circuits, these approaches are, therefore, unlikely to comprehensively capture the multivariate spectrum of traits, behaviors and physiological characteristics that defines us.

Nowhere is the characterization of this spectrum more important than in the study of mental health, neurological disorders and neurodiversity. In hope of reducing costs and offering diagnoses and treatments at scale, much clinical research has focused on identifying specialized behavioral or physiological markers, rather than diversifying the tasks and measures used. One example that illustrates the risk of this specialization is the recent meta-level test of the serotonin hypothesis of depression, which did not confirm the long-standing assumption that depression is associated with lowered serotonin levels[82]. Ultimately, it is important to acknowledge that conditions such as depression, and neurodiversity more generally, are grounded in physiological and behavioral idiosyncrasies that are best understood in terms of their mutual constraints[83], which cannot be captured or treated using single, optimized measures or tasks.

Therefore, advancing the understanding of individual differences and health requires a move away from the model of the critical or 'silver bullet' experiment, and an increase in the diversity of tasks, measures and tested populations (for example, patient groups and different cultures). Multitask studies, especially when combined with rich behavioral and neural sampling over longer time periods (for example, All of Us initiative), are ideal to capture both within-participant and across-participant variability, which is key for assessing each individual in light of the spectrum defined by the population. In doing so, patterns that generalize across individuals (for example, activity during language processing[84]) can be identified, in addition to gaining a better understanding of how variation in individual histories shapes these patterns. Importantly, achieving this experimentation at the scale needed requires an expanded approach to behavioral testing (for example, ref. 28), which can reveal meaningful and stable individual differences (for example, ref. 85) and predict neurological disorders such as epilepsy (for example, in rodents[86]). Linking specific behavioral patterns to corresponding diagnoses could further enable earlier and more personalized interventions, which is especially crucial for diseases with late neurological symptoms such as Alzheimer's disease[87]. Lastly, it is important to acknowledge the interdependence between physiology and behavior for developing treatments: integrating medication-based and behavioral therapies is probably key for a holistic treatment of any neurological or mental health condition.

while quantifying the effect of the perturbation on the wider network and behavior across multiple task demands[39,40]. Although established perturbation techniques often limit experimental design and behavior (for example, they restrict the agent's movements), new methodological developments can overcome these limitations (for example, wireless optogenetic stimulation[41]). Combining multitask designs with activity-dependent tracing techniques (for example, ref. 42) is a promising approach to measure how local activity dynamics influence the wider network in a task-specific manner. Most importantly, interpretations of results should adopt an integrated view of the nervous system in which an interconnected network produces local activity dynamics that contribute to behavior and mental states in a task-dependent manner.

There is no singular function

The interconnected and dynamic nature of neural activity inherently complicates defining brain functions and their localization to specific circuits (for example, refs. 43,44). For example, although the function of area V5/MT has been described as motion perception or motion integration (for example, ref. 45), its neural responses reflect task aspects that extend beyond the movement of stimuli (for example, behavioral choice[46]). These findings are in line with the idea that mixed selectivity exhibited by neurons may be central for their flexible engagement in different tasks[47]. Mixed selectivity, together with strong dependencies in activity between circuits[34], suggests that neurons and neural ensembles can serve multiple functions depending on the agent's goal (Fig. 2). The difficulty in ascribing clear, single functions is underscored by research suggesting that the selectivity of neural circuits is not innate, even those traditionally thought to have evolved for specific sensory or motor functions. For example, language processing engages the early visual cortex in people born without sight[48], and circuits thought to control hand movements are engaged during foot movements in people born without hands[49]. Akin to the presumed functions of neurons, it is common to make a complementary assumption about the function of behaviors. For example, our thumb has a clear set of potential articulations, but those articulations serve different functions when grasping a mug, communicating through sign language, or swimming. Collectively, these examples illustrate that the function of neural or behavioral patterns can only be understood in the context of what the agent is aiming to do. Extending these ideas, the presence of an activity pattern in an experiment does not necessarily signify the engagement of a particular mental process. Although this task dependency complicates the definition of function, the question of function cannot be eschewed; it serves as a reminder that the formulation of a question steers toward a certain answer[50]. For example, identifying one function of a neuron or ensemble in one task may lead to a modular view of the nervous system that overlooks the complexity described above.

Capturing the complexity and task dependence of empirical measures starts with formulating the question: rather than asking about singular functions of neurons or behaviors, we suggest reformulating the question to probe their contribution to task performance. By exploring these contributions across various tasks and relating data to task demands, we may find not one but many answers, in keeping with the task dependence of our measures and the interconnected nature of the brain. Through analyzing similarities across results, principles that generalize across multiple tasks can be established for

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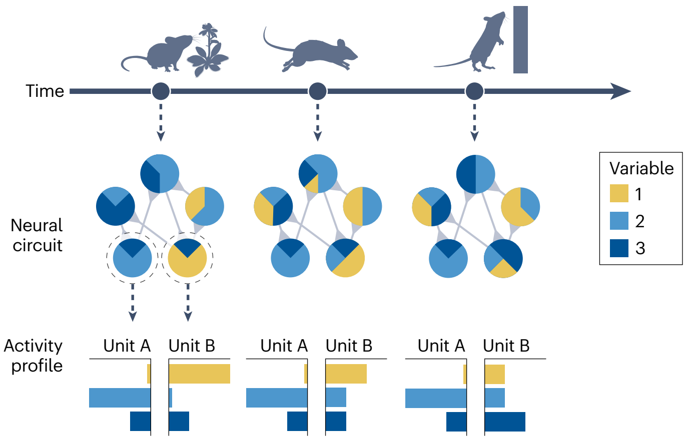

Fig. 2 | Interconnected neural circuits generate activity dynamics in service of mental and behavioral flexibility. Top, Goals, behavior and sensory impressions of the environment change over time in an interdependent manner. For example, a mouse prioritizes different aspects of the environment depending on whether it is eating, running or climbing. Middle, Neural circuit schematic with five example units, each of which may reflect an individual neuron or a local population of neurons. Each unit simultaneously codes for multiple variables (mixed selectivity, for example, color, head direction and optic flow), which depends on what the agent is trying to do (for example, posture may explain activity of a unit during running and climbing, but not during eating). Bottom, Activity profile of two example units (for example, explained variance in spike trains of two neurons or two neural populations). The activity profile of unit A generalizes across behavioral states, whereas the one of unit B does not. However, within unit B, certain elements do generalize across states (for example, portion of variance explained by variables 1 and 3). To discover the principles that are unique to each state, and those common to all states, a multitude of sensory and behavioral variables must be tracked and related to neural activity. Moreover, because each unit's activity depends on the activity of other units, large-scale neural recordings and network-level investigations are required. Finally, mixed selectivity and its task dependency suggest that neural circuits do not have one but many functions, which are definable only within the context of a task.

formal testing (Box 3). This approach leverages multitask studies that manipulate instructed goals in conjunction with other experimental components in a theory-driven manner, assessing how these goals affect our empirical measures (for example, inferring experimental goals from gaze patterns[51]).

Behavior is ubiquitous and fundamental

A central idea throughout our Perspective is that an organism's physiology can only be fully understood in the context of the behavior it produces. Behavior could in fact be viewed as the natural means to extend physiology into the environment to maintain homeostasis[16], and is therefore intrinsically linked to the mental states that arise (for example, visual experiences inherently reflect sensorimotor integration[20]). Even seemingly passive tasks involve behaviors in ways that may not be intuited (for example, saccades reveal recall content[22], pupil size indexes brightness of imagined stimuli[52]). Behavior is thus an essential consideration when interpreting neural activity recorded in any and all tasks used. Although many have already highlighted the importance of incorporating behavior in our understanding of the nervous system (for example, ref. 53), cognitive neuroscience often narrows behavioral analysis to a limited set of actions deemed relevant by experimenters, such as quantifying the accuracy and efficiency of a small set of instructed or cued actions (for example, lever presses). Typically, task-relevant actions are included, and task-irrelevant actions are often neglected (for example, fin strokes in the curious zebrafish, eye movements in the disengaged participant) or restricted (for example, head fixation). However, relying on intuition for classifying behaviors as task relevant or task irrelevant builds on strong assumptions that may obscure our understanding of task performance and risks overlooking important explanatory accounts of the data (for example, uninstructed behaviors explain V1 activity during auditory stimulation in mice[54]).

We contend that even seemingly task-irrelevant behaviors should not be considered epiphenomenal or a nuisance, as they could emerge as a direct expression and inherent part of any mental state. Thus, it is vital to consider behavior for all experiments, analyses, interpretations and models in cognitive neuroscience[53,55] (Box 5). Total control or restriction of behaviors is neither feasible nor desirable, because it disrupts task performance and undermines the ecological validity of an experiment. Instead, behavior should be comprehensively tracked and analyzed in relation to neural activity and the experimental components that were varied. Because behaviors are ubiquitous and their expression often unpredictable a priori, dense behavioral tracking is crucial even in seemingly passive tasks (for example, active sampling during recognition[56]), when behaviors are restricted (for example, fixation tasks and head restriction), or when no specific responses are required (for example, free foraging in mice and resting state in humans). Recent advances in machine learning are central to this aim as they enable the quantification of the rich behavioral repertoire of animals (for example, ref. 57) including humans (for example, ref. 58), which can then be linked to neural dynamics (for example, through behavioral encoding models[13]) or modeled together with neural activity in a joint framework[59]. A particularly exciting avenue in this direction is the automated quantification of behavioral syllables (that is, stereotyped behavioral patterns with learnable transition probabilities[57]), which allows for across-task comparisons of complex repeated action sequences. Especially when different behavioral measures are combined, this approach could uncover regularities in patterns that span different tasks at unanticipated levels of abstraction, and reveal task demands that are shared between experiments and would otherwise remain hidden (Box 2). Moreover, comparing behavioral syllables observed in an experiment to those measured in the wild would enable the estimation of the experiment's ecological validity, help to differentiate experimental phases[60] and allow individual traits to be examined with respect to behavioral repertoires obtained over ontogenetic and phylogenetic timescales (Box 4).

Adaptive theories of flexible demands

We have argued that cognitive neuroscience can articulate concepts that jointly explain behavioral, neural and mental states by centering the empirical approach on multitask studies and tests of generalization. The feasibility of formulating generalizable concepts has been demonstrated, for example, by work on attractor models that explain both neural and behavioral dynamics and their relationship[61]. This perspective calls for strengthening integrative efforts across all disciplines that fuel the field (for example, philosophy, psychology, biology and computer science), and overcoming tensions inherited from them (for example, outside-in versus inside-out debates; Fig. 3 and Box 1). Cognitive neuroscience can and should grow to be more than the sum of its constituent disciplines. Doing so requires moving beyond utilizing specialized tasks to map psychological concepts to neural or behavioral data, or mapping neural dynamics to natural behavior without constraints. Instead, we should aim to uncover patterns that generalize across data types and across tasks chosen based on theory, which will serve as the basis for new taxonomies.

Critically, we should not replace one rigid taxonomy with another, nor should theories and taxonomies be abandoned altogether in favor of purely data-driven quantifications. Cognitive neuroscience seeks to link utterly disparate phenomena (for example, scent and attraction) in pursuit of understanding a system that optimizes itself continuously from channels to networks, and whose state depends on environmental factors and on its own history. A single taxonomy cannot cover the necessary range of abstraction and spatiotemporal scales for such an endeavor[50], and new taxonomies must be capable of accommodating

BOX 5

Implications for computational models of brain and behavior

The present article highlights an action-oriented, dynamic and integrated view of the brain, with broad implications for computational models in cognitive neuroscience and psychiatry[88,89].

Models need behavior. First, as sensory impressions, goals and behavior are inextricable, neural, behavioral and mental states can never be fully understood based on stimulus features alone (that is, they are not stimulus computable). Therefore, models need to go beyond stimulus computability and incorporate goal-driven behavior, even models restricted to sensory processes. This includes popular deep neural network models (for example, of recognition[56]), which should vastly extend their behavioral repertoire (for example, active sampling) if used as models of the brain[89]. Other common modeling approaches incorporate actions more actively, typically to minimize the error between sensory inputs and predictions, to maximize reward, or a combination of both (for example, Bayesian models[90], active inference[91] or reinforcement learning[92]). Depending on how these models are trained, they can learn to perform complex behaviors and tasks similar to rodents and humans (for example, navigation[93]).

Models need to generalize across tasks. To capture the task-dependent nature of behavior and neural activity, models should incorporate task dependencies[3] and be formally tested on across-task generalization. Depending on the type of training, reinforcement learning models, for instance, can learn to generalize the structure of problems they solve across tasks (for example, ref. 94). A powerful approach to promote generalization, and to generate highly flexible models that reproduce real-world behavior is multitask learning (for example, ref. 95). Indeed, training deep neural networks on multiple tasks leads to the emergence of units with task-dependent mixed selectivity[96], to a representational geometry[97] similar to the brain, and to abstract representations that support generalization[98]. Although the properties of multitask trained networks depend on the relatedness of tasks that are chosen[99], and on which aspects of the tasks are relevant[98], such reports show that multitask models are feasible and can provide mechanistic insights, especially when their components are directly tested on task transfer[100].

Models need naturalistic tasks. Extending the behavioral repertoire and across-task generalization of modeling approaches must go hand in hand with the development of new naturalistic tasks and stimulus sets, for which rich behavioral and neural data need to be acquired in a wide range of species. Even those models currently capable of learning task-general representations are often limited to artificial scenarios, or even to static stimuli with defined onsets and offsets. However, in natural experience, objects and features can often be predicted by context and peripheral cues, which are then actively sampled, or by statistical regularities in their temporal co-occurrence. In the absence of direct quantifications of performance and the generalization of that performance under naturalistic conditions, the models will remain constrained to tasks that do not capture the real-world experience of living organisms. Likewise, because the precise tasks on which models are trained can have an important role in determining a model's properties[99], a large and diverse set of naturalistic tasks and stimulus sets is needed.

the changing nature of physiological, behavioral and mental states (for example, smartphones have rapidly become ubiquitous). These considerations do not mean that our current theories are inconsequential—theories are required for any experimentation and understanding (Box 3), but they do imply that cognitive neuroscience is a field in continuous evolution, without a definitive endpoint. A sustainable cognitive neuroscience is one that enables the creation of adaptable theories that capture the inevitable and ongoing changes in the system it is trying to understand. We propose that achieving this requires centering the approach on task demands, as they can parsimoniously account for a wide range of behavioral and neural dynamics observed across experiments, species, methodologies and research domains (Box 2).

Transforming the culture of cognitive neuroscience

It is broadly accepted that understanding the nervous system is a multigenerational endeavor that extends well beyond the capabilities of any single laboratory or institution, but fully embracing that understanding necessitates a radical shift in the current research culture. As a field, we need to maintain a mindset of sustained science and quantitative convergence (that is, reuse, refinement and extension of data and techniques by others), which starts with vastly increasing the depth and breadth of paradigm, data and code sharing and implementing standards for all of them[62]. Such open-science practices, by making research more accessible and inclusive, invite a diversification of perspectives urgently needed for challenging and refining theories. Open science is essential to the long-term objectives of cognitive neuroscience, such as unifying theories of behavioral, mental and neural states, and its practice should be strongly incentivized and rewarded, from experimental design to publication and tenure considerations.

Importantly, individual studies can follow the core suggestions outlined in this article, such as embracing multitask study designs and formal tests of generalization (Box 3). However, realizing the full potential of this approach will also require new large-scale initiatives that explore the influence of task demands across diverse populations and species with a variety of data collection techniques. Existing initiatives have already made important strides, for example by advancing data standards (for example, Brain Imaging Data Structure) and analysis pipelines (Brainlife), making datasets and code publicly available online (for example, OpenNeuro, GitHub), and increasing sample sizes while diversifying the types of data acquired for each individual (for example, All of Us initiative).

Notably, several initiatives have shared datasets involving multiple tasks (for example, CNeuroMod, Human Connectome Project, Adolescent Brain Cognitive Development project and Healthy Brain Network). However, most initiatives deployed small sets of specific tasks built around putative psychological concepts, often rather passive in nature (for example, resting state). By doing so, they miss much of the critical covariance in behavioral and neural dynamics (Box 3), and the utility of the data may not always justify the economic investments. Critically, the specificity of tasks is designed to test preexisting putative psychological concepts (for example, working memory) and thus the resulting datasets inherently favor those concepts, limiting opportunities to formulate new ones (Box 1). To maximize the utility of future data collection, initiatives should systematically vary multiple experimental components (for example, instructions and stimuli) while densely sampling neural activity and behavior under conditions that mimic natural settings as closely as possible[10]. Realizing such initiatives may necessitate new infrastructures (for example, community platforms for coordinating efforts across groups) and a consensus on priority research questions and methodologies. Ideally, research should

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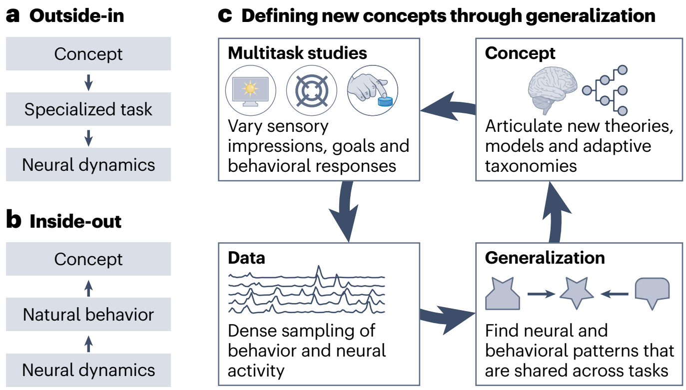

Fig. 3 | Task demands bridge mental concepts and data. a, Outside-in approach. Predefined psychological concepts are mapped to neural data using highly specialized tasks (for example, 'working memory task'). New concepts cannot be discovered. **b**, Inside-out approach. Neural dynamics recorded during natural behavior are mapped to actions and environmental factors. New concepts could be discovered, but mappings are non-unique and search space is underconstrained. **c**, Defining new concepts through generalization. Top left, Multitask studies systematically vary task demands by varying multiple experimental components (that is, sensory information, goals and behavior). Bottom left, Multitask experiments combined with neural recordings and behavioral tracking create datasets designed to leverage variability while maintaining experimental control. Bottom right: Formal tests of generalization identify data patterns that are shared across tasks and across behavioral and neural data. Top right, Generalizable patterns can be described, labeled and organized into a new taxonomy, which then informs experimental design.

prioritize understanding the demands placed on agents in their natural environments, and the potential societal benefits that may emerge from the work (for example, applications and therapeutic advances).

Concluding remarks

We have outlined a framework for cognitive neuroscience that centers on task demands, which emerge from interactions between an agent's goals, behavior and sensory impressions of the environment, and thus shape the activity and structure of the nervous system across spatial and temporal scales. To understand how task demands constrain behavior and neural activity jointly—and how these two domains are linked—varying multiple experimental components is essential (for example, instructions and stimuli). We further highlight the importance of dense behavioral sampling alongside large-scale recordings of neural activity, data sharing and code sharing to foster convergence, and integrative efforts across disciplines. By focusing on theoretical and practical implications, the proposed framework aims to pave the way toward the discovery of new concepts and theories that unify accounts of behavioral, physiological and mental states, in pursuit of results that generalize beyond the laboratory to the real world.

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Competing interests

The authors declare no competing interests.

Additional information

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