Chapter 6
What Is a Task and How Do You Know If You Have One or More?

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Introduction

Understanding how the brain uses incoming sensory information to activate motor systems to produce goal-based behavior is a fundamental question in psychology and neuroscience. Not only are the links between the events in the environment and the desired actions potentially arbitrary (i.e., any stimulus can signal that any response should be made), but they must change according to the current context and the needs of the individual. Moreover, the environment does not consist of a single stimulus but rather presents a constantly changing torrent of objects and events, each of which may lead to multiple candidate actions. How does our brain navigate this sea of drives and affordances to chart a desirable course?

To develop rigorous theories for how we perform coherent behaviors in complex environments, psychologists and neuroscientists have proposed a range of accounts with a common theme. The overarching idea is that stimulus-response (SR) associations are activated by the environment and control processes are engaged so that only one goal drives behavior at a time. That is, theories of voluntary behavior differ along multiple dimensions, including how control is implemented (see, e.g., Badre et al., 2021; Braver, 2012; Cookson et al., 2020; Duncan, 2013; Grant et al., 2020; Hazeltine et al., 2011a; Koch et al., 2018; Logan, 2002; Weissman et al., 2014) and how control processes are organized (see., e.g., Badre & D'Esposito, 2009; Badre & Nee, 2018; Courtney et al., 2007; Dosenbach et al., 2008; Fuster, 2008; Koechlin & Summerfield, 2007; MacDonald et al., 2000; Petrides, 2006; Sakai, 2008), but they share the notion that control processes govern which SR associations become most

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D. Gozli, J. Valsiner (eds.), *Experimental Psychology*, Theory and History in the Human and Social Sciences, https://doi.org/10.1007/978-3-031-17053-9_6

active and ultimately drive behavior. The persistent reliance on SR associations may stem from the fact that the connection between stimulus codes, consisting of diverse representations of environmental events, and response codes, consisting of motor states, is mysterious, so the necessary computations to move from one to another is difficult to specify (Hommel et al., 2001; Prinz, 1990). The concept of an SR association provides a convenient shortcut for tackling this problem.

Psychological theories have applied this approach in a variety of ways. Early accounts proposed that a unitary central executive monitors the activation of SR associations and allows the most appropriate one to access motor structures (e.g., Norman & Shallice, 1986; Shallice, 1982). More contemporary theories have fractionated the central executive (e.g., Miyake et al., 2000; Monsell & Driver, 2000), but the basic division of labor has remained the same: A set of control processes enables some SR associations to win out over others and drive behavior. For example, the conflict adaptation model (Botvinick et al., 2001; see also Cohen et al., 1990) proposes that the coactivation of competing responses activates attentional systems that bias input, allowing task-relevant information to more strongly activate the relevant responses. Thus, according to this account, control is implemented through attentional processes modulating the activation of sensory representations (Desimone & Duncan, 1995). In this model, to diminish the activation of inappropriate SR associations, the corresponding stimuli are inhibited.

Some recent behavioral evidence suggests that the control processes mediating the effects explained by the conflict adaptation model involve more than just input attention (e.g., Grant et al., 2020; Hazeltine, et al., 2011b). In response, some modifications of the model have incorporated learning – that is, changes in the strengths of SR associations – rather than changes in the activation of stimulus representations to account for the dynamic control of behavior (e.g., Schmidt et al., 2016; Verguts & Notebaert, 2008). However, the basic idea remains that control processes external to the SR pathway modulate the activation of responses by stimuli.

Neuroscience accounts of cognitive control also largely rely on the notion of SR associations. Miller and Cohen's (2001) model of prefrontal cortex (PFC) function, for example, assumes the PFC essentially provides a set of intervening links between stimuli and responses, so contextual information can guide the activation from the stimulus to alternative responses that are more appropriate in a particular setting. While this approach adds intervening links between stimulus representations and response representations, it is consistent with the notion that behavior is driven by SR associations. Representations of context can bias which SR association is most active, but the contextual information, in conjunction with the stimulus information, still activates responses in a feedforward way. What has changed is that the input driving the selection of the response is now more complex, incorporating multiple aspects of the environment (e.g., context) or even information that is not present in the environment (e.g., the contents of working memory).

The idea that behavior is driven by SR associations is also at the heart of several popular theories of PFC function. These theories propose that the control of behavior is achieved through the coordinated activity of hierarchical modules in PFC that act on different levels of information that together determine which SR association guides behavior (for reviews, see Badre, 2008; Badre & D'Esposito, 2009; Badre & Nee, 2018). The exact nature of the hierarchy differs across theories, but they share the idea that associations between stimuli and responses are mediated by the most caudal regions of PFC. Which particular SR association drives behavior depends on goal-related or other contextual information mediated by modules in more rostral PFC regions. The more rostral in the hierarchy, the more abstract is the representation, and the less dependent it is on the current stimulus input.

In sum, the development of complex models of voluntary behavior has fractionated control processes so that a homuncular mechanism (i.e., a control process that has access to all relevant information and "decides" what to do) is no longer necessary for the selection of appropriate actions. However, in part to maintain computational tractability, these approaches continue to rely on the notion of the SR association as the basic unit driving goal-directed behavior.

Addressing the Limitations of SR Associations

Despite the widespread reliance on SR associations to explain how we behave, they do not provide an adequate framework to account for a range of voluntary behaviors (see Hazeltine & Schumacher, 2016). In fact, the SR association account does not even adequately explain phenomena from the behaviorist tradition from which the idea emerged. For example, Rescorla (1988a, b) argued that conditioning is better characterized as learning the relationship between the external environment and an animal's internal representation of that environment. Similarly, Tolman (1932) argued that animals create an internal representation of their world as they explore it. These, and other examples from behavioral psychology (c.f., Hazeltine & Schumacher, 2016), demonstrate that even non-human behavior involves more than simple SR associations. Indeed, an internal representation of the world (i.e., the animal's *task*) is fundamental.

In cognitive psychology, early evidence that complex mental representations guide behavior comes from Bartlett (1932) (and subsequently by Brewer & Treyens, 1981; Gozli, 2019; Tolman, 1948), who showed that the way we organize the relationship between learned information and our existing knowledge guides what we remember and how we remember it. For example, how witnesses represent an incident affects what and how they remember (Tuckey & Brewer, 2003). In addition to the effect of mental representations on memory, mental representations of our goals may also guide how we attend to and respond to the world.

In the area of cognitive psychology investigating human performance, the specific mental representations and processes required to perform a task are often called a *task set* (for reviews, see Monsell, 2003; Sakai, 2008). These representations are often explicitly hierarchal, combining different levels of our proximal and distal goals and additional information about the nature and organization of the task (e.g., Gozli, 2019; Schumacher & Hazeltine, 2016). The way we represent a task has behavioral consequences – from task-switching effects (discussed in more detail below) to guiding attention (Dreisbach, 2012) and to how and when we remain focused on an external task or allow our minds to wander (Bezdek et al., 2019; Murray et al., 2020).

To characterize the various approaches to understanding how complex representations can impinge on control processes and guide behavior, Badre et al. (2021) draw a distinction between modulatory accounts and transmissive accounts. Modulatory accounts assume that control processes monitor and adjust the activation of SR associations depending on independent representations of context and goal states (e.g., Botvinick et al., 2001; E. K. Miller & Cohen, 2001; Shallice, 1982). Thus, the SR associations are represented separately from the information that determines their appropriateness. Transmissive accounts, on the other hand, hold that SR associations are part of complex representations that include context and goal states (e.g., Duncan, 2013; Hazeltine, Lightman, et al., 2011; Hommel et al., 2001; Hommel et al., 2004; Kikumoto & Mayr, 2020; Schumacher & Hazeltine, 2016; see below). In this way, behavior is guided by the complex representations of actions rather than separate control processes that influence their activation.

We argue that, at least regarding voluntary behavior, the transmissive approach appears to have greater explanatory power because tasks are not simply collections of SR associations but are structured to include elaborate relationships that are not obviously related to the current context or goals. Consider, for example, when one reaches for a coffee mug to clean it rather than to fill it with coffee, which may be the more frequent behavior associated with the mug. In such cases, there are sometimes “action slips” (Norman, 1981) in which the presently undesired (and usually more frequent) action is performed with the object, suggesting that inhibitory processes must suppress actions that are inappropriate for the current circumstance. However, action slips typically occur when the individual is initiating an action (e.g., reaching for the mug), not in midstream (e.g., scrubbing the mug), suggesting that once the action is embedded in an ongoing task context, control is more stable. This is consistent with the proposal that the surrounding, related actions activate the current, appropriate response through the associations that have formed as part of the task representation.

A groundbreaking example of a transmissive account by Hommel and colleagues (Hommel, 2004; Hommel et al., 2001) proposed that voluntary actions are coded as *event files*. Event files are representations that bind stimulus features with the response features along with the current environmental context. The empirical foundation for this theory comes from studies showing that behavior is worse when only some task features overlap from one trial to the next (partial overlap) compared to both when all features overlap or non-overlap (Frings et al., 2020; Hommel, 1998). These results suggest that the context in which the stimulus and response appears is also encoded into the action representation (viz., the event file), even though they are extraneous to the actual SR applied to generate the action. In short, in event files, context is intrinsically bound with features of the stimuli and responses. This transmissive approach contrasts with modulatory accounts where contextual information activates control processes that activate or inhibit separate SR associations (as in, Botvinick et al., 2001; Miller & Cohen, 2001). Event file theory has generated a wealth of studies demonstrating that the production of a response leads to the encoding of multiple contextual factors, which, when repeated, may cause the retrieval of the same response, producing facilitation or conflict. However, the account does not directly address how this conflict is resolved and actions are ultimately selected.

Kikumoto and Mayr (2020) provided neuroscientific evidence for event files using EEG. They performed representational similarity analyses on the spectral profiles of EEG data to identify components associated with the stimulus, response, task set, and SR conjunction on a given trial in a task-switching procedure. The component associated specifically with the SR conjunction predicted intertrial variation in reaction time (RT). That is, the stronger this component, the faster the participants responded. This suggests that the strength of the event file or task set, which includes combined representations of the stimuli and responses, mediates performance. In a second experiment, they used tasks with overlapping SR rules. That is, some stimuli in the two tasks required the same response, and some stimuli required different responses. In this way they could distinguish between the effects of SR conjunctions with an integrated rule vs. rule-independent SR conjunctions. Consistent with their first experiment, they found that SR conjunction representations were more predictive than the stimulus and response representations alone. Additionally, the SR conjunction that was also integrated with the task set was more predictive than the task set-independent SR conjunction, suggesting that higher-order information plays a major role throughout action selection. Takacs et al. (2020) reported additional evidence for task set representations in EEG data where an identifiable cluster of activity for a task set remains after factoring out stimulus and response activity. Together these data support the idea that the combined representation of stimuli, responses, context, goals, etc. (i.e., the task set) is maintained by the brain and has consequences for goal-directed behavior.

One limitation with the event file theory is that the contextual information included in the event file is underspecified. Indeed, the original evidence for the theory focused on stimulus and response features – implicitly limiting context to environmental context, although recent formulations have been more inclusive (e.g., Frings et al., 2020). Schumacher and Hazeltine (2016) noted that the focus on stimulus and response information neglects the contribution of representations that include abstract relational information about actions. To emphasize that the organization of behavior is largely imposed by internal representations rather than the environment, Schumacher and Hazeltine proposed the task file hypothesis (see also Bezdek et al., 2019; Cookson et al., 2020; Grant et al., 2020; Hazeltine et al., 2011b; Smith et al., 2020). Like an event file, a task file is a mental representation that binds stimulus and response features with contextual information. However, task files explicitly include goals and motivations. Task files are also explicitly hierarchical, so that perceptual and response information is integrated as competition is resolved across a range of interactive levels (e.g., stimulus features, stimulus affordances, motor codes, intentions, etc.). Thus, resolving competition at a higher level in the hierarchy may alter the nature of the competition at lower levels (see Cookson et al., 2020; Hazeltine et al., 2011b; Smith et al., 2020).

As evidence for task files, Schumacher and Hazeltine point to findings in which the interactions between concurrent and consecutive actions do not appear to be driven by stimulus factors but rather the participants' conceptualizations of the task (e.g., Dreisbach, 2012; Halvorson & Hazeltine, 2015; Hazeltine, 2005; Schumacher & Schwarb, 2009). Note that, as the event file account allows for the integration of more diverse types of information (c.f., Frings et al., 2020), including intentions and goals, it converges with the task file framework. Nonetheless, theories of event files emphasize the role of the various sources of information as retrieval cues (Frings et al., 2020), and, by contrast, theories of task files would assume these sources operate at different levels of a control hierarchy.

Task Switching and Task Representation

The recognition that actions are embedded in larger representations that organize behavior in terms of information beyond what is available in the environment makes strong links with the extensive task-switching literature (c.f., Kiesel et al., 2010). Task switching investigates how the performance of one action affects the performance of an immediately subsequent one, and in many cases, the stimulus is ambiguous as to what action should be performed. In a typical procedure, it is assumed that the experimenter has a priori knowledge of the task structure. Participants are asked to make consecutive actions. Performance is compared when the actions belong to the same task to when the actions belong to different tasks. The general finding is that performance is worse (e.g., RT and error rates increase) when the actions belong to different tasks (i.e., a switch is required) compared to when they belong to the same task – even when no cues are used to generate expectations regarding the upcoming task (Jersild, 1927). In fact, performance costs associated with switching tasks are observed when the switch is determined solely by the participant (Arrington & Logan, 2004; Mittelstädt et al., 2018). Because switch costs are observed when neither the stimulus nor the response repeats (e.g., Mayr et al., 2006; Monsell, 2003; Rogers & Monsell, 1995; Ruthruff et al., 2001), these relationships do not depend solely on stimulus and response overlap. Thus, the standard interpretation of such findings is that SR associations are (somehow) grouped into task sets.

Neuroimaging experiments have largely accepted this interpretation and used task-switching procedures to identify brain regions and networks underlying the switch from one task to another. Meta-analyses of these studies have identified dorsolateral, ventrolateral, and medial PFC, as well as posterior parietal cortex as critical for task switching (Derrfuss et al., 2005; Kim et al., 2012). More recent studies, using pattern classification and functional connectivity analysis techniques, confirm the role that regions in the frontoparietal brain network play in task switching (e.g., Qiao et al., 2017; Qiao et al., 2020; Waskom et al., 2014; Wisniewski et al., 2015; Woolgar et al., 2011). The assumption is that frontoparietal regions encode the currently active SR associations. When a switch occurs, the network is reconfigured to represent the newly relevant set. For example, Qiao et al. (2017) used compound stimuli consisting of an overlapping face and building. Participants responded to the gender of the face or the size of the building on each trial. They found evidence that the representation of one of the tasks increased in frontoparietal cortex as the number of repeat trials increased, suggesting that this network maintains the current task set.

Limits of Task Switching

Yet, despite the wealth of studies examining how individuals switch from one task to another, the understanding of the underlying processes and how these processes are determined by the experimental procedures is weak. It is generally assumed that task sets are loaded into working memory together (e.g., Meiran et al., 2000; Rogers & Monsell, 1995), but this has received little experimental investigation (e.g., Logan, 2004). For example, if task sets are sets of SR associations that are necessarily loaded together in WM, their size should reflect capacity limits of working memory, which to the best of our knowledge has never been directly tested. That is, are tasks divided into separate sets when the number of possible stimuli or responses exceeds the capacity of working memory? If so, on what basis are these divided into sets? There is preliminary evidence that the number of responses, rather than the number of stimuli, provides the primary constraint on task set size (e.g., Wifall et al., 2015). The outsize weight that responses have compared to stimuli on task sets seems inconsistent with the simple idea that sets consist of SR associations. However, much of this experimental space has yet to be investigated. Moreover, we do not know how task boundaries are shaped by instructions, practice, and situational demands.

Not only are the operations associated with task switching not well-defined (see, e.g., Kiesel et al., 2010; Monsell, 2003; Wylie & Allport, 2000), they are likely not uniform across experiments. That is, the performance costs associated with switching tasks are often measured under conditions in which other operations might be affecting RT and accuracy. For example, in many task-switching experiments (e.g., Allport et al., 1994; Barcelo et al., 2006; Hayes et al., 1998; Poljac et al., 2009; Qiao et al., 2017), the switches involve reorienting from one stimulus dimension (e.g., color) to another (e.g., shape). This reorienting process may take time and may not be possible to complete before the onset of the stimulus indicating the response. There are experimental tasks that avoid this attention shift confound by using stimuli for which the relevant feature is identical across tasks. In these tasks (e.g., Kikumoto & Mayr, 2020; Logan & Schneider, 2006; Mayr & Bryck, 2005), a single relevant stimulus attribute is used (e.g., location), and the mappings between the attribute values and responses is changed on switch trials. While this approach eliminates shifts of attention as a possible source of the costs, it is by no means standard in the literature.

Moreover, because the same stimulus is associated with multiple responses, inhibition may be required to resolve the resulting response conflict. This is true in procedures using unidimensional stimuli (e.g., Logan & Schneider, 2006; Mayr & Bryck, 2005) as well as more procedures with multiple relevant stimulus dimensions (Kiesel et al., 2010; Mayr, 2002; Rogers & Monsell, 1995). Response conflict lengthens RT and increases error rates in many experimental paradigms, such as flanker (Eriksen & Eriksen, 1974), Stroop (Stroop, 1935), and Simon (Simon, 1969) tasks. These procedures are generally thought to engage cognitive control processes, but they are not thought to involve switching task sets. Thus, it can be argued that the inhibition of previously relevant mappings is part of the set of processes associated with task switching, but it is present in different degrees across the various procedures used to tap task-switching operations. In fact, when univalent stimuli (i.e., each stimulus associated with a single response) are used, switch costs are much reduced compared to when bivalent stimuli (i.e., each stimulus associated with multiple responses) are used (Rogers & Monsell, 1995), indicating that inhibitory process can play a sizeable role in the magnitude of switch costs. In sum, given the considerable differences in tasks, it is likely that the processes associated with task switching are not homogeneous across studies. In fact, researchers have exploited differences in the various procedures in efforts to isolate these putatively separate components associated with attention and inhibition (e.g., Gopher et al., 2000; Kim et al., 2012; Mayr et al., 2006; Rogers & Monsell, 1995), which raises the question of what components are essential to task switching.

Finally, our understanding of task switch costs is hindered by the fact that there is no independent definition of a task or task boundary (see Gozli, 2019). It is generally assumed that the experimenter controls or knows the task representation and then measures how crossing the boundary between tasks affects performance. The obvious limitation of this approach is that the task representation is not independently measured, so, while observed costs indicate that one set of transitional RTs (i.e., those that putatively cross the task boundary) are generally longer than the other set of transitional RTs (those that do not cross the boundary), there is limited evidence that the task structure consists of distinct sets of related SR associations. That is, because all the possible transitions are lumped into a small number of groups (usually two), the observation of a difference between these two groups is not highly diagnostic of a particular task structure. As the number of possible transitions increases, so does the risk that such differences are taken as support for a task structure that is quite different from what is actually supported by the data (see below). An unbiased approach would examine all possible transitions to provide a data-driven description of the task structure. In this way, one could verify that the task boundary identified by the observed switch cost was in fact the only (or even the dominant) boundary between different sets of responses. This approach is examined here.

Switching Costs May Not Always Reflect Switching Tasks

We conducted an experiment to compare task switch costs to the task structure as measured by a richer characterization of all the transitional RTs (see also Dykstra et al., in prep). To minimize the roles of inhibition and attention, we used univalent stimuli, presented one at a time in the center of the screen. Each response was mapped to a single stimulus, each of which was equally probable on every trial. For one group of participants, all the stimuli were numbers, whereas for the other group, the stimuli indicating left-sided responses were numbers, and the stimuli indicating right-sided response were faces. The question was whether switch costs would be observed under such conditions. Note that previous studies have observed switch costs with univalent stimuli although they are typically smaller than those observed with bivalent stimuli (e.g., Hirsch et al., 2016; Rogers & Monsell, 1995).

To increase the likelihood that some task structure would be imposed (i.e., the SR associations would be divided into task sets), we used a relatively large number of SR alternatives (8) and (in one condition) stimuli belonging to different categories (i.e., some were numbers and some were faces). As noted above, there is a reason to expect larger SR sets will be divided into smaller ones, even if the stimuli are univalent, to accommodate capacity limitations in working memory, although we are not aware of this being directly tested. Moreover, we are aware of no formal account that makes clear predictions about how this collection of SR alternatives will be divided into tasks (i.e., which SR pairs will be grouped together). Our aim is to consider all transitional RTs and thereby provide preliminary data on the role of stimulus properties on the organization of task representations.

Our analytical approach had two parts. First, to examine how stimulus set affected performance (a traditional task-switch cost), we used a two-way mixed design with a number of stimulus sets (1 or 2) as a between-subjects factor and switch (repeat or switch) as a within-subjects factor. The two groups of participants differed in terms whether the eight stimuli all belonged to one set (numbers 1–8) or two distinct sets (4 numbers and 4 black and white images of faces). Switches were defined as trials in which the stimulus on the previous trial indicated a response with the opposite hand as the stimulus on the current trials. For the two-set group, this meant that the stimulus set also switched (number ➔ face or face ➔ number) on consecutive trials.

Second, we evaluated the individual transitional RTs to generate a more complete, less theory-driven depiction of the task structure. Because we were not testing specific hypotheses about how tasks are organized with this alternative approach, we did not perform any inferential statistics on these transitional RTs. Instead, our goal was to compare how switch costs reflect more complete depictions of task structure gleaned from consideration of all transitions. To do this, we normalized RTs for each response and computed the normalized RT as a function of the previous response. Thus, we made no assumptions about which responses belong to the same set but instead used a data-driven approach to assess how responses appear to be grouped together according to the transitional RTs.

Method

Participants responded to a single stimulus appearing on each trial. A stimulus could appear in one of eight locations (four to left of center and four to right). Participants in the one-set group saw only numbers 1–8, each of which indicated one of the eight possible responses, the keys “s,” “d,” “f,” “g,” “h,” “j,” “k,” and “l” on the middle row of the qwerty keyboard. The four leftmost responses were made with the four fingers of the left hand, and the four rightmost responses were made with the four fingers of the right hand. The mapping was compatible so that 1 indicated the leftmost response, “s,” 2 the response second from the left “d,” etc. Participants in the two-set group saw numbers 1–4 and four faces that differed in terms of age (i.e., there was a child, college-aged adult, a middle-aged adult, and an older adult). The numbers were mapped to the leftmost responses so that the exact mappings for these stimuli were the same as in the one-set group. The faces were mapped to the rightmost responses in a compatible way so that the (clearly differentiable) ages were mapped in order from left to right. Pilot work in other studies has indicated that using this mapping is easy for participants and there are compatibility effects when performance on this mapping is compared to performance with other mappings. All stimuli (letters and numbers) were 0.8° visual angle presented in the center of the display.

Each trial began with presentation of a fixation cross in the center of the display for 500 ms. This was immediately followed by the stimulus which remained on screen for 1000 ms. The screen remained blank for 3000 ms. If the response was incorrect, a feedback screen showing the response mapping for all possible stimuli was displayed. If the response was correct, the next trial would begin.

Participants first completed a practice block of 16 trials and then 8 blocks of 32 trials in which each stimulus was presented four times. They then completed 2 blocks of 32 trials in which only a subset of the stimuli was presented. Data from these final two blocks will not be discussed here.[1]

Data Analysis

RTs from the first two blocks and first two trials of each block were not used in any of the analyses. Pilot data indicated that decreases in mean RT were much smaller after the first two blocks, making these data more stable for our transitional analyses. Moreover, we also eliminated all trials with an incorrect response and those immediately following an incorrect response. Error rates were low across all conditions (mean accuracy, 97%) and not analyzed further. RTs less than 200 ms and greater than 2000 ms were eliminated from the analyses.

First, we took the conventional approach and performed a 2 × 2 ANOVA on the RTs with group (one-set vs. two-set) as a between-subjects factor and switch (i.e.,

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[1] The blocks were included to examine the separate question of whether the decreases in RT associated with reducing the number of stimulus and response alternatives depended on which stimuli were removed from the set. This question is not related to our focus, which whether conventional measures of task switching capture the structure of task as determined by the complete set of transitional RTs.

whether the response on the current trial required the same hand as the response on the previous trial) as a within-subjects factor.

Second, we evaluated every possible transitional RT excluding exact repetitions. To eliminate differences between the various effects (e.g., participants may be faster responding with their right index fingers than their left little fingers), we computed the mean and standard deviation of the RT for each response for each participant and recoded this as a Z-score. The Z-scores were computed after eliminating stimulus repetition trials from the data set. In this way, we could evaluate how much slower or faster a particular response was for a particular participant given the response of the previous trial. To simplify and increase the number of observations per cell, we ignored the direction of the transition and grouped together pairs of responses regardless of which occurred on the previous trial and which occurred on the present trial. This approach is justified by the strong correlation between opposite direction transitions (e.g., response 3 ➔ response 6 and response 6➔ response 3), r = 0.90. Thus, each Z-score represented the relative speed of that particular response for that particular participant.

Because this is presently an exploratory analysis, we attempted to visualize the data by using an open software package called Gephi (gephi.org) that depicts the underlying structure of networks. Each response was given a node, and the connections between the nodes (edges) were given a weight depending on the mean RT Z-score for that transition regardless of direction:

$$weight = e^{-5Z}$$

where Z represents the mean RT score from the particular response transition. The constant 5 was chosen to provide a range of weight strengths (e.g., 0.2–12). These weights were then used to create a force atlas that assumed each node (response) repelled the others with a force dependent on a global parameter but was also attracted to each other node depending on the weight.[2] This caused the nodes to be distributed in two-dimensional space such that nodes with shorter transitional RTs are represented by thicker edges and are closer to each other. That is, if making one response led to making another response on the subsequent trial faster than average (and vice versa), the two are represented close together and connected by a thick line, and if making one response led to the slower production of the other (and vice versa), the two are represented farther apart and connected by a thin line. The goal is to create a depiction of the transitional RTs that allows all of them to be considered simultaneously.

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[2] The actual parameters used were as follows: inertia, 0.1; repulsion strength, 20,000.0; attraction strength, 10.0; maximum displacement, 10.0; auto-stabilized function, true; autostab strength, 80.0; autostab sensibility, 0.2; and gravity, 30.0. Only the repulsion strength was changed from the default value.

Results

The ANOVA performed on the RTs revealed no significant effect of group, $F(1,28) = 2.45$, $p = 0.13$, $\eta_p^2 = 0.08$ (one-set, 753 ms; two-set, 817 ms), but the effect of switch was significant, $F(1,28) = 43.75$, $p < 0.0001$, $\eta_p^2 = 0.61$ (repeat, 760 ms; switch, 810 ms) (Fig. 6.1). There was little indication of an interaction, $F(1,28) = 0.08$, $p = 0.78$, $\eta_p^2 = 0.003$ (one-set switch costs, 55 ms; two-set switch costs, 48 ms). In short, the ANOVA indicated that there was a significant cost of switching from the right hand to the left hand or vice versa but that this effect was the same for both groups. The magnitude of this costs was consistent with other studies reporting switch costs with univalent stimuli (e.g., Rogers & Monsell, 1995). Thus, based on the conventional approach, there is evidence for two task sets in both groups (separated by hand) and little evidence that the stimulus set manipulation affected the task representation as switch costs were nearly identical for the two groups. Alternatively, one could argue that costs do not reflect switch costs but instead indicate that the single task was organized by hand (e.g., Adam et al., 2003; Rosenbaum, 1980, 1983). In either case, the conventional analysis indicates that the SR mappings are grouped according to hand.

However, when we plotted the connection strengths of the responses for the two groups (Fig. 6.2), differences in the underlying structure became apparent.[3] For the one-set group (Fig. 6.2, Panel a), the structure was not readily characterized as two sets (clusters) but rather as a single chain that includes all responses. The connections between adjacent fingers, including left index [L4] and right index [R5], were stronger than the other connections, regardless of whether they were on the same or opposite sides. That is, the model recreated the relative positions of the eight

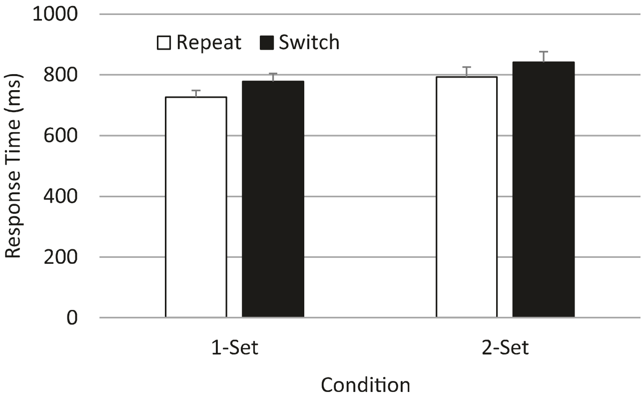

Fig. 6.1 Reaction times and standard errors for the four conditions of the experiment

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[3] The Gephi software does not make an identical graph each time it is run. That is, the positions vary from run to run; although with networks this is simple, they are generally similar. The graphs we have chosen are highly typical of those produced by the software. Moreover, our conclusions are based on the strengths of the connection between responses, depicted by the edge thickness. This is a property of the data and does not change across runs.

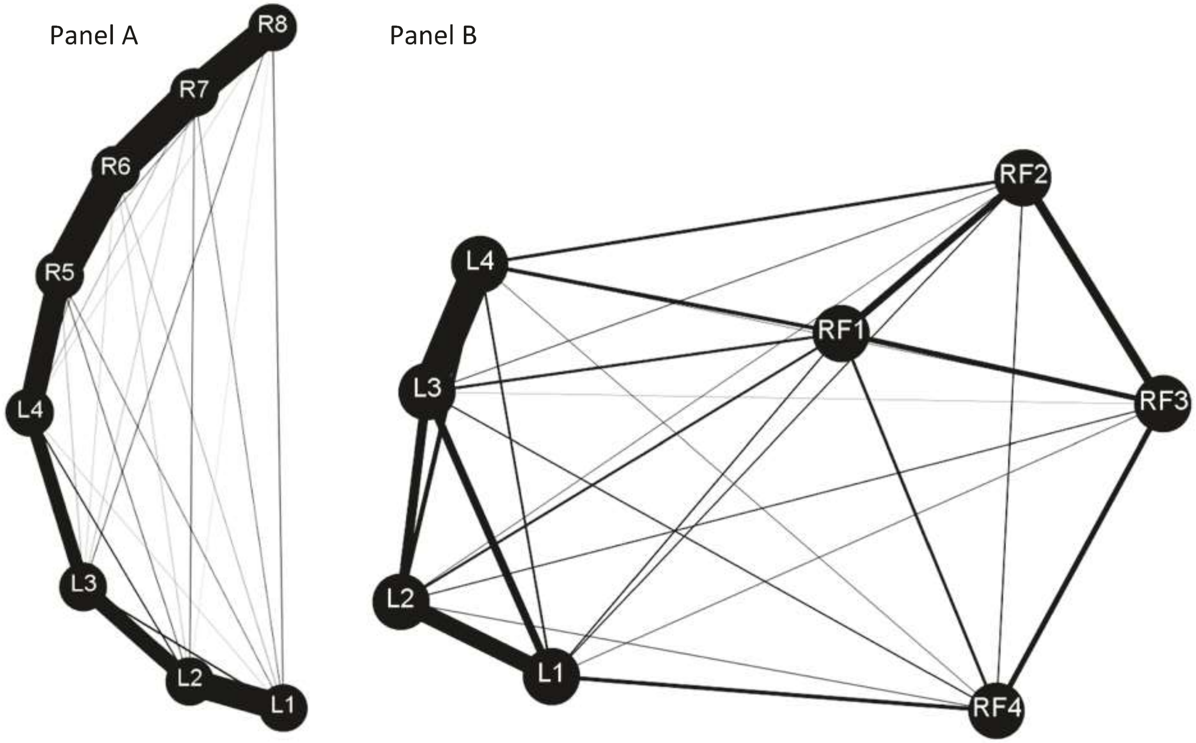

Fig. 6.2 Visual depictions of the structure of the transitional RTs from the two conditions of the experiment. Thickness of the lines and distance between nodes (edges) represent the transitional RT between responses, with thicker edges and shorter distances signifying shorter transitional RTs. Panel (**a**) shows the structure observed when numbers 1–8 were mapped to eight responses, four for the left hand (L1–L4) and four for the right hand (R5–R8). Panel (**b**) shows the structure when the left responses (L) were mapped to the numbers (1–4) and the right responses (R) were mapped to four faces (F1–F4)

responses in physical space given only the transitional RTs. However, because neighboring responses were much more common among responses that also share the same hand, this pattern produced a robust switch cost.

The pattern of transitional RTs produced a different task structure for the two-set group (Fig. 6.2, Panel b). Here, although the switch costs were nearly identical (and numerically smaller), the structure looked more like there are two subtasks, with the left-hand responses in one cluster and the right-hand responses in another. Moreover, while the left-hand responses, which were mapped to numbers, were aligned so that neighboring responses were closely associated with each other, the right-hand responses, which were mapped to faces, formed a quadrilateral. The right-hand responses are represented as quadrilateral because the edges are relatively weak and vary less (c.f. the range of edge thicknesses between left-sided responses and between right-sided responses).

Discussion

Although we designed the tasks to minimize attentional and inhibitory processes, robust switch costs were observed when participants switched from a left-sided response to a right-sided one or vice versa. Critically, the switch costs were nearly identical for the one-set and two-set groups. The traditional interpretation of these switch costs would suggest that both groups divided the tasks into sets based on response hand. That is, based on the switch cost, it appears that the stimuli had little effect on how the groups represented the tasks.

However, when we examined all the transitions between responses, it appeared that the switch costs reflected different factors across the two groups that differed in terms of the stimulus sets. Visualizations of the structure of the transitions suggested that, for the one-set group, the switch cost reflected the short RTs associated with neighboring responses, which were much more frequent for same-side response than for different-side responses (Fig. 6.2, Panel a). In contrast, for the two-set group, the cost appeared to reflect something more closely related to the conventional conceptualization of task sets (Fig. 6.2, Panel b). The left-side and right-side responses formed an approximation of two clusters – one for each task/stimulus set/hand.

Intriguingly, there were also differences among the strengths of edges within the two clusters, particularly the edges between left-hand responses. This provides evidence that the left- and right-side sets were structured differently: the left-side set was organized as a chain, with neighboring responses exclusively showing strong connections, whereas the right-side set was less organized less like a chain. Thus, the left-hand alternatives appear to be organized by the ordinal relationships of the stimuli and/or the relative locations of the responses, not simply as unstructured "set" of SR mappings.

We make no strong claims about the factors that affect the task representation or how tasks are generally represented. The patterns of transitional RTs may reflect a variety of factors, including switching from making the response with one hand to the other, processing different types of visual information, and retrieving mappings from memory. This was an exploratory analysis without a priori hypotheses. Our point is that different tasks that produce near-identical switch costs can have distinct underlying structures when the full set of transitional RTs is considered. The structure observed for the one-set condition does not appear consistent with the encoding of two task sets even though a significant switch cost was observed.

Thus, the present data demonstrate the pitfalls of taking switch costs as indicators of how tasks are represented. Instead, we propose that considering all possible transitions and visualizing the resulting structure may be useful for generating new hypotheses that do not rely on the premise that the experimenter has a priori knowledge of the task representation. With further work, testable hypotheses can be developed that specify the factors that determine the task representation. Consideration of these alternative hypotheses is not clearly motivated by traditional measures of switch costs but may only become apparent when finer-grained analyses of transitional RTs are used. For example, the present data suggest the use of numbers with a compatible SR mapping leads to strongly "linear" (i.e., strong connections between neighboring responses, weak connections elsewhere) representations, whereas other types of stimuli that may be distinguished in terms of non-ordinal relationships may produce different organizational clusters. In this way, evaluating the task structure can provide insight into how the encoding of tasks produces SR compatibility. That is, the connections can reveal interrelationships among items that reflect element-level compatibility (Fitts & Deininger, 1954; Kornblum et al., 1990).

The broader implications of this finding are that, at least when the tasks are sufficiently complex (i.e., have a sufficiently large number of stimuli and/or responses), there are effects on transitional RT (i.e., effects of the previous response on the current one) that are not readily attributable to attention and inhibition but appear to relate to the structure of the task representation. Therefore, caution is recommended when interpreting transitional RT effects, including switching (e.g., Rogers & Monsell, 1995), binding (e.g., Frings et al., 2020; Hommel, 1998), and anatomical effects (e.g., Collins & Frank, 2016).

Given that task representations affect transitional RTs when attentional, inhibitory, and binding demands are minimal, it is likely that they also contribute to RT when they are present. It is unclear how to disentangle the contributions of these various effects. However, it may be prudent to consider how binding or inhibitory effects, for example, are impacted by changes in the number of SR alternatives or other manipulations that affect the structure of a task to argue against alternative explanations. Considering all the possible transitions individually may reveal the factors that have the most salient effects on RT across an array of possible transitions.

Finally, we note that events that do not require responses, such as task cues (e.g., Allport et al., 1994; Kikumoto & Mayr, 2020; Mayr & Bryck, 2005; Qiao et al., 2017) and precues (e.g., Adam et al., 2003; Cookson et al., 2016; Cookson et al., 2020; Miller, 1985; Rosenbaum, 1980), can be evaluated in terms of their effects on specific responses. It is possible that such an approach would reveal that some task cues or precues show variable effectiveness for different responses within the set that they indicate (see Lien et al., 2005). Such variability might reflect the structure of the task representation as particular responses may be more strongly associated with the other members of the cued group.

Summary

Cognitive control is often framed as a process of selecting some SR associations over others, but there is a wealth of evidence indicating that SR associations are not adequate for describing how voluntary behavior is guided by sensory systems (see Hazeltine & Schumacher, 2016). Not understanding how tasks are represented poses a serious obstacle for theories of cognitive control. A better conceptualization of the task representations governed by control processes will help specify how they operate.

The dominant description of task representations is the task set, a collection of SR associations, whose presence is inferred primarily through task-switch costs. However, we argue that this approach has serious limitations that are often ignored. First, task switch costs likely reflect numerous processes, including those relating to attention and inhibition, that vary across experimental procedures and complicate their interpretation. While attention and inhibition, for example, are considered related to cognitive control, their roles in task representation are less clear. The present data indicate that even when all responses are made to univalent stimuli presented alone, structure in the transitional RTs is observed.

Second, the switch cost measure is coarse in that it lumps transitions into a small number of (usually two) categories. As we demonstrate empirically, this procedure can produce misleading results. Observing a performance cost when a putative task boundary is crossed may be too coarse a measure to adequately describe how a task is organized. Unfortunately, alternative organizations that may produce the observed cost are rarely considered.

It may be productive to abandon the notion that task representations consist of packets of SR associations. Instead, we should consider how tasks are structured by evaluating how the performance of different components of task affects others. This can be done without assuming that the task representation relies on grouped SR associations. Each action may be bound to others at different levels of a hierarchical representation (Gozli, 2019; Schumacher & Hazeltine, 2016), which may produce complex effects that are not easily categorized in terms of membership in a task set. Coarse measures of transitional effects such as task switch costs may reify this simplistic task set account and therefore should be used with caution. In short, the observation of task switch cost does not necessarily indicate that behavior is generated by SR association organized into task sets.

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