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Research Report

Prefrontal and parietal activity is modulated by the rule complexity of inductive reasoning and can be predicted by a cognitive model

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ABSTRACT

In neuroimaging studies, increased task complexity can lead to increased activation in task-specific regions or to activation of additional regions. How the brain adapts to increased rule complexity during inductive reasoning remains unclear. In the current study, three types of problems were created: simple rule induction (i.e., SI, with rule complexity of 1), complex rule induction (i.e., CI, with rule complexity of 2), and perceptual control. Our findings revealed that increased activations accompany increased rule complexity in the right dorsal lateral prefrontal cortex (DLPFC) and medial posterior parietal cortex (precuneus). A cognitive model predicted both the behavioral and brain imaging results. The current findings suggest that neural activity in frontal and parietal regions is modulated by rule complexity, which may shed light on the neural mechanisms of inductive reasoning.

1. Introduction

Number series completion (e.g., "2, 5, 8, 11, 14") is a typical numerical inductive reasoning task that has been widely used in studies of intelligence tests, problem solving, scientific discoveries and inductive reasoning (Simon and Kotovsky, 1963; Kotovsky and Simon, 1973; Holzman et al., 1983; Lefevre and Bisanz, 1986; Girelli et al., 2004). Two key component processes are required to solve number series problems (Girelli et al., 2004; Kotovsky and Simon, 1973): (1) rule identification, which includes relation detection, discovery of periodicity and the completion of pattern description; (2) rule extrapolation, which includes the detection of the answer position, isolation of part of the rule and the application of the rule to complete the blanks.

Relation detection involves examining the series and generating a hypothesis regarding how one element of the series is related to another. For example, in the series "2, 5, 8, 11, 14", the relation between the adjacent numbers is "+3". The discovery of periodicity involves the detection of period boundaries, and this component applies to complex series only (with period lengths > 1). The period length of the series is the number of elements that constitutes one complete cycle of the pattern. For example, the series "2 5 8 11 14" has a period length of 1 (with rule "+3"), while the series "3 7 5 9 7 11" has a period length of 2 because two relations occur before a cycle is completed (i.e., the rules "+4 −2"). The completion of a pattern description is the generation of a rule that accounts for the positions of all elements. This rule is used in the final processing stage of rule extrapolation. In this stage, the subject must complete the following processes: (a) assess the position within a period to which the answer will correspond, (b) isolate the part of the rule that applies to that position, and (c) apply that part of the rule to compute the answer. Notably, these steps apply to complex series only; simple series (with period lengths = 1) can be answered simply by applying the rule. Functional imaging studies have suggested that the complexity of a task which is critical to the pattern of activation elicits (Drager et al., 2004; Davalos et al., 2011). In our previous studies, we investigated the neural correlates of inductive reasoning using a number series completion task (Zhong et al., 2011; Jia et al., 2011; Liang et al., 2007, 2014; Yang et al., 2009). However, these studies either focused only on the priming effect in which the exposure to a number series facilitates the subsequent number (Zhong et al., 2011), only on the cognitive components of simple number series completion tasks (Jia et al., 2011), or only on strategy effects (Liang et al., 2014) and did not examine the effect of rule complexity. The inclusion of complexity may improve our ability to interpret task-related responses. Increased task complexity may lead to increased activation in task-specific regions or the activation of additional regions. The question of how the brain adapts to increased task complexity during inductive reasoning remains unanswered.

The present study aimed to explore the neural substrates of the effect of rule complexity on inductive reasoning. Because discovering

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periodicity and isolating a part of the rule are only involved in complex number series tasks (Girelli et al., 2004), we hypothesized that the neural systems of rule complexity in inductive reasoning would include cortical areas related to relational complexity integration and the mental representation of the problem state. Specifically, we expected to observe the involvement of the following areas: (1) the prefrontal cortex, which is known to support relational complexity (Christoff and Prabhakaran, 2001; Kroger et al., 2002; Crescentini et al., 2011), and (2) the posterior parietal cortex (PPC), which is known to support internal representations of problem states (Qin et al., 2004; Anderson, 2007; Danker and Anderson, 2007).

1.1. The ACT-R cognitive architecture

The adaptive control of thought-rational (ACT-R) cognitive architecture describes human cognition as a set of independent modules that interact through a central production system (Anderson, 2005, 2007). As illustrated in Fig. 1, the ACT-R uses visual and aural modules for perception and motor and vocal modules to interact with the external world. Additionally, the ACT-R also has a number of central cognitive modules: a procedural module for implementing the central production system, a declarative memory module for retrieving information, a goal module for state control, and a imaginal module for the problem state representation. The modules of the ACT-R have been mapped onto different regions of the brain (Anderson, 2005, 2007). Of particular relevance to the current study, one visual input module that is responsible for visual encoding has been associated with the fusiform area (Talairach center at ± 42, -61, -9). The motor and vocal output modules responsible for key presses and oral reporting have been associated with motor regions (centered at ± 41, -20, 50 and ± 43, -14, 33, respectively). The retrieval and imaginal central modules responsible for the retrieval of declarative memories and mental representation have been associated with the lateral inferior prefrontal region (LIPFC; centered at ± 43, 23, 24) and posterior parietal cortex (PPC; centered at ± 23, -63, 40), respectively. The external world and internal system interact through a set of buffers that hold information. There are two types of knowledge representations in the ACT-R, declarative knowledge and procedural knowledge. Declarative knowledge corresponds to things that are consciously known and can commonly be described to others. Procedural knowledge is knowledge that is displayed in behavior but is not conscious. In the ACT-R, declarative knowledge is represented in structures called chunks, and procedural knowledge is represented as rules called productions. Thus, chunks and productions are the basic building blocks of the ACT-R model.

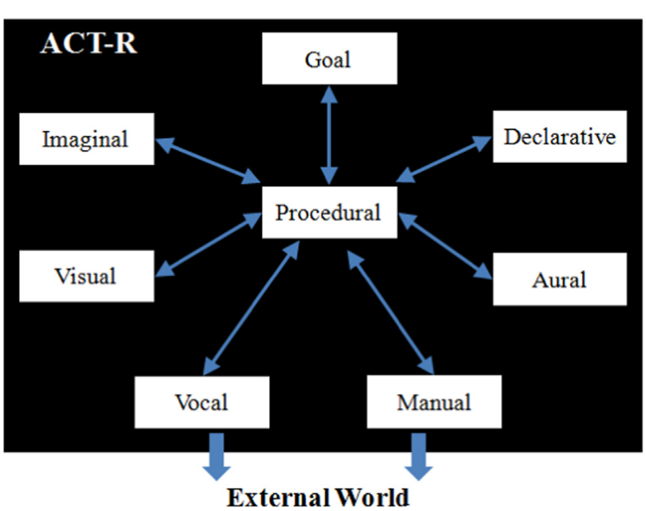

Fig. 1. The interaction among modules in ACT-R 6.0.

There are several parameters of the ACT-R that can be estimated. For example, in terms of the fitness of behavioral performance, the parameters of the times required to transfer visual attention from the screen to retrieve a declarative memory fact and modify the contents of the imaginal module can be estimated. Additionally, to make predictions about the exact time course of the BOLD response, the ACT-R module activity can be convolved with a gamma function. If the module is engaged, it will produce a BOLD response t time units later according to the following function (Boyton et al., 1996; Anderson et al., 2003):

$$H(t) = m(t/s)^{\alpha} e^{-(t/s)}$$

where m is the magnitude parameter and determines the height of the function, s is the scale parameter and determines the time scale, and α is the shape parameter and determines the narrowness of the function. The cumulative BOLD response in a particular module is the sum of the individual BOLD responses driven by a module's activities. This response can be modeled by convolving the hemodynamic response $H(t)$ with a demand function $D(t)$, which has a value of 1 when the module associated with that region is active and 0 otherwise:

$$B(t) = \int_0^t D(x)H(t-x)dx$$

Once the timings of the buffer actions are all determined, the BOLD functions can be predicted by estimating the magnitude parameter m, the shape parameter α, and the latency scale s for each brain region.

The second focus of the current study was to employ computational cognitive modeling to make specific predictions about the rule complexity effect. To further develop the roles of these regions in the rule complexity effect in inductive reasoning and to make our predictions more precise (in terms of the timing and level of activity), we tested our understanding of these processes by modeling the data within the ACT-R cognitive architecture.

2. Materials and methods

2.1. Subjects

Fifteen paid healthy undergraduate and postgraduate students (8 males) with a mean age of 24.3 ± 2.1 years participated in the experiment. All subjects were right-handed and had normal or corrected-to-normal vision. None of the subjects reported any history of neurological or psychiatric diseases. Written informed consent was obtained from each participant, and this study was approved by the Ethics Committee of Xuanwu Hospital, Capital Medical University.

2.2. Stimuli

Sixty number series tasks were evenly organized into *simple induction* (SI, with rule complexity = 1) and *complex induction* (CI, with rule complexity = 2). Additionally, 20 perceptual judging tasks with five “0” items (e.g., “0, 0, 0, 0, 0”) were taken as control tasks. Specifically, some interferential tasks that were identical in pattern to the inductions but without common rules (e.g., “1, 3, 8, 11, 14”) were included with the SI and CI tasks based on a pilot study. Twenty interferential tasks were included. The differences between the SI and CI tasks involved the period rule lengths and the cognitive components involved in the tasks. Specifically, the patterns of the SI tasks could be described by simple rules with period lengths of one, whereas the patterns of the CI tasks could be described with relatively complex rules with period lengths of two. For example, “+3” would be the relation for the SI task “2, 5, 8, 11, 14”, whereas “+8 −2” would be the relations for the CI task “21, 29, 27, 35, 33”. In contrast, in addition to the cognitive components of encoding, relation detection, pattern description, and answer production involved in the SI task, periodicity discovery and isolation of a part of the rule were also involved in the CI task. For all types of tasks, five numbers were presented. In total, 30 SI tasks, 30 CI tasks, 20 control tasks, and 20 interferential tasks were included, and all tasks were organized into 4 sessions. Each session contained 25 tasks that