TASK SWITCHING OVER THE LIFESPAN

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Abstract

People often switch from one goal to another, in response to changing environmental demands. Task switching affords flexibility, but at a price. A robust switch cost ensues, whereby individuals are slower and less accurate when switching between tasks than when repeating tasks. The current dissertation investigated the factors that contribute to a switch cost, using an exceptionally large sample of over 25,000 individuals (ages 10 to over 65) collected online.

Switch costs are interpreted as the duration of psychological processes that are recruited to shift between tasks. In Study 1, shifting a task took 576 ms (or 108%) longer than performing a single task. Shifting tasks resulted in a 34% immediate decrease in productivity. An additional 74% long-term decrease in productivity occurred from maintaining readiness for a shift, and for using a cue to select a task, both of which occur even without an actual shift taking place. The results show that the seemingly simple switch cost involves multiple processes.

Understanding these processes is crucial to interpret how flexibility varies with age. In Study 2A, task switching process developed until adulthood and then declined, similar to general cognitive ability. However, each process changed differently with age. Findings show that decline is not simply development in reverse: The rate of decline in mid to late adulthood was up to 20 times slower than the rapid development in adolescence; Middle-aged adults were slower than young adults, but as accurate; They maintained less advance readiness but used contextual cues as well as their younger counterparts. In Study 2B, the effects of age were replicated in an independent sample using identical methodology. These findings highlight the usefulness of web-based data collection, effect size estimation, and segmented regression techniques.
Keywords: executive function, lifespan cognition, switch cost, task switching, web-based research, cognitive psychology, development, aging, multitasking, context switching

Dedication

To Keith LaPlume

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1. General Introduction

Writing a dissertation or a research paper is not an easy task. The task of writing is made more difficult if a person frequently changes to an alternate task, such as responding to email notifications that pop up or to students who drop in for meetings. Writing is influenced even when changing to a simple task, such as briefly looking up a citation or formatting a page. The price of constantly moving between competing goals is reflected in the common saying, ‘having one’s fingers in too many pies’. Academic researchers often find that their greatest productivity comes when working on one task at a time, a notion built into the sabbatical year that gives university professors a year off from their teaching and service responsibilities to focus on their scholarly agenda.

The expense of trying to do too many things at once seems obvious. However, people are regularly faced with constantly changing environmental demands. Nearly a millennium ago, the ancient philosopher Heraclitus hyperbolically proposed that change is the only constant in life (Graham, 2015). Although such a claim is exaggerated, many everyday environments require moving from one action to another, and often back and forth between different goals. When driving a vehicle for example, one must frequently shift between pressing the brake and gas pedals in response to the fluctuating surroundings.

Since the need to respond adaptively is inevitable, individuals learn to coordinate their performance between the multiple goals afforded by their changing environments. What is more, they do so rather successfully. For example, experienced drivers switch between actions very quickly, but also accurately. Similarly, when not on a sabbatical, professors achieve the noteworthy feat of wearing the ‘many hats’ of researcher, teacher, mentor, and university service worker.

In experimental psychology, flexibility is studied by how individuals alter their behaviour when shifting between different goals (*task switching*) as quickly and accurately as possible. Studying task switching gives researchers an insight into the mental processes that are recruited to adapt to changing environments. The principal finding from task switching research is that humans demonstrate remarkable flexibility, but at a price. There is a performance cost (*switch cost*) when changing from one goal to another compared to repeating a single goal.

The switch cost represents one of the most robust effects in cognitive psychology (Dreisbach, Goschke, & Haider, 2007). As researchers looked further into the nature of a switch cost, they found that what appeared to be a simple phenomenon encompassed several contributing cognitive processes (Kiesel et al., 2010; Meiran, 2010; Vandierendonck, Liefooghe, & Verbruggen, 2010). Thinking of task switching as a single process is an oversimplification of the different processes that contribute to a switch cost.

1.1 Goals of the dissertation

“*It can be argued within the sciences that the most important approach to the understanding of complex systems, such as mental processes, is to analyse them into parts or modules—to decompose them—and then discover what each part does, what other parts influence it, and what influence it has on other parts. Thus one of the goals of cognitive science in understanding the mental process that underlies the performance of even a simple task, such as naming a digit, is to determine what the parts of that process are*” (Sternberg, 1998, p. 705).

This dissertation targets the goal of understanding mental processes, specifically, the mental processes that constitute a switch cost. A useful way of understanding a complex process is to break it down into its constituent parts. The current dissertation aims to parse the complex ability of task switching into its multiple underlying processes.

Research studies on individual differences in task switching with age have also found that these control processes are expressed differently at different points in life (Cepeda, Kramer, & Gonzalez de Sather, 2001; Reimers & Maylor, 2005). Disentangling the interplay between processes is essential to interpret age differences on task switching. The aims of the dissertation are to

1. fractionate a switch cost into contributing processes (Study 1), and
2. measure effects of age on each of these processes (Study 2).

Study 1 uses a fine-grained breakdown into parts of a switch cost, which furthers existing knowledge on the coarser grain of task switching, and more generally, on cognitive control of behaviour in changing environments. Study 2 applies the breakdown of task switching processes to lifespan development, complemented with a fine-grained analysis of the effects of age. To test whether effects of age can be replicated, Study 2A was repeated using identical methodology and a separately collected sample in Study 2B. Before presenting versions of submitted manuscript publications for each study, the dissertation will summarize the background for each study.

1.1.1 Goal 1: Processes that contribute to a switch cost

1.1.1.1 Defining the switch cost

Switch cost refers to the finding that individuals perform worse when shifting between different goals (*tasks*) that could be performed on the same set of stimuli, compared to repeating goals. Switch costs consistently occur during task switching, despite the actual requirements of each task being the same whether shifting or repeating. The size of the switch cost is substantial—it occurs for hundreds of milliseconds while standard reaction time effects occur for tens of milliseconds (Monsell & Driver, 2000). It persists even after practice, additional time to prepare, or advance knowledge of an upcoming switch. It generalizes across a range of different domains, including numerical, visual, and verbal tasks (Kray & Lindenberger, 2000).

A switch cost is experimentally demonstrated using a *task switching paradigm* (Figure 1.1). In a typical task switching paradigm, individuals are given blocks of trials with one task at a time to perform (*non-switch blocks*), followed by a mixed block of trials in which they are instructed to shift between tasks (*switch block*). In the *explicit cuing* version of the paradigm, shifting occurs randomly, in response to a signal (a *cue*) that indicates which task is to be performed. The paradigm consistently shows that individuals are slower and less accurate when changing tasks than when repeating tasks.

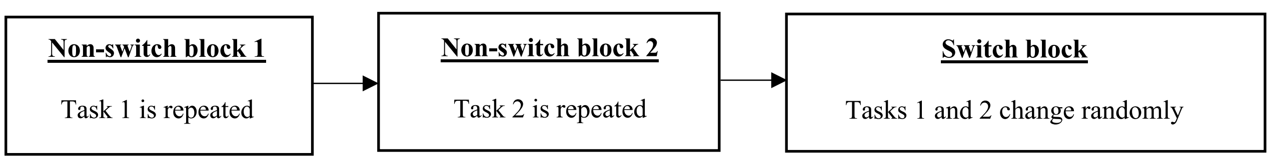

Figure 1.1: A standard task switching paradigm

One task is performed on a set of stimuli (non-switch block 1), followed by a different task (non-switch block 2). Finally, individuals switch between performing the different tasks. A switch cost describes the finding that individuals perform worse when changing tasks compared to repeating tasks.

An example of task switching is the emotion-gender paradigm, which was used in the current project (Figure 1.2). Individuals are shown stimuli of faces that vary on two dimensions: emotion (happy or sad), and gender (male or female). Participants perform the tasks by pressing a key to select a response based on the task: happy or sad for the emotion task, and male or female for the gender task. The words ‘emotion’ and ‘gender’ are presented below the faces as cues on which task to perform. Individuals first categorize the faces according to emotion (non-switch block 1), then according to gender (non-switch block 2). Finally, they shift between responding to emotion and gender (switch block).

Figure 1.2: An example stimulus presentation

In the emotion-gender task switching paradigm, a face stimulus is presented in the centre of the screen (in this case, a happy female), with a cue below the stimulus (the word 'EMOTION') on which task to perform. Keyboard presses with the response options for each task ('MALE' or 'FEMALE', and 'SAD' or 'HAPPY') are indicated on the left ('Z') and right of the screen ('M'). The correct response in this demonstration is 'K'.

Task switching falls under the broader umbrella of executive functions, a family of control abilities that produce goal-oriented behaviour (Miyake, Friedman, Emerson, Witzki, Howerter, & Wager, 2000). Task switching and other executive functions are linked to real-world outcomes such as academic scores, job success, physical health, and mental health (Diamond, 2013). Since it is widely replicated and practically relevant, a growing literature is exploring ways of improving task switching and other executive functions. These applications range from lab training via computer activities (Karbach & Kray, 2009), to real-world training activities such as bilingualism (D'Souza & Wiseheart, 2019), dance (D'Souza & Wiseheart, 2018), music (D'Souza, Moradzadeh, & Wiseheart, 2018), and visual art (Johnson, D'Souza, & Wiseheart, 2019).

1.1.1.2 Fractionating a switch cost

The introduction of the task switching paradigm is attributed to Jersild (1927). Jersild created an *alternating runs paradigm*, in which participants were given lists of items and asked to perform pairs of tasks on them (e.g., adding, subtracting, creating antonyms) by alternating between one task and another. Large costs were observed on accuracy when alternating between tasks compared to repeating tasks. There was a revival of interest in the paradigm nearly 50 years later, when the alternation cost was replicated using choice reaction time experiments, with the addition of a cue to enable random switching. However, it was only in the mid-90s when a surge of interest in the task switching paradigm developed (Monsell, 2003). The following decades experienced an increase in task switching research.

As researchers investigated the switch cost in greater detail, several fascinating discoveries emerged. First, the original switch cost was further divided into the *within-block* difference between trials in a switch block, and the *between-block* difference between the switch block and non-switch blocks. The within-block difference demonstrates a *local switch cost* of changing a task, measured as the slowing on trials when a task changes compared to trials when a task repeats (Rogers & Monsell, 1995). In the example introduced at the start of this dissertation, a local switch cost could represent slowing down on writing a paper after you switched to meeting a student.

The between-block difference demonstrates a *global switch cost* of maintaining increased readiness to prepare for a possible task change in a switch block, regardless of whether a task change occurs. The global switch cost measures the slowing when a task repeats in a switch block compared to when a task repeats in a non-switch block (Los, 1996). An example of a global switch cost is slowing down on your writing in the anticipation that a student may come in to your office for a meeting, even if the student does not actually come in (and sadly, they often do not!).

A decade later, local switch was further divided into the *task switch cost* of changing a task and the *cue switch cost* of changing a cue. The cue switch cost was measured by adding a second cue per task, creating a *double cuing* version of the standard task switching paradigm (Logan & Bundesen, 2003; Mayr & Kliegl, 2003). The double cuing paradigm was an important advancement, as the original paradigm involved a cue change and a task change together. Using two cues isolated a cue change from a task change, allowing measurement of a cue switch cost regardless of whether a task change occurs. An example of a cue switch cost is a student emailing you to say they are coming in to meet you, then also phoning your office to say they are coming in to meet you. Both cues provide the same information, and either is sufficient to indicate the necessary action—that you need to prepare for the student's arrival. Such cues mean the same thing (yet students will sometimes use multiple redundant ways to reach you!) and have the effect of slowing you down even if the goal that they signal (the student's arrival) does not actually occur.

A third interesting discovery is that not all task switches are the same. Some tasks used in a task switching paradigm may be easier or more practiced than others. A classic demonstration of unequal tasks is the Stroop paradigm, in which individuals are asked to either read the colour name or identify the ink colour of a list of words (MacLeod, 1992). People are much quicker and more accurate when reading the colour name than when identifying the ink colour, since they have much more practice with reading in daily life. During task switching with tasks of different difficulty levels, one might expect a smaller cost of switching to the easy task than of switching to the difficult task. Yet sometimes, the opposite occurs. A counterintuitive finding has been observed of a larger cost of switching to the easy task than of switching to the difficult task (Allport, Styles, & Hsieh, 1994). This backward effect (*asymmetric switch cost*) is considered to reflect the 'stickiness' from carryover of the previous difficult task onto the current easy task. An example of an asymmetric switch cost is that it may be more taxing to switch back to the difficult task of writing after the easier task of meeting with a student, than the other way around (meeting a student is also a difficult task, but one could argue it is less difficult in comparison to writing!).

These effects can be applied to the illustration of the emotion-gender paradigm. A local switch cost is demonstrated by changing from the emotion to the gender task (or from the gender to the emotion task) in the switch block versus repeating either task. A global switch cost is demonstrated by repeating the emotion or gender task in the switch block versus the non-switch block, since only the switch block has the possibility of a switch to the other task.

A double cuing version of the emotion-gender paradigm can be creating by adding two cues per task: the words 'emotion' or 'feeling' for the emotion task, and the words 'gender' or 'sex' for the gender task. A task switch cost is demonstrated by changing from the emotion task to the gender task (i.e., from the 'emotion' or 'feeling' cue, to the 'gender' or 'sex' cue, or vice versa), while a cue switch cost is demonstrated by changing from one cue for a task to another cue for the same task (i.e., from 'emotion' to 'feeling', or vice versa, and from 'sex' to 'gender', or vice versa; Figure 1.3).

The tasks also have different difficulty levels. Individuals process emotional expression and gender in faces using different pathways, and it is sometimes a bit easier for individuals to discriminate gender than emotion in faces (Bruce & Young, 1986; Haxby, Hoffman, & Gobbini, 2001). An asymmetric switch cost would be demonstrated by a smaller cost of changing to the difficult task of emotion than of changing to the easy task of gender.

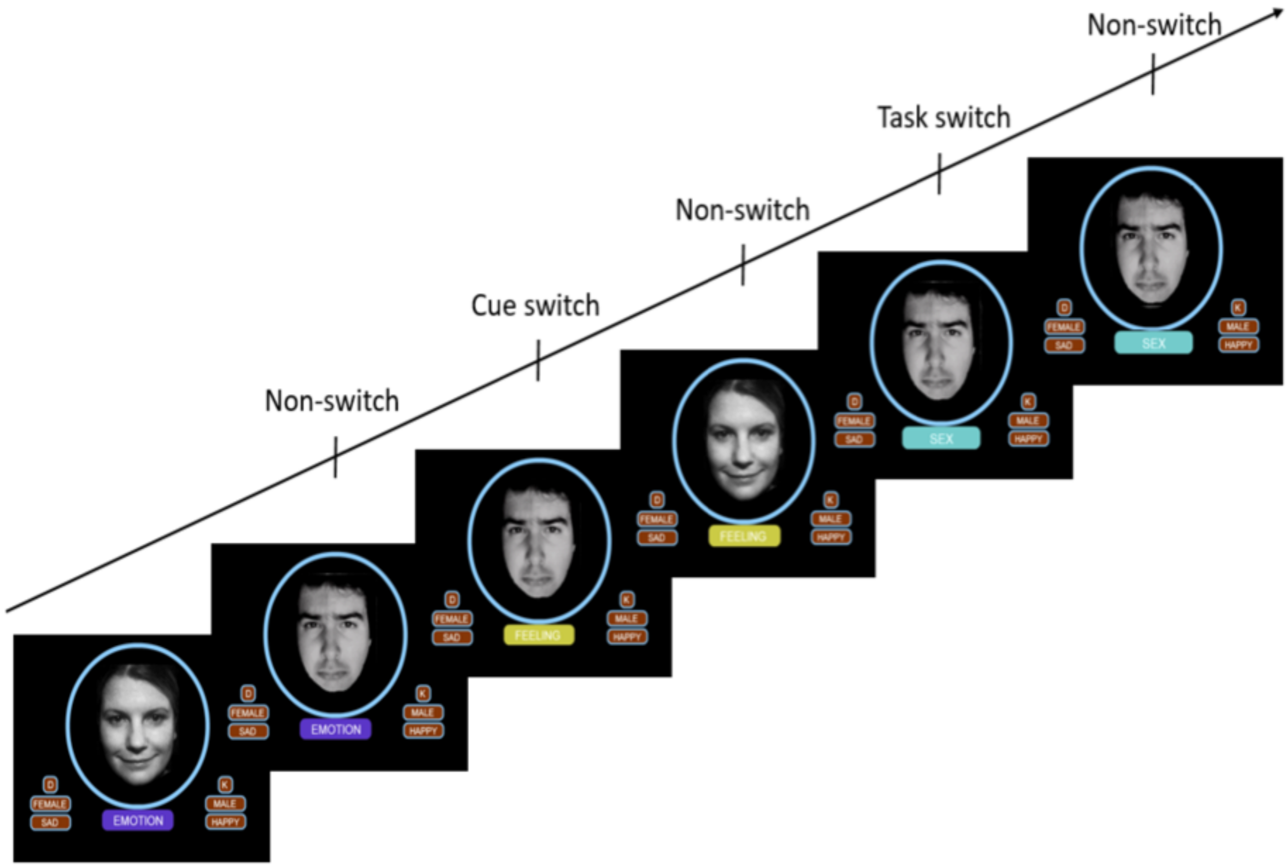

Figure 1.3: Trial types in the double cuing paradigm

Transitions from one trial to another are used to create trial types. When a new stimulus is presented, the task and cue could stay the same (non-switch trial; e.g., ‘EMOTION’ to ‘EMOTION’), the cue could change but not the task (cue switch trial; e.g., ‘EMOTION’ to ‘FEELING’), or both could change (task switch trial; e.g., ‘FEELING’ to ‘SEX’).

In summary, evidence clearly demonstrates that part of the switch cost arises from the supporting processes to prepare for a task change. These demonstrations show that a switch cost represents a number of contributing effects in addition to changing a task itself. Global switch cost and cue switch costs are widely replicated (Braver, Reynolds, & Donaldson, 2003; Jost, De Baene, Koch, & Brass, 2015; Los, 1999). However, these two findings have not been measured in relation to each other, thus all existing studies on cue switch cost build on the assumption that a cue change is dependent on global switch cost. The entire cue switch literature makes this assumption, yet it has not been formally stated or tested. Study 1 fills this gap by combining the standard task switching paradigm and the double cuing paradigm, with the primary aim of investigating the consequence of the standard observation of a global switch cost on the cue change manipulation. The unexpected asymmetric switch cost is not always found (Arbuthnott, 2008; Koch, Gade, Schuch, & Philipp, 2010). The secondary aim of study 1 is to test this effect.

1.1.1.3 Explaining a switch cost

Measuring a switch cost is theoretically interesting to understand how individuals organize their mental resources to act flexibly in a changing environment. Although switching between tasks is common in everyday life, most cognitive psychology paradigms focus on performance of a single task. The task switching paradigm thus offers a unique way of testing goal-directed behaviour and has widely been cited as a prime example of measuring cognitive control (Monsell, 2003).

The question of cognitive control dates back to philosophical speculations about the nature of human mental faculties. On one hand, people feel able to exert voluntary control over their behaviour. On the other hand, people also feel at the mercy of their habits or impulses. The ability to reflect on one's behaviour implies that humans can act intentionally, and in accordance with their free will. Yet, humans also exhibit seemingly uncontrolled behaviours when something triggers a previously learned response or reflex. The interplay between voluntary and involuntary behaviour is seen in that people do things that they do not intend to do, and do not do things that they intend to do.

Psychological evidence supports the dilemma between voluntary and automatic behaviour. A number of complex human behaviours can be explained by automatically learned patterns triggered in a *bottom-up* way by the environment (Roediger, 1990; Tulving & Schacter, 1990). However, other complex human behaviours need to recruit conscious thought for the intentional *top-down* control of behaviour (Miyake et al., 2000; Norman & Shallice, 1986). Investigating task switching addresses the voluntary-involuntary debate by looking at how conscious control operations and automatic causal associations each contribute to goal-directed behaviour.

Researchers have proposed several theories to explain the constellation of processes that underlie a switch cost. One set of early theories claim that a switch cost reflects a voluntary process to configure a plan of action when *shifting to* a new task (*task preparation theories*). Task preparation theories build on the intuitive notion that task switching requires intentionally configuring a task to select a response (Rogers & Monsell, 1995). Opposing theories proposed that a switch cost reflected automatically triggered associations that have been learned for tasks (*task priming theories*) or cues (*cue priming theories*). Task priming theories use the finding of an asymmetric switch cost to claim that a switch cost involves automatic carryover when *shifting away from* a previous task (Allport & Whylie, 1999). Cue priming theories use the finding of a cue switch cost to claim that a switch cost involves using a cue to automatically trigger *shifting to* a new task. Study 1 tests how these contrasting theoretical predictions fit with observed effects from fractionating a switch cost.

1.1.2 Goal 2: Effects of age on switch cost

1.1.2.1 Cognition over the lifespan

The second aim of the dissertation is to examine how switch cost varies with age. Studying age is especially relevant to studying flexibility. The only constant is change, and that applies to human lifespan development. Humans are constantly adapting: Development begins in the womb and continues for the rest of a person's lifetime. The study of change is the cornerstone of the study of development. Investigating development therefore offers an excellent vantage point to address the question of how individuals respond adaptively to a changing environment.

Heraclitus' position on the constancy of change was complemented by his position on the symmetry of change, that 'the path up' and the 'path down' are 'one and the same' (also called the unity of opposites, Graham, 2015). It is common to apply this notion to think of human development and aging as symmetrical processes. The symmetry of development and aging is well-characterized in William Shakespeare's popular seven stages monologue, in which human life begins with frailty in infancy and ends with frailty at the end of life. The beginning and end of the path are considered to mirror each other, making old age a reversion to a "second childishness" (Shakespeare, 1998, 2.5.139-166). Shakespeare was a pioneer in many ways, but his notion of the ages of man was not new; it was a convention in art and literature that his audiences would have been familiar with, and one that dated back a few centuries earlier to Greek philosophers before him (Baldwin, 1944).

Lifelong change can be thought of as an inverted U-curve, beginning with a building up of ability, followed by a peak in the middle of life, and ending with a wearing down of ability. Physically, we are weak and dependent in infancy and childhood, strong and independent in youth and middle age, and weak and dependent again in old age. Vision, movement, and speech all grow and then fade away. Underlying neural structures in the brain follow a similar pattern of structural consolidation and atrophy.

On the surface, cognitive abilities appear to follow the same pattern of improvement and decline (Figure 1.4). However, a closer look into cognition through the lifespan shows a much more complex picture. Individual cognitive abilities—and even processes underlying the same cognitive ability—exhibit different patterns of change with age. For example, cognitive abilities can be divided into abilities for representation of learned knowledge about the world (crystallized pragmatics), and abilities for producing goal-directed adaptive behaviour (fluid mechanics; Craik & Bialystok, 2006). Both abilities increase from childhood to adulthood, as individuals accumulate representation and control of information. However, fluid mechanics decline soon after adulthood is reached, while crystallized pragmatics are generally maintained through life. More realistically, there are further divisions within the categories of fluid and crystallized abilities. Some fluid abilities are well-maintained for longer, while some crystallized abilities are lost or inaccessible, and other crystallized abilities (such as vocabulary) continue to develop into old age.

The simple mirror-image model was popular in early lifespan studies of overall cognitive ability. Since then it has been rejected by increasing evidence that lifespan change differentiates for individual abilities, and even differentiates for the components underlying cognitive abilities (Hartshorne & Germine, 2015; Sander, Lindenberger, & Werkle-Bergner, 2012). In summary, a mirror-image view of lifespan cognitive change oversimplifies findings that individual cognitive abilities—and even the underlying processes for each ability—change differently over the lifespan.

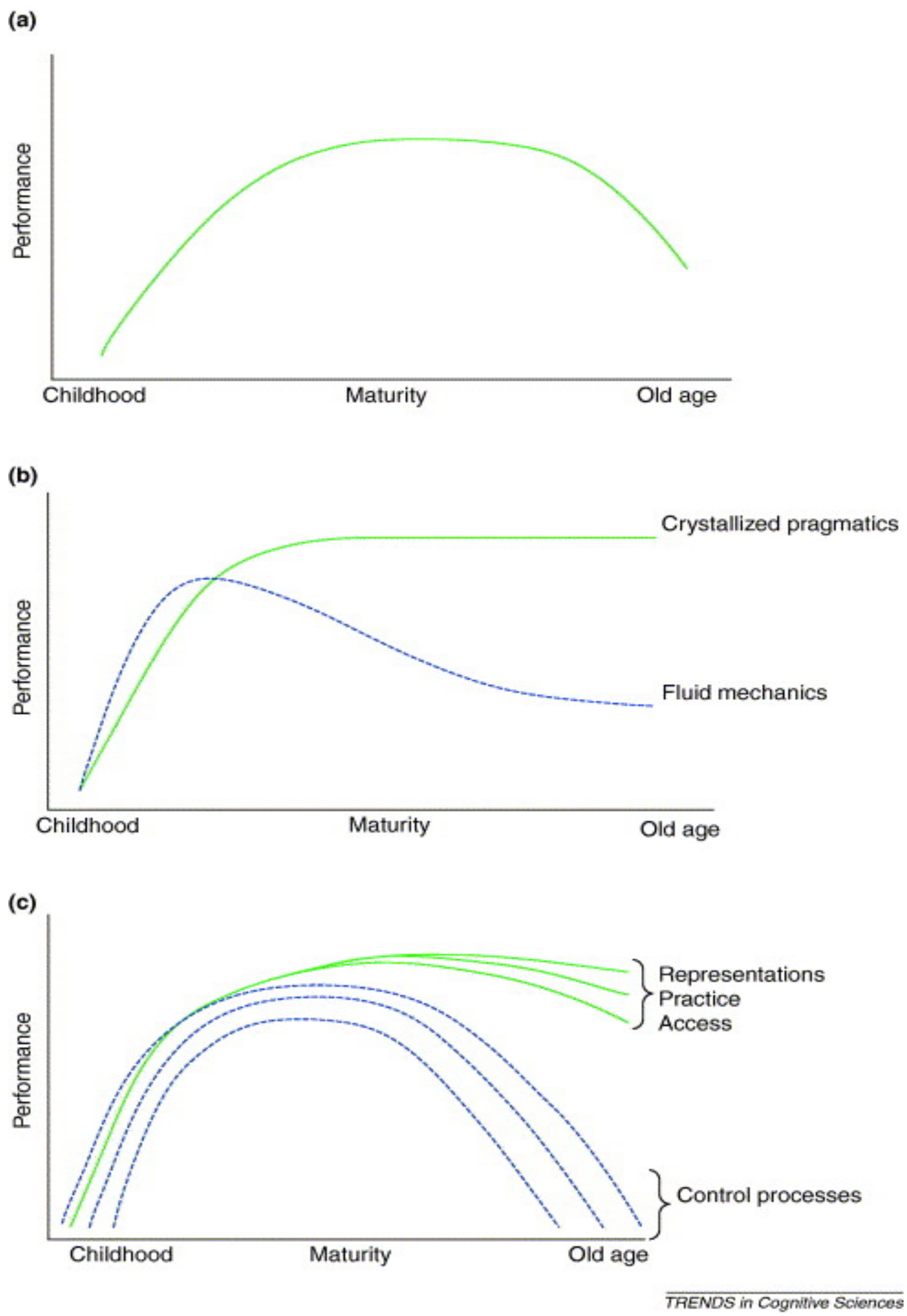

Figure 1.4: Speculative models of lifespan cognition change

The simplest model (**a**) proposes a mirror image of a rise in development and a fall in aging. A more complex model (**b**) separates between categories of crystallized pragmatics and mechanics. An even more complex model (**c**) separates individual cognitive abilities within categories. Note: Reprinted from Craik & Bialystok (2006, Figure 1).

1.1.2.2 Fractionating age differences in switch cost

On the surface, the effects of age on task switching also demonstrate development and decline. Developmental studies show that groups of children perform worse than younger adults (Crone, Bunge, van der Molen, & Ridderinkhof, 2006; Huizinga, Dolan, & van der Molan, 2006). Aging studies show that groups of older adults also perform worse than younger adults (Wasylyshyn, Verhaeghen, Sliwinski, 2011). Lifespan investigations found a U-curve characterized by development through infancy and childhood, a peak in adulthood and middle age, and decline in old age (Cepeda et al., 2001; Reimers & Maylor, 2005).

Different patterns were found after effects of age were fractionated into the cost of a task change (local switch cost) and the cost of cost of readiness to possibly switch (global switch cost). Age differences were larger and more consistently observed for global switch cost than local switch cost (Crone et al., 2006; Huizinga et al., 2006; Wasylyshyn et al., 2011). The cue switch cost, or any interaction between the cue and global switch cost, has been widely replicated in research on processes, but has not been accounted for in development or aging research. Study 2 fills this gap to test the effects of age on the processes for task switching.

Study 2 makes a second important contribution of breaking down the effects of age into its multiple contributing stages. When thinking about the lifespan, it is common for people to list a series of stages. Medieval philosophers and writers such as Shakespeare divided human life into seven stages. Psychology researchers usually conceptualize three stages: childhood, adulthood, old age. The three stages could be further divided—for example, childhood could be separated into prenatal development, infancy and toddlerhood, early childhood, middle childhood, and adolescence.

The number and division of lifespan stages has varied considerably. For example, the period of adolescence (ages 13–19) has been measured as a single group, two groups (e.g., ages 13–15, and 16–19), or more than two groups (Cepeda et al., 2001; Huizinga et al., 2006). The age boundary at which groups are formed also varies (e.g., 10–12, 13–20, 21–30, 31–40…71–82 in Cepeda et al., 2001; or 10–17, 18–30, 31–45, 46–66 in Reimers & Maylor, 2005). These discrepancies could reflect either arbitrary divisions of age, or divisions based on different theoretical conceptualizations of developmental stages. There is a lack of empirically tested observations of stage timings. The start and end of each lifespan stage has to be established.

Moreover, age is a single process that dynamically unfolds from conception to death. While there are transitions over life, there is also continuous change within a transition.
For example, when measuring adolescents aged 15 to 20 years, it is unclear how development across individuals in this group. That is, development may occur on average at a steady rate from 15 to 20 years, or perhaps, rapidly until age 16 years (a 'milestone', per se), and then more slowly for the rest of adolescence. Grouping ages is unable to distinguishing between continuous and discontinuous change per year of age. To address this, a technique must be used that simultaneously models continuous change and non-continuous transitions.

Study 2 fills this gap by modelling the effects of age on task switching using segmented regression. This technique measures continuous age-related change, but then further tests non-continuous change for different periods of life. Segmented regression examines whether there is a need to partition age groups bounded by relatively abrupt transitions, by testing if clusters of age transitions display different performance within the transition period. Segmented regression models fit the exact number of transitions that occur and can then be used to estimate the timing and rate of change per transition. In summary, Study 2 applies the non-unitary nature of task switching from Study 1 to investigate the unitary and non-unitary nature of age-related change.

1.1.2.3 Explaining age differences in a switch cost

Investigations of cognition over the lifespan are extremely rare. Most research endeavours on cognitive development and cognitive decline occur independently of each other. Developmental researchers confine their inquiries on the emergence of cognitive abilities from conception until the end of adolescence, while aging researchers confine their inquiries to after middle age. A key item on the agenda of lifespan cognitive psychology is to explore the commonalities between development and decline of cognitive abilities, and thus to uncover the mechanisms for change across the entire lifespan.

Although development and aging research efforts are divided, both attempts have the goal of studying age-related change in cognitive ability. Both use a similar technique of comparing cognition in their select stage to its peak in young adulthood. Developmental researchers compare children to young adults, and aging researchers compare older adults to young adults. Both propose theories on how cognitive ability varies during the stage of life that they study. It is striking that the fields of cognitive development and cognitive aging make little contact with each other's methods and theories (Craik & Bialystok, 2006). The lack of connectivity is problematic as childhood and aging have the same underlying structures, same underlying processes, and same surrounding environments, all three factors of which contribute to cognitive change.

A unified description of lifespan change has the benefit of parsimoniously integrating developmental and aging findings. However, the few lifespan investigations of individual cognitive abilities reveal that there are commonalities across abilities, but distinctions per ability

(Hartshorne & Germine, 2015; Sander et al., 2012). There is a need for research to address the extent to which lifespan theories adequately account for empirical demonstrations on individual cognitive abilities. This dissertation addresses this goal in the context of task switching.

The division of labour occurs in task switching research as well. At the start of the lifespan, developmental researchers have compared task switching in children to young adults, and at the end of the lifespan, aging researchers have done the same with older adults and young adults. Study 2 examines the unique theories proposed from each endeavour, and whether a single lifespan theory is sufficient. Extremely large online datasets are used to model effects of age on task switching in a more fine-grained way than past efforts.

1.2 Overview of the project

1.2.1 Data collection

The current project used an Internet-based version of the emotion-gender task switching paradigm. The task was hosted on the website of one of the research collaborators (Dr. Stian Reimers). The majority of participants accessed the paradigm by a prominent link on the BBC Science website, related to a TV series that involved the same collaborator. Data for Study 1 and Study 2A were collected online for 5 years (2006–2011), which produced an unprecedently large sample of n = 13,718. Data for Study 2B were collected for another 5 years (2011–2016), which produced a second massive sample of n = 13,031. Data are available at https://osf.io/z5j96/.

1.2.2 Collaborative nature of this work

The data for this project was collected as a result of a research collaboration that began in 2005 between Dr. Melody Wiseheart and Dr. Stian Reimers, with the goal of a large online study on cognitive aging and task switching. Data collection for the original study took place from

2006 to 2011, prior to myself (A. D'Souza) joining the collaboration. The work presented in this dissertation represents my contribution to the project, and was accomplished from 2015 to 2019.

The three studies in this dissertation are edited versions of manuscripts submitted to peer-reviewed journals for publication. On all three studies I conducted extensive literature reviews, created research hypotheses and a theoretical framework, ran data analyses, and wrote the papers. I am primary author on all three papers.

Running and reporting a massive online study is no easy feat. As with any large project, it can be challenging to distinguish between where the contributions of one individual end and another begins. Each member of the collaboration has taken part of the responsibility of the project, and all three members share ownership of the resulting publications. I was an integral part of the collaboration, but a lot of credit must also be given to the other members. Dr. Wiseheart conceptualized and designed the original study, ran the original literature review, and pre-processed the data for analysis (I post-processed data). Dr. Reimers programmed and managed the running of the online task, and the relationship with the BBC for participant recruitment.

I analyzed the dataset and wrote up the original study (Study 2A of the current dissertation). I also conceptualized and designed a second study to add to the project (Study 1 of the current dissertation). The goal of Study 1 was to investigate the theoretical basis for the components of task switching that would be measured in Study 2A. Study 1 was necessary to understand the underlying processes for each component before measuring how they were influenced by cognitive aging in Study 2A. After I joined the collaboration, we decided to add a third study (Study 2B of the current dissertation). The goal of the Study 2B was to test whether results from Study 2A could be replicated with exactly the same methodology in a new sample.

Study 1: Fractionation of Task Switching into Underlying Processes

2.1 Abstract

The ability to shift flexibly between goals is a hallmark of adaptive human behaviour but comes at a price. Past studies using a task switching paradigm have demonstrated a cost of shifting a task (local switch cost), and a cost of readiness for the possibility of a switch (global switch cost). Past studies using a double cuing paradigm have demonstrated that part of the local switch cost is due to processing task cues (cue switch cost). Using a massive sample collected online (*n*=13,718), the current study combined these two paradigms. Results showed that cue switch cost depended on whether there was the possibility of a switch (global switch cost). Results also showed no asymmetric switch cost. The findings support theoretical models of cue priming rather than task priming and task preparation. Overall, the study showed that shifting a task took 576 ms (or 108%) longer than performing a single task—219 ms (or 41%) longer to maintain readiness for a possible shift, 148 ms (or 28%) longer to use a cue to decide on the task to perform (but just 25 ms, or 5%, to detect a cue when it is not useful in signalling a task), and 183 ms (or 34%) longer for a shift itself.

Keywords: task switching, cue switch cost, cue priming, double cuing paradigm, asymmetric switch cost

2.2 Introduction

The mental control of human actions is a central issue in cognitive psychology. A key theme in studying how actions are controlled is flexibility: Being able to perform the relevant action among possible alternative actions, and to ignore competing actions or distracting information. Since everyday life involves constantly changing environments, the ability to flexibly shift between actions (termed task switching) is crucial for the control of human behavior. Task switching produces adaptable behaviour, but at a cost. Individuals are slower and less accurate to respond when a task changes compared to when a task is repeated. This *switch cost* is ubiquitous when individuals rapidly shift from one task to another and reflects one of the most robust effects in cognitive psychology (Dreisbach, Goschke, & Haider, 2007).

A useful way of understanding a complex cognitive process is by dividing it into underlying processes. Switch costs are assumed to represent the control processes used in task switching, of which there are several. The goal of this paper is to investigate these control processes, by integrating empirical and theoretical perspectives toward a comprehensive fractionation of the switch cost into observed components[1] determined by comparing performance across different trial types. We first review the calculation and empirical evidence for the two most commonly used empirical fractionations into components of a switch cost: local and global switch costs to isolate effects of a switch block, and cue and task switch costs to isolate effects of a cue. Both of these have been widely supported, but not measured in combination with each other. Testing the combination between these effects is important,

[1] For the purpose of this paper, components are defined as empirically observed measures of a switch cost, while processes are defined as unobserved functions that have been theoretically proposed to underlie a switch cost. Similar terms have been used in previous papers (e.g., Meiran, 2000). Note that components cannot be directly measured but rather refer to the measurements used of observed performance.

because the cue switch literature makes the untested assumption that effects of a cue only occur in a switch block. By combining these literatures, we gain insight into the theoretical explanations for cue and task-related processing. As a secondary aim, we also account for the type of task to test the direction of a switch cost between different types of tasks.

2.2.1 Fractionation of a switch cost

2.2.1.1 Task switching paradigm: Local and global switch cost

Switch costs have been extensively studied using the task switching paradigm (Jersild, 1927; Spector & Biederman, 1976). A standard task switching paradigm contains two types of *trials*: trials in which the task changes (switch trials), and trials with no task change (non-switch trials). The paradigm is set into two types of *blocks*: a block of trials in which one task is performed, followed by a block of trials in which the other task is performed (non-switch blocks), and finally a mixed block in which both tasks are performed (switch block; Figure 2.1). In the alternating runs version of the paradigm, a switch occurs predictably, with a pre-specified switch pattern informing the participant the task sequence to perform. This paradigm was updated to the explicit cuing version of the paradigm, in which an external cue per trial informs the participant which task to perform. The explicit cuing paradigm enables measurement of unpredictable or random switching, and we use this paradigm in the current study.

An intuitive method for measuring switch cost is to compare switch trials in a switch block to non-switch trials in a non-switch block. This measurement was used in early studies, but it was soon pointed out that the measurement is confounded by both trial types being in different blocks (Rogers & Monsell, 1995; Meiran, 1996; Los, 1996). The confound of a switch block is problematic since all trials in a switch block include the possibility of a task switch from the presence of switch trials. This means that the localized costs of shifting response sets from one task to another are confounded with the more general global costs of having to maintain additional response mappings in working memory during a switch block. To address this issue, the switch cost can be dissociated into within-block effects (local switch cost) and between-block effects (global switch cost).

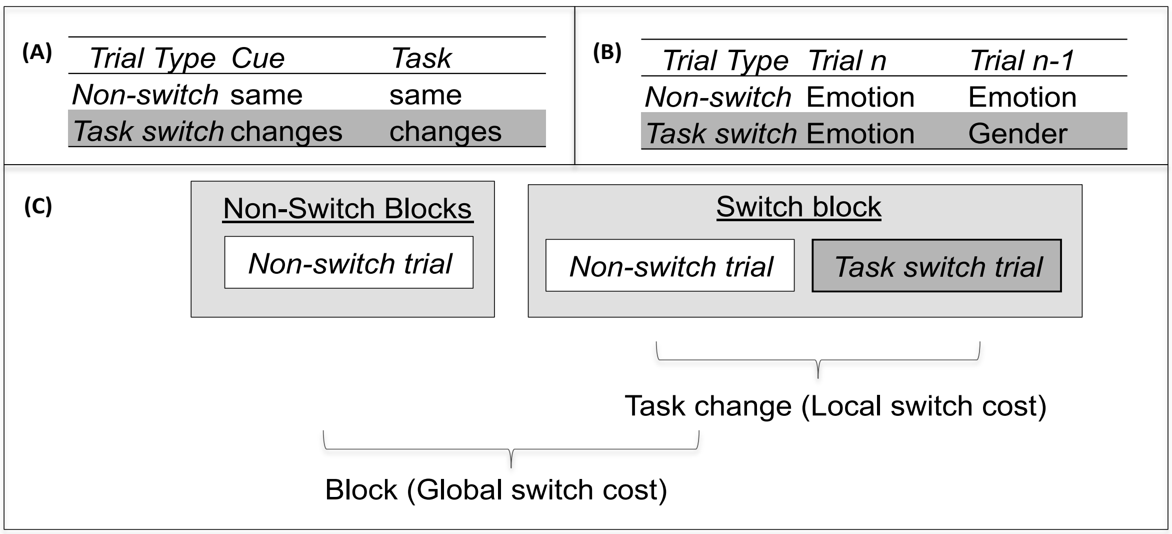

Figure 2.1: Trial transitions in a task switching paradigm

(A) Trial types and (B) sample transitions for the standard task switching paradigm. On a non-switch trial, the task repeats from the previous trial (n-1). On a task switch trial, the task changes from the previous trial. Sample transitions are based on the gender-emotion task used by Reimers and Maylor (2005). (C) Trial types can be compared within a block to calculate local switch cost (difference in reaction times between non-switch and task switch trials in a switch block) and between blocks for global switch cost (difference in reaction times between non-switch trials in switch and non-switch blocks). There are two non-switch blocks, one for each task.
Note: For each subtraction, the center of the bracket ticks indicates which trial type is used in the switch cost calculation. For example, for global switch cost, the left tick is centered on non-switch trials in switch blocks, and the right tick is centered on non-switch trials in the switch block. Sample transitions (B) are adapted from Jost, De Baene, Koch, and Brass (2015, Figures 1A and 2A).

Local switch costs (also called switching or specific costs) contrast switch trials in a switch block with non-switch trials in the same switch block. Global switch costs (also called mixing costs or general switch costs) contrast non-switch trials in a switch block with non-switch trials in a non-switch block (Figure 2.1). A performance decrement occurs for both measurements, in which there is a cost of a task change itself (local switch cost), as well as a cost of readiness for a task change regardless of whether a task change occurs (global switch cost; Los, 1996). Global switch cost tends to be larger than local switch cost, indicating that a notable proportion of the overall switch cost is due to the cost of being prepared to possibly switch.

Dissociation studies found that local switch cost, but not global switch cost, is influenced by manipulating trial-specific parameters of preparation time for a task change (such as presentation times of stimuli and cues on a trial). Conversely, global switch cost is influenced by manipulating block-specific parameters of preparation over trials, such as the number of tasks to be held in mind (Braver, Reynolds, & Donaldson, 2003; Dreisbach, Haider, & Kluwe, 2002; Meiran, 1996, 2000; Rogers & Monsell, 1995). Structural equation modeling has supported separation into two functionally distinct processes that consistently emerged across measurement variations (figural, numeric, and verbal stimuli; Kray & Lindenberger, 2000).

Lifespan research indicates that the local and global switch cost follow different trajectories with age, with global switch cost showing considerably more variability (Reimers & Maylor, 2005; Verhaeghen & Cerella, 2002; Wasylyshyn, Verhaeghen, Sliwinski, 2011). Different neural regions are activated for within-block and between-block contrasts (Braver et al., 2003). Overall, evidence from the task switching paradigm suggests that local and global switch costs reflect separate components of a switch cost.

2.2.1.2 Task difficulty: Asymmetric switch cost

Another limitation of the standard task switching paradigm is that two tasks are combined when calculating condition means. Tasks often have different levels of difficulty or familiarity. The effects of task difficulty are problematic since it takes longer to complete a difficult task than an easy task. To address this issue when using tasks of unequal difficulty, the switch cost for switching to an easy task can be considered separately from the switch cost for switching to a difficult task.

Isolating task difficulty means that local switch costs can contrast task switch trials in which there was a change from an easy task to a difficult task (difficult task switch trials; Figure 2.2) with a change from a difficult task to an easy task (easy task switch trials). Similarly, global switch costs can compare the subtraction of difficult task repetition trials in a switch block from difficult task repetition trials in a non-switch block with easy task repetition trials in a switch block from easy task repetition trials in a non-switch block.

Research studies that accounted for task difficulty found, surprisingly, that local switch cost was larger when switching to the easy task than when switching to the difficult task (asymmetric local switch cost; Allport, Styles, & Hsieh, 1994). This asymmetric switch cost occurred within a switch block, and even between blocks. There was a global switch cost of readiness for a task change, but a larger global switch cost on the task that is easier to perform than the task that is more difficult to perform (asymmetric global switch cost).

The asymmetric local switch cost indicates a backward effect of switching away from the previous task: there is a greater cost to shift away from a difficult task to an easy task than the other way around. The asymmetric switch cost is considered to reflect the automatic carryover of a previous task to the current task (refer task priming theory section below). This suggests that the difficulty that causes a switch cost is in *shifting away from* the past task, and not in *shifting to* the new task. Meanwhile, the asymmetric global switch cost implies a worst-case scenario, in which participants slow down responding throughout a switch block to prepare optimally for the difficult task, at the expense of the easy task (Monsell, Patterson, Graham, Hughes, & Milroy, 1992).

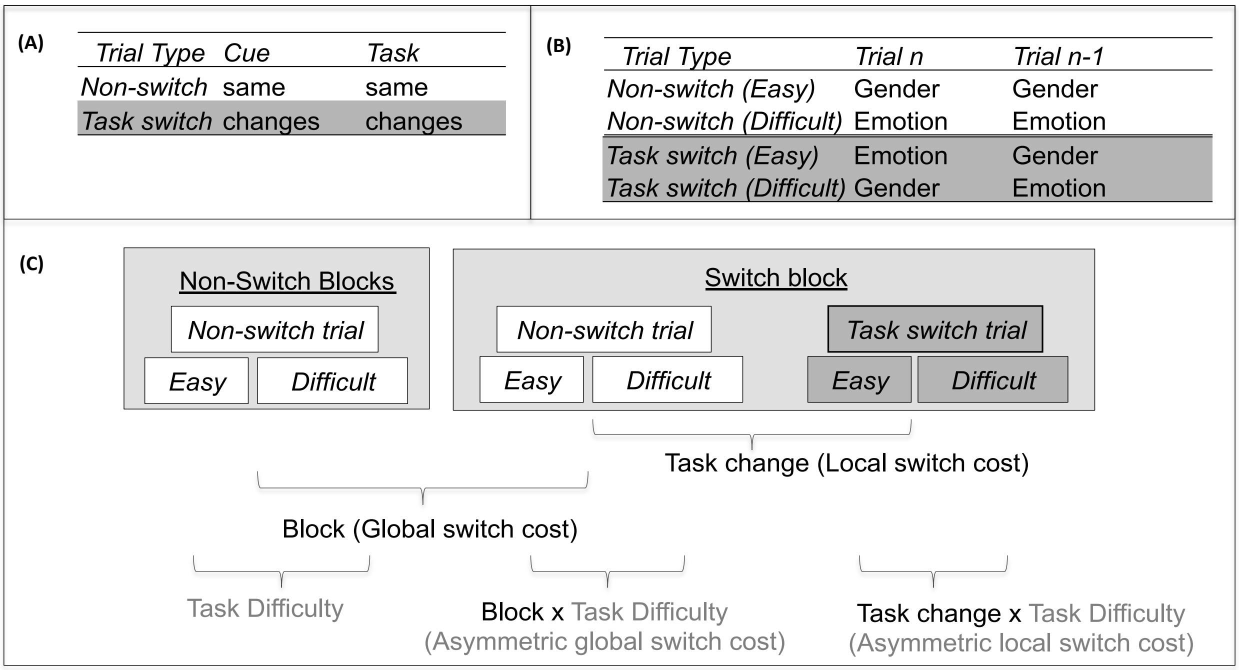

Figure 2.2: Task difficulty for trial transitions in a task switching paradigm

(A) Trial types and (B) sample transitions for the standard task switching paradigm after accounting for task difficulty. In the gender-emotion paradigm (Reimers & Maylor, 2005), it is more difficult to respond to emotion than gender. On a non-switch trial, the task repeats from the previous trial (n-1) for either an easy task (easy non-switch trial; gender) or a difficult task (difficult non-switch trial; emotion). On a task switch trial, the task changes from the previous trial, from either a difficult task to an easy task (easy task switch trial; emotion to gender), or an easy task to a difficult task (difficult task switch trial; gender to emotion). (C) Trial types can be compared within a block to calculate the interaction between local switch cost and task difficulty, and between blocks to calculate the interaction between global switch cost and task difficulty.

Findings with tasks of unequal difficulty have demonstrated both asymmetric local and global switch costs (Bobb & Wodniecka, 2013; Koch, Prinz, & Allport, 2005). Asymmetric global occur in switch blocks with and without tasks of different difficulties, or in global switch costs of difficult and easy tasks in switch blocks; Los, 1996, 1999). Not all studies have replicated asymmetric local or global switch costs. Instead, some studies have shown no influence of task difficulty on switch costs, a homogenization pattern (a switch cost for the easy task and a switch benefit for the difficult task), or even a reverse asymmetric switch cost (a greater cost of switching to the difficult task; Lupker, Kinoshita, Coltheart, & Taylor, 2003; Rubinstein, Meyer, & Evans, 2001; Ruthruff, Remington, & Johnston, 2001).

A review of data on task switching and task difficulty found that the demonstration of the asymmetric switch cost varied according to the type of relative task difficulty (Monsell, Yeung, & Azuma, 2000). Further, asymmetry may be masked by control processes to prepare for a switch to a new task. Manipulating the amount of interference from a previous task (via pre-experiment practice, intra-experiment practice, or stimulus-response compatibility) influences whether an asymmetric switch cost is found, and can reduce, remove, or even reverse the asymmetric switch cost effect (Arbuthnott, 2008; Monsell et al., 2000; Yeung & Monsell, 2003).

The lack of a reliable asymmetric switch cost is considered to reflect intentional control processes to prepare for the current task and resolve interference from carryover of the previous task (see task preparation in the theory section below). Overall, evidence from the task switching paradigm suggests that an asymmetric switch cost is not universal.

2.2.1.3 Double cuing paradigm: Cue and task switch cost

Around a decade after the introduction of the task switching paradigm, another limitation was pointed out. All local switch cost measurements confound a task change with a cue change (Logan & Bundesen, 2003; Mayr & Kliegl, 2003). The confound of a task and cue change is problematic since each time a task changes in switch blocks, a cue also changes. Similarly, each time a task repeats, a cue also repeats. To address this issue, a local switch cost can be further dissociated into a task change itself (a pure task switch cost), as well as a cost of processing a change in cue regardless of whether a task change occurs (a cue switch cost).

The double cuing paradigm was proposed to isolate the role of the cue (Logan & Bundesen, 2003; Mayr & Kliegl, 2003). The double cuing paradigm uses two cues per task, instead of one cue per task in the standard paradigm. This enables a 2:1 mapping of cue per task, instead of the 1:1 mapping in the standard paradigm. The double cuing adaptation includes the two traditional trial types in the task switching paradigm—trials in which neither the cue nor task changes (non-switch trials, also known as cue repetition trials), and trials in which both the cue and task change (task switch trials). The double cuing paradigm adds a third trial type—trials in which the cue changes and the task stays the same (cue switch trials, also known as a task repetition trials; Figure 2.3). The paradigm includes two blocks, as in the standard paradigm, with the addition of cue switch trials into both non-switch and switch blocks.

Cue switch costs contrast cue switch trials in a switch block with non-switch trials in a switch block to isolate the costs of processing a new cue while continuing to perform the same task. Task switch costs contrast task switch trials in a switch block with cue-switch trials in a switch block to isolate the additional costs shifting tasks. A performance decrement occurs for both measurements, in which there is a cost of a task change itself (task switch cost), as well as a cost of processing the cue regardless of whether a task change occurs (cue switch cost). Cue switch costs can be larger than task switch costs (Logan, Schneider, & Bundensen, 2007), indicating that a nontrivial proportion of the overall switch cost associated with task switching is due to the cost of switching a cue.

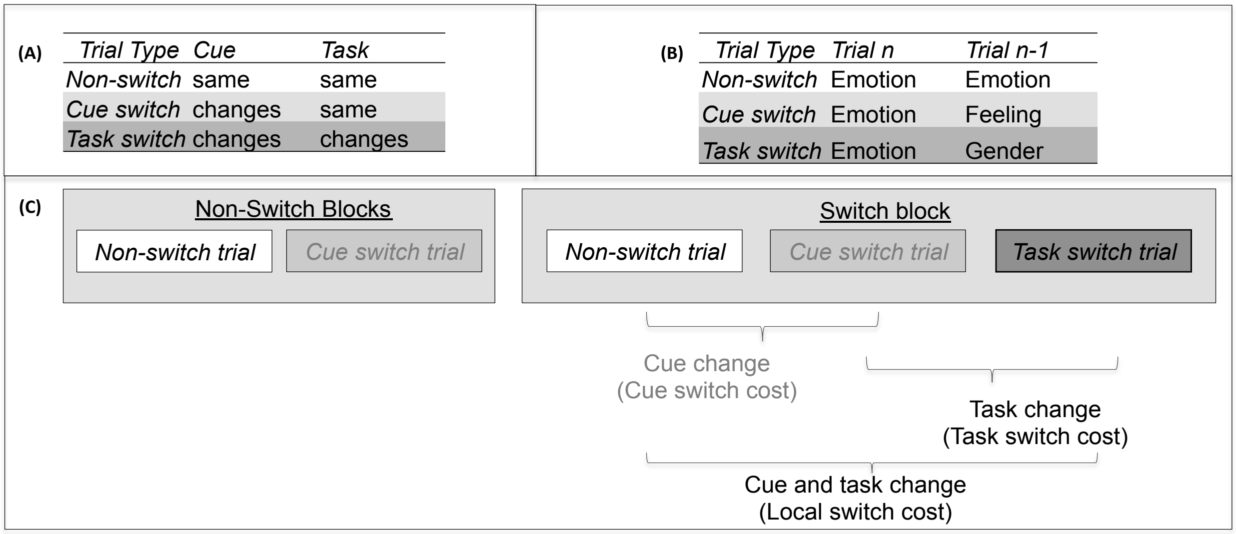

Figure 2.3: Trial transitions in a double cuing paradigm

(A) Trial types and (B) sample transitions for the double cuing (2:1 cue mapping) paradigm. Three possible transitions can occur. The paradigm enables addition of cue switch trials (shaded in light grey) in which a cue changes from the previous trial(n-1) but the task remains the same. The paradigm is used in the current study and uses two cues per task: 'emotion' and 'feeling' for one task, and 'sex' and 'gender' for the other task. (C) Trial types can be compared within a switch block to fractionate local switch cost into separate components for cue switch cost (difference in reaction times between non-switch and cue switch trials) and task switch cost (difference in reaction times between cue switch and task switch trials). Traditional global switch cost has not been calculated in past studies with the 2:1 paradigm.

Dissociation studies found that manipulating parameters related to preparation for a new task influenced the cue switch cost, but not the task switch cost. Conversely, manipulating parameters related to interference of the previous task influenced the task switch cost, but not the cue switch cost (Mayr & Kliegl, 2003; Altmann, 2006, 2007; Gade & Koch, 2008; Horoufchin, Philipp, & Koch, 2011; Koch, Gade, Schuch, & Philipp, 2010; Mayr, 2006; Monsell & Mizon, 2006, c.f., Logan & Bundensen, 2003, 2004; Arrington & Logan, 2004, 2005; Arrington, Logan, & Schneider, 2007). Overall, evidence from the double cueing paradigm suggests that cue switch and task switch costs reflect separate components of local switch cost (see Jost, De Baene, Koch, & Brass, 2015, for a review).

2.2.1.4 Combining the task switching and double cuing paradigm in the present study

A limitation of previous studies is that cue switch costs have only been measured in a cue switch block. Standard cue switch cost measurements confound a cue change with being prepared for a possible task change. This is problematic, since as described earlier, all trials in a switch block involve the possibility of a task switch. To address this issue, cue switch cost must be dissociated into a cue change itself (a pure cue switch cost) and a cue change when there is a possibility of a task switch (a cue switch cost in a switch block).

A related limitation is that global switch costs have only been measured with non-switch trials. Standard non-switch trials confound task repetition with cue repetition. This is problematic, since as described earlier, each time a task repeats, a cue also repeats. To address this issue, a global switch cost must be dissociated into the possibility of a task switch itself (a pure global switch cost) and the possibility of a task switch when there is a cue change (a cue switch cost in a switch block).

Global switch costs have been widely replicated using the task switching paradigm. Cue switch costs are also widely replicated using the double cuing paradigm. A missing link is to measure the global and cue switch costs in a single experiment. We fill this gap in the current study using a combined paradigm. We integrated measurements from the standard task switching paradigm (Figure 2.1) and the double cuing paradigm (Figure 2.3) to produce a combined paradigm (Figure 2.4).

Measuring the effects of a switch block on a cue change is possible since the double cuing paradigm includes cue switch trials in both non-switch and switch blocks. The original local switch cost measurements compare the difference between a trial in which both task and cue change (task switch trial) and a trial in which both task and cue repeat (non-switch trial). The double cuing paradigm has been used to separate the original local switch cost into a pure task switch cost and a cue switch cost. Similarly, the original global switch cost measurements compare the difference between the same trial type (non-switch trials) between a block where a switch may occur (a switch block) and a block where a switch does not occur (a non-switch block).

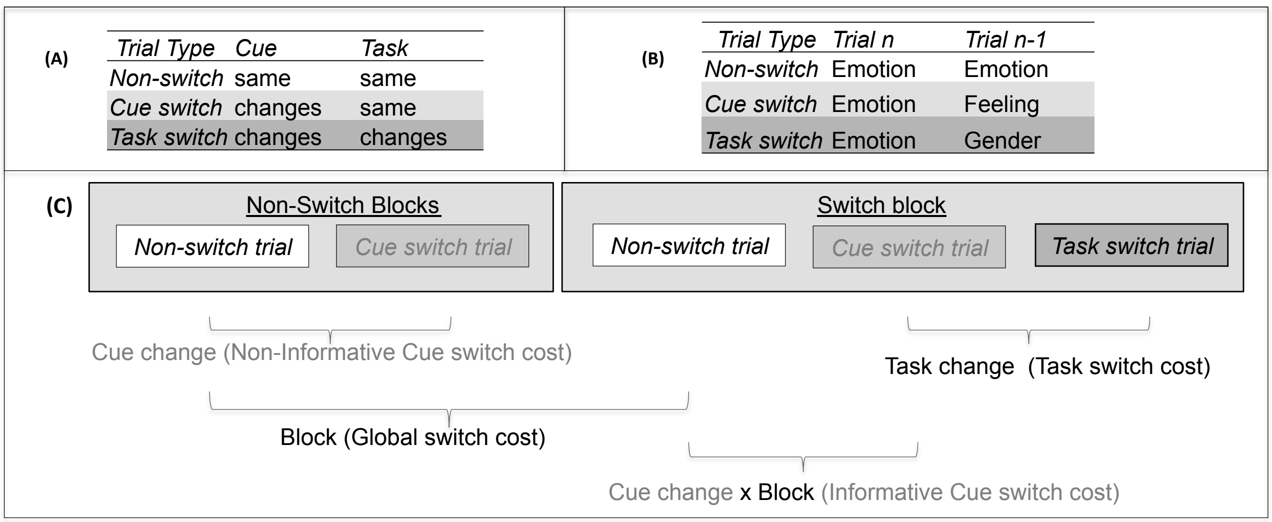

Figure 2.4: Trial transitions in the combined paradigm

(A) Trial types (B) and sample transitions for the combined paradigm. (C) Trial types can be compared within and between blocks to calculate separate components for global and local processes. The paradigm measures a cue change after accounting for the effect of block, and the interaction between a cue change (cue switch cost) and block.

The double cuing paradigm can be used to separate the original global switch cost measurement of a trial in which a task and cue repeat (non-switch trial) into a pure global switch cost and a cue repetition benefit. We expect that a performance decrement will occur for all of these measurements: a cost of a task change itself (local switch cost), a cost of readiness for a task change regardless of whether a task change occurs (global switch cost), and a cost of processing a cue for a task change regardless of whether a task change occurs (a cue switch cost). The double cuing paradigm also allows separating a cue switch cost into a cue change when there is the possibility of a task change (cue change in a switch block) and a pure cue change without the possibility of a task change (cue change in a non-switch block; Figure 2.5).

On one hand, it is possible that measuring a cue change alone (in a non-switch block) is a purer measure of a cue switch cost than measuring a cue change in a switch block. On the other hand, it is possible that measuring a cue change alone is a qualitatively different measure, since the cue is not informative in a non-switch block. The latter case is more likely as processing a cue may be dependent on the usefulness of the cue in signaling a task change, such that a cue would only have an effect in a switch block. Hence it is plausible that the cue interacts with the global switch cost. The current study is the first attempt to directly measure this possibility. Although it is very likely that there would be a strong interaction between block type and the magnitude of a cue change effect, to our knowledge this has not been tested directly before.

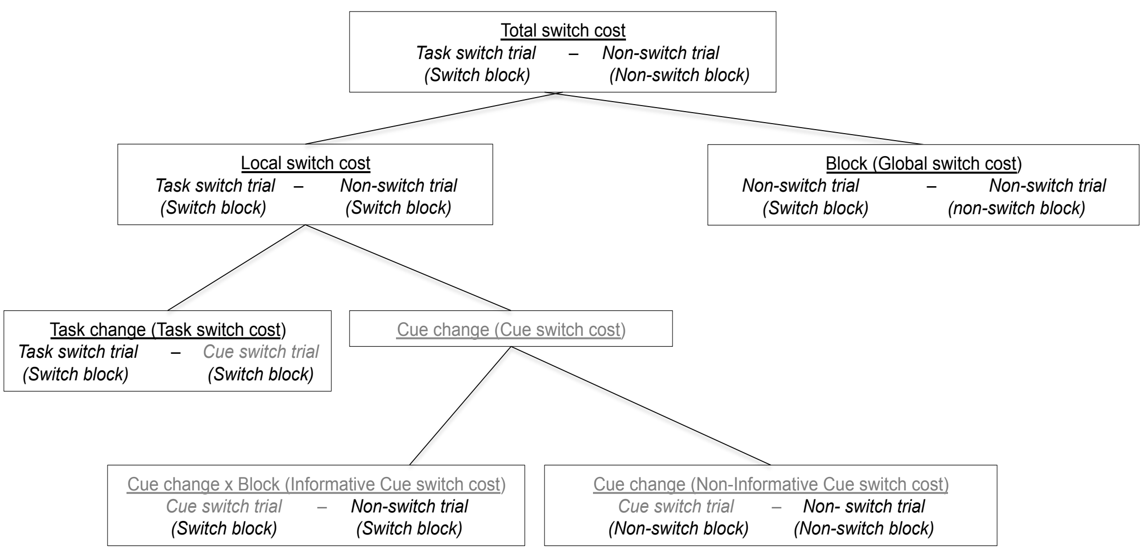

Figure 2.5: Framework of task switching components

Components of the task switch cost, and calculations for each component.
Note. Image based on Meiran, Chorev, & Sapir (2000, Figure 16)

Studies with the standard task switching paradigm have indicated that the cue may have a role across trials in a switch block (i.e., when there is a possibility of a task switch), and not only on trials in which the task changes. The underlying process proposed to prepare for the possibility of a task switch in a switch block has been found to rely on task cuing (Rubinstein et al., 2001). The information provided by a cue may be used across trials in a switch block to efficiently achieve a state of readiness (Altmann & Gray, 2008). The cue is specifically useful as it provides context on how to respond by linking a task cue to a semantic task category (Reynolds & Braver, 2002; Braver, Paxton, Locke, & Barch, 2009).

It is reasonable to expect that cue-related effects may vary depending on the context of a switch block, since the context qualitatively influences the role of the cue. In a switch block, a cue is informative even when a task change does not occur, since the cue can be used to signal whether or not a change might occur. In a non-switch block, a cue is not informative since no task change will occur. The role of the cue has been found to vary depending on how informative a cue is for the context in which it occurs. Fully and partially informative cues (that specified an upcoming switch) were linked to a switch cost, while uninformative or invalid cues were not (Karayanidis, Mansfield, Galloway, Smith, Provost, & Heathcote, 2009; Ruthruff et al., 2001). In a similar vein, subjective expectancy of a switch is moderated by whether cues are informative (the cues signal which task to switch to), but not when cues are partially informative (i.e., they provided information that a task would change or repeat, but not on which task type was needed when a task changed; Dreisbach et al., 2002). Switch costs did not vary with different switch probabilities, but reaction times were faster on both switch and non-switch trials if the cue indicated a task with high probability, indicating that the cue is used to inform responding in a non-switch-specific way.

To date, cue switch costs have been limited to measuring the effects of a cue change in switch block trials only, when there is a possibility of a task switch. Cues appear to have an effect throughout a switch block. Moreover, a cue change may not have an effect in a non-switch block, when there is no a possibility of a task switch, as the cue is not informative.

2.2.2 Theoretical accounts of task switching

Before proceeding to outline the research questions tested in the current study, we review the existing theoretical explanations for the control processes that underlie the effects observed with the task switching paradigm. Earlier psychological work had difficulties with addressing the question of control as studies were focused on testing a single task (Monsell & Driver, 2000). The task switching paradigm directly addresses this problem by examining how individuals configure mental resources when switching between two tasks. The task switching paradigm has been widely cited as a promising way to measure control processes that produce goal-directed behaviour (Rogers & Monsell, 1995; Rubinstein et al., 2001; Monsell, 2003; Monsell & Driver, 2000; Sohn & Anderson, 2001).

2.2.2.1 Executive and automatic control processes

The origin of cognitive psychology focused on the search for an agent (termed a *homunculus*) who directed complex behaviour. The notion of a single goal-oriented agent has been framed under several terms: a central executive (Baddeley, 1996), a supervisory attention system (Norman & Shallice, 1986), or frontal control (Duncan, 1986). However, subsequent research has indicated that cognitive abilities arise from a number of control processes rather than a single agent. These goal-directed processes have been broadly termed executive control (Miyake, Friedman, Emerson, Witzki, Howerter, & Wager, 2000; Monsell & Driver, 2000).

As cognitive psychology developed an understanding of cognitive control processes, a body of evidence accumulated to show that automatic processes could also underlie cognitive abilities (Roediger, 1990; Tulving & Schacter, 1990). Complex cognitive abilities could occur as the result of priming, in which exposure to one stimulus or event automatically triggers a response to another stimulus, without the need for conscious intention (Mayr & Buchner, 2007; Weingarten, Chen, McAdams, Yi, Hepler, & Albarracin, 2016). Priming falls under the episodic retrieval account in which the initial application of an action (such as a task rule) to a stimulus creates a binding in episodic memory that is automatically retrieved every time the same stimulus is presented later. The retrieval episode influences all other episodes. In priming, learned associations between stimuli compete in a race process until a dominant representation emerges. Associations with past stimuli could facilitate processing (*positive priming*) or inhibit processing (*negative priming*).

The control of attention in cognitive processing is considered to be a result of both executive control (endogenous or top-down control) and automatic control (exogenous or bottom-up control). Executive control is internally driven and intentional, while automatic control is stimulus-driven and non-intentional. Executive control is directed towards a goal, while automatic control occurs regardless of a certain goal, and occasionally even in conflict to a goal. Both executive and automatic processes contribute to cognitive processing (Norman & Shallice, 1986; Monsell & Driver, 2000).

The debate between executive and automatic processes also applies to task switching. Many researchers have proposed that the task switching paradigm is a representative measure of executive control (Brown, Reynolds, & Braver, 2007; Rogers & Monsell, 1995; Rubinstein et al., 2001; Monsell, 2003; Monsell & Driver, 2000; Sohn & Anderson, 2001). Intuitively, a switch cost reflects a conscious control process to coordinate mental operations when switching. This line of thought is reflected in *task preparation* theories, which posit an internal executive control to shift to a new task, and to anticipate a task change. A separate line of thought posits that switch costs can be suitably explained by priming of automatically learned associations between the stimuli and tasks (*task priming* theories; Allport & Whylie, 1999, 2000) or stimuli and cues (*cue priming* theories; Logan & Bundensen, 2003). This line of thought suggests that the task switching paradigm may not necessarily measure executive control (Altmann, 2003). We explore these theories in more detail below, and how they can be used to explain components of the switch cost.

2.2.2.2 Executive control: The task preparation theory of local and global switch cost

A seminal study with the task switching paradigm proposed that switch costs reflect a *reconfiguration* process to prepare the system for an upcoming task (Rogers & Monsell, 1995). Reconfiguration produces a *task set*, a specification of rules that specify which response should be made for a given stimulus (i.e., stimulus-response mappings). An executive control process (*endogenous reconfiguration*) selects a task internally when a task changes, by retrieving rules for the current task into mind (i.e., working memory) from long-term memory (Mayr & Kliegl, 2000; Meiran, 2000; Meiran, Chorev, & Sapir, 2000). Endogenous reconfiguration has been termed a *preparatory component* (Meiran, 2000; Meiran et al., 2000), *task expectancy* (Ruthruff et al., 2001), *rule retrieval* (Mayr & Kliegl, 2000), or *task preparation* (Sohn & Anderson, 2001). Endogenous reconfiguration is supported by evidence that a switch cost is reduced by increasing the time for advance preparation, such as a longer interval between a cue and a stimulus (cue-target interval, CTI, or cue-stimulus interval, CSI), more practice, or lower task retrieval demands (Mayr & Kliegl, 2000; Meiran et al., 2000).

Advance preparation cannot completely eliminate a switch cost. *Residual switch costs* occur even after long advance preparation intervals of up to 3500 ms, and despite information of a task change (de Jong, 2000; Rogers & Monsell, 1995; Sohn, Ursu, Anderson, Stenger, & Carter, 2000). Residual switch costs support a second process (*exogenous reconfiguration*) to complete task selection using environmental information. Exogenous reconfiguration selects a task by stimuli automatically triggering task sets habitually associated with them. A match is selected by a contention scheduling process in which a race takes place between stimulus-task associations until a dominant task emerges. Exogenous reconfiguration has been termed a *residual component* (Meiran, 2000; Meiran et al., 2000), *rule activation* (Rubinstein, Meyer, & Evans, 2001), *transient control* (Braver et al., 2003), *online reconfiguration* (Braver et al., 2009), or *failure to engage* (de Jong, 2000). Endogenous reconfiguration intervenes if stimuli activate a task that does not fit with the desired goal, indicating endogenous and exogenous reconfiguration work together to produce local switch costs (Rogers & Monsell, 1995).

Reconfiguration theories assume that preparation is specifically required when a task changes (on task switch trials). Later studies expanded on this notion to propose that *general preparation* is also required to prepare for a possible task change, producing a global switch cost (Los, 1996, 1999; Lupker et al., 2003). General preparation involves an executive control process (*sustained preparation*) to internally prepare for the possibility of a task change by a set mode of responding over trials in a switch block. Sustained preparation has been termed *working memory load* (Los, 1996; Rogers & Monsell, 1996; Rubin & Meiran, 2005), or *sustained attention* (Braver et al., 2003), and is in line with a class of *criterion* models which propose that global switch are completely internal and set over a switch block (Los, 1999). Sustained preparation is supported by evidence that a global switch cost is influenced by increasing preparedness over a block of trials, such as the number of tasks to be held in mind, or uncertainty in physical task features (Los, 1996, 1999; Rubin & Meiran, 2005).

General preparation also involves an executive control process (*dynamic preparation*) to account for the trial-by-trial variability from changing environmental information in a switch block. Dynamic preparation internally completes preparation and resolves any automatically-triggered interference from external stimuli (Los, 1999; Rubin & Meiran, 2005). Dynamic preparation has been termed *task decision* (Rubin & Meiran, 2005), *goal shifting* (Rubinstein et al., 2001), re-positioning of a *time criterion* (Lupker et al., 2003), *task expectancies* (Dreisbach et al., 2002), or *dynamic task maintenance* (Braver et al., 2009), and is line with *alternate processing* models, which propose that global switch costs require internal processes to resolve externally triggered interference (Los, 1999). Dynamic preparation is supported by evidence that a global switch cost is influenced by preparation when mixing between trials in a switch block, such as switching between categorically different tasks (with computationally different processes), and increasing ambiguity between tasks (Los, 1996, 1999; Rubin & Meiran, 2005). These manipulations have an independent effect to sustained preparation, indicating sustained and dynamic preparation work together to produce global switch costs (Los, 1996, 1999; Lupker et al., 2003).

2.2.2.3 Automatic control: The task priming theory of asymmetric switch cost

A second seminal study with the task switching paradigm proposed an alternate theoretical viewpoint. Inspired by the asymmetric switch cost of a larger cost when switching away from a difficult task than when switching away from an easy task, researchers proposed that a switch cost is caused when interference from the previous task carries over to the current task (Allport, Styles, Hsieh, 1994). Leftover activation of the previous task interferes with the current task (negative *task priming*). Task priming has been termed *task set inertia* (Allport & Whylie, 1999), a *dissipating* component (Meiran et al., 2000), *task repetition* (Sohn & Anderson, 2001), or *task recency* (Ruthruff et al., 2001). Task priming is supported by evidence that a local switch cost is reduced by reducing interference from decay of a previous task, such as a longer interval between a response on the previous trial and the cue for the next trial (response-cue interval, RCI; Meiran et al., 2000). Task priming is also demonstrated by backward inhibition that it is more difficult to switch to a task that has just been switched away from, than to switch to a task that has not been recently performed (Dreisbach et al., 2002; Dreisbach, 2012; Mayr & Keele, 2000; Mayr, 2002).

Long-term effects of task priming have been observed over trials in a switch block (Allport & Whylie, 2000). *Proactive interference* from persisting interference of a previous task occurs after a lag of many intervening trials (Allport & Whylie, 2000; Waszak, Hommel, & Allport, 2003; Whylie & Allport, 2000). Thus, task priming is not specific to switch trials and can influence both the local and global switch cost. Proactive interference is in line with a class of *stimulus-driven* models which propose that global switch cost is completely externally driven (Los, 1996). Proactive interference is supported by evidence on an asymmetric global switch cost, as a result of interference from carryover of a difficult task over a switch block.

2.2.2.4 Both executive and automatic control: Multi-component theories

Early theories proposed a single component that produced a switch cost - either an executive control component for task preparation, or an automatic control component for task priming. However, experimental evidence supported both processes, indicating that the single components did not account for the complete range of phenomena with a task switching paradigm. Later researchers proposed multi-component theories of task switching, with an executive control process for task preparation[2], as well as an automatic process for task priming (Cognitive Control Model, CCM, Altmann & Gray, 2008; Three-Component Model, Meiran, 2000; Meiran et al., 2000; Configuration-Execution Model, Ruthruff et al., 2001; Adaptive control of thought-rational theory, ACT-R, Sohn & Anderson, 2000).

Multi-component theories have been mostly supported by orthogonal manipulations of timings or trial types. The standard task switching paradigm found that advance preparation (cue-target interval, response-cue interval, or practice) influences an component related to the cue that was considered to involve executive control, while carryover of a task set (response repetition, task inhibition) influences a second component related to a task switch cost that was considered to be automatic (Goschke, 2000; Hsieh & Liu, 2005). The selective influence of each manipulation was taken to conclude that independent processes underlie performance, since they originate from different sources (endogenous or exogenous) and occur at different times (before or after stimulus onset, and per trial or across trials) in a task switching paradigm.

Further insights into the nature of the cue-related stage have come from studies that used an electrophysiological approach to distinguish task cuing by observing continuous neural activity and locking the onset of the stimulus, cue, and response to peak latencies (review by Karayandis, Mansfield, Galloway, Smith, Provost, & Heathcote, 2009). A significant effect of task cuing, but not task switching, was found on an index of working memory updating (P_{300}

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[2] Some multi-component theories extend to add a second executive control component for global switch cost (Rubinstein et al., 2001). These processes may be separately influenced: global switch costs for general preparation occur even after manipulating advance preparation factors that decrease time for reconfiguration (Dreisbach et al., 2002). Neural evidence has also supported three types of preparation process: a reconfiguration process for local switch cost (activated per trial on switch trials, linked to the superior parietal cortex), a dynamic preparation process for global switch cost (activated per trial on both switch and non-switch trials, linked to the lateral prefrontal cortex), and a sustained preparation process for global switch cost (activated across trials for switch and non-switch trials, linked to the right anterior prefrontal cortex; Braver et al., 2003, 2009).

amplitude; Hsieh & Liu, 2005). These findings have converged with behavioural evidence to suggest separate task cuing and task switching stages.

However, researchers have noted that the same processes can arise from different sources or at different times (Los, 1999; Sohn & Anderson, 2001; Rubinstein et al., 2001). For example, the task preparation process could occur in advance of a trial with pre-specified knowledge about a task change, or per trial when using an explicit cue (Rubinstein et al., 2001). Thus, the distinction between multiple independent components may be superficial, since observations of independent times or trial types are not sufficient to indicate independent underlying processes. Rather, the functional role of the theoretical underlying process must be directly tested.

A recent review of switch cost theories has proposed that not only do task preparation and priming both occur, but that they are also necessarily linked (Vandierendonck, Liefooghe, & Verbruggen, 2010). It is not possible to prepare for a task without also inhibiting a previous task (Monsell, 2000), and it is not possible to inhibit a task without simultaneously activating another (Dreisbach, 2012). Task preparation and priming interact, and therefore components for automatic and executive control may not be mutually exclusive sources of a switch cost (Hsieh & Liu, 2005; Yeung & Monsell, 2003).

A seminal study using the double cuing paradigm built on multi-component models to propose independent components for task preparation and priming (Mayr and Kliegl, 2003). An executive control process selects the task in advance using the cue (*cue retrieval*), followed by an automatically triggered process that executes the task (*task application*). Cue retrieval is similar to endogenous reconfiguration, and internally prepares a task by retrieving rules for the current task into working memory from long-term memory. Task application is similar to task priming or exogenous reconfiguration, and externally completes task preparation to produce a response based on the stimulus. The double cuing paradigm separates these processes: Task retrieval occurs on a cue switch trial; task application occurs on a task switch trial.

Similar to findings on multi-component theories from the task switching paradigm, findings with the double cuing paradigm suggest that the executive control process is related to the cue and influenced by advance preparation (cue-target interval, response-cue interval, or practice), while the automatic component is related to the stimulus and influenced by task interference (response repetition, task inhibition; Altmann, 2006, 2007; Gade & Koch, 2008; Horoufchin et al., 2011; Koch et al., 2010; Mayr, 2006; Mayr & Kliegl, 2003; Monsell & Mizon, 2006).

Earlier, the task preparation process had been attributed to the cue. Effects of the cue were measured using the cue interval but had not been formally isolated from a task change. The invention of the double cuing paradigm provided a way to isolate cue changes, and thus isolate the processes that underlie a cue switch cost.

2.2.2.5 Automatic control: The Cue Priming theory of cue switch cost

A second seminal study with the double cuing paradigm presented an alternate perspective: that switch costs arise from a single component for using the cue to automatically select an upcoming task. Building on the theoretical framework of priming, the cue and stimulus are jointly encoded into a compound that uniquely determines the correct response (positive *cue priming* or *compound cue encoding*; Logan and Bundensen, 2003, 2004; Schneider & Logan, 2005; Logan & Schneider, 2006; Schneider, 2016). The current cue compound is compared to the previous cue in short-term memory and to other cues in long-term memory. A race takes place between the cue-stimulus compounds in short-term and long-term memory, until a match is found to the current cue-stimulus compound.

A semantic representation of the task to be performed is produced as a result of the comparison process, and then automatically retrieves a task[3] from memory using learned cue-task associations. Although *cue-task retrieval* is a second stage of cue priming, it is a product of the compound cue encoding process rather than being a separate stage, so cue priming is considered to be a single process theory.

Cue priming is supported by evidence that data from the double cuing paradigm were fit better by a mathematical model with a single cue switch component than a model with an additional independent task switch component (Logan & Bundensen, 2003, 2004; Arrington & Logan, 2004, 2005; Arrington et al., 2007). The single component of cue priming accounts for the stages of compound encoding and cue-task retrieval without the need for an independent task switch component (Schneider, 2016).

The cue-related process can occur over trials in a switch block (Logan & Bundensen, 2003, 2004; Schneider, 2016). A cue can be used to select tasks whether a task changes or not, as long as there is the possibility of a task change. Thus, the cue-related process may also be linked to global switch cost.

The cue can be used for advance preparation intervals (Logan & Bundensen, 2003). The cue can also be used to resolve interference from a previous task. Findings on ERP waveforms that were time-locked to the presentation of a cue found evidence for task set inhibition during the cue-target interval (Nicholson, Karayanidis, Davies, & Michie, 2006). Hence the cue-related process could replace the roles previously attributed to task preparation and task priming and may be used to explain both cue switch costs and task switch costs in local switch cost.

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[3] Although the type of task representation is unclear (either a task goal, task-name mediator, or task set), the account is clear that it is related to a product of the compound cue encoding rather than a separate process.

2.2.2.6 Summary of past theories

Previous models can be grouped into three categories. *Task preparation* theories propose an executive control component to program a task in advance and resolve externally triggered bottom-up interference from the stimulus. Preparation theories have also been termed additional process theories, since they propose an additional—and therefore, top-down—control process to intentionally shift or anticipate a shift. In contrast, *task priming* and *cue priming* theories propose a single automatic process that uses previously learned associations to select a task, using the stimulus (in task priming) or the stimulus and cue (in cue priming). Priming theories challenge the need for an active cognitive control process when shifting, and instead suggest an automatic—and therefore, bottom-up—priming effect. Multi-component theories combine task preparation and task priming to propose a top-down control process, and an additional bottom-up control process. Since multi-component theories build on the predictions of existing theories, they will not be further described here.

Task preparation theories propose that switch costs reflect a cost from an additional internal process, that could occur either on a task switch trial (task reconfiguration or cue retrieval), or over trials in a switch block (general preparation). An internal process is needed to select the task using the cue (endogenous reconfiguration), and to apply the task in response to the stimulus (exogenous reconfiguration), producing a *switching cost*. An internal process is needed to maintain readiness (sustained general preparation) and to resolve interference in response to the stimulus (dynamic general preparation) across a switch block, producing a *mixing cost*.

Task priming occurs on non-switch and task switch trials in a switch block, since carryover from a previous task could persist over time. Task priming proposes a *task repetition* *benefit* on a non-switch trial in a switch block, since the previously activated task in short-term memory can be applied to the new stimulus. Switch costs reflect a lack of the task repetition benefit, since carryover of the previous task is helpful when repeating a task but costly when changing a task on a task switch trial, as it automatically interferes with performance of a current task, and the interference can extend over trials in a switch block.

Cue priming occurs on non-switch, cue switch, and task switch trials in a switch block, since a cue can be used to select a task whenever there is the possibility of a switch. Cue priming proposes that cue switch costs reflect a *cue repetition benefit* on a non-switch trial in a switch block, since the previously activated cue-stimulus compound in short-term memory can be quickly matched to the current cue-stimulus compound. Cue switch costs reflect a lack of the cue repetition benefit, since changing a cue on a cue switch trial takes a longer time to find a match in long-term memory. Task switch costs reflect a further process on a task switch trial, since a match must be found in long-term memory, and must then be used to retrieve a task representation.

2.2.3 Present study

2.2.3.1 Goals

The general goal of the current study was to investigate the underlying processes that contribute to switch cost, by fractionating cue switch cost. An extensive body of evidence has used the standard task switching paradigm to investigate the source of local and global switch costs. An independent body of evidence has used the double cuing paradigm to investigate the source of task switch costs. However, little attention has been paid in the double cuing paradigm to the source of cue switch costs (Schneider, 2016). The current study addresses this gap. The current study makes the novel empirical and theoretical contribution of measuring cue switch cost in light of a global switch cost and asymmetric switch cost.

2.2.3.2 Comparing past theories

Past models can be distinguished by the nature of the processes that they propose underlie a shift in task (Table 2.1). According to task preparation theories, a top-down updating process loads task rules into working memory on trials in which a task changes or might change.

Table 2.1: Theoretical processes proposed to underlie task switching.

Measure (calculation)	Class of theory	Name of process	Type of control	Trigger	Mechanism (manipulation)	Effect
Local switch cost (cue and task switch trials in switch block - non-switch trials in switch block)	Task preparation	*endogenous reconfiguration* (Meiran, 1996; Rogers & Monsell, 1995); *preparatory component* (Meiran, 2000; Meiran, Chorev, & Sapir, 2000); *task expectancy* (Ruthruff, Remington, & Johnston, 2001)*; rule retrieval* (Mayr & Kliegl, 2000); *task preparation* (Sohn & Anderson, 2001)	executive	cue	preparation for new task using cue to retrieve task from long-term memory into working memory (advance preparation)	switching cost (cue-related)
	Task preparation	*exogenous reconfiguration* (Meiran, 1996; Rogers & Monsell, 1995); *residual component* (Meiran, 2000; Meiran et al., 2000; *rule activation* (Rubinstein, Meyer, & Evans, 2001); *transient control* (Braver, Reynolds, & Donaldson, 2003); *online reconfiguration* (Braver, Paxton, Locke, & Barch, 2009); *failure to engage* (de Jong, 2000)	executive and automatic	stimulus	application and response selection of new retrieved task and inhibit competing tasks (residual cost)	switching cost (task-related)
	Task priming	*task set inertia* (Allport, Styles, & Hsieh, 1994); *dissipating component* (Meiran et al., 2000); *task repetition* (Sohn & Anderson, 2001); *task recency* (Ruthruff et al., 2001); *backward inhibition* (Mayr & Keele, 2000); *task application* (Mayr & Kliegl, 2003)	automatic	stimulus	interference on new task from learned task associations on previous task (negative task priming)	task repetition benefit
Global switch cost (non-switch trials in switch block - non-switch trials in non-switch block)	Task preparation	*sustained preparation* (Braver et al., 2003); *mental load* (Los, 1996); *strategic view* (Los, 1996); *response criterion* (Los, 1999); *working memory load* (Rogers & Monsell, 1996; Rubin & Meiran, 2005)	executive	none	static preparedness across all trials (block strategy)	mixing cost
	Task preparation	*dynamic preparation* (Braver et al., 2003); *alternate processing* (Los, 1999)*; task decision* (Rubin & Meiran, 2005); *goal shifting* (Rubinstein et al, 2001); *time criterion* (Lupker, Kinoshita, Coltheart, & Taylor, 2003); *task expectancies* (Dreisbach, Haider, & Kluwe,	executive and automatic	stimulus	preparation per trial: adjusting readiness and inhibit competing tasks on a trial-by-trial basis (task mixing)	mixing cost

		2002); *dynamic task maintenance* (Braver et al., 2009)				
	Task priming	*proactive interference* (Allport & Whylie, 2000)	automatic	stimulus	interference across trials from learned task associations (negative task priming)	task repetition benefit
Cue switch cost (cue switch trials in switch block - non-switch trials in switch block)	Task preparation	*cue retrieval* (Mayr & Kliegl, 2003)	executive	cue	preparation for new task using cue to retrieve task from long-term memory into working memory (advance preparation)	switching cost (cue-related)
	Cue priming	*compound cue encoding* (Logan & Bundensen, 2003; Schneider, 2016)	automatic	cue and stimulus	selection for new task using learned cue-stimulus compound associations (positive cue priming)	cue repetition benefit
Task switch cost (task switch trials in switch block - cue switch trials in switch block)	Task priming	*task application* (Mayr & Kliegl, 2003)	executive	cue	execution of new retrieved task and inhibition of competing tasks (negative priming)	switching cost (cue-related)
	Cue priming	*cue-task retrieval* (a product of *compound cue encoding;* Logan & Bundensen, 2003; Schneider, 2016)	automatic	cue and stimulus	application of the produce from compound cue encoding (positive cue priming)	cue repetition benefit
Baseline (all trials in both blocks)	Processing speed	*processing speed* (Salthouse, 1996, 2005); *perceptual and motor task processes* (Rubinstein et al., 2001)	executive and automatic	stimulus	perceptual, motor, and general cognitive processes	

The mechanism of updating a task per trial makes a key testable assumption: that only one task set can be actively represented at a time in working memory (Schneider, 2016). A task must be updated per trial in response to a stimulus, because two tasks are associated with the same stimulus, and so a single stimulus is associated with two competing responses. An updating mechanism that only loads one task into memory at a time does not allow for multiple active or interfering tasks in working memory.

Therefore, a distinguishing feature among previous theories is how many tasks can be simultaneously held in working memory. Task preparation models propose that a single task can be held in mind. Hence an additional executive control process is required to load a task into working memory and inhibit any other tasks. In contrast, task and cue priming theories propose that more than one task representation can be active in working memory, such that tasks can facilitate or interfere with each other (via positive or negative priming). Task priming assumes that multiple task representations can interfere with each other in working memory, since a new task representation is automatically implemented when interference from a competing task representation dissipates (Allport et al., 1994; Mayr & Kliegl, 2003; Meiran, 2000). Similarly, cue priming also assumes that multiple task representations can be held and compared between in working memory, since the cue is automatically used to select a task by comparison with other representations in short-term and long-term memory (Logan & Bundensen, 2003).

The assumption that the rules for only one task can be held in working memory contradicts substantial evidence from the task switching paradigm that multiple task representations can be simultaneously active and can compete or interfere with one another in a task switching paradigm. The global switch cost literature offers a strong demonstration that multiple task representations can be concurrently active. We examine how the different theoretical frameworks account for each of these effects.

2.2.3.2 The cue switch cost and global switch cost

Past theories propose different explanations for global switch cost, and also on how it interacts with cue switch cost. Findings on global switch cost challenge the core assumption of task preparation accounts. This issue has been previously outlined with the logic that "If one set of task rules were retrieved into working memory on the previous trial, then it is unclear why a task repetition on the current trial (for which the relevant task rules are already in working memory) would be affected by the block context" (Schneider, 2016, p. 1113). In other words, task preparation accounts propose that a cue is used for the updating mechanism of retrieving one task into working memory, but they do not account for how a cue change (i.e., a task repetition) is influenced by the context of a switch block.

Task preparation theories propose an updating process for global switch cost, since the overlapping stimulus-response mappings mean that all the task representations cannot all be simultaneously held in working memory over a switch block (Rubin & Meiran, 2005). However, the updating process for global switch cost (dynamic preparation) is not linked to the updating process (cue retrieval or task reconfiguration) for the cue switch cost. However, as described in an earlier section, the standard measurement of a cue switch cost could interact with a global switch cost. Task preparation theories account for each these separately but fail to explicitly describe whether effects of the cue are influenced by the context of a switch block.

Task priming theories account for the context of a switch block by proposing that carryover from a previous task can occur over trials in a switch block. They account for non-switch trials and task switch trials in a standard task switching paradigm, but not for cue switch trials in a double cuing paradigm. However, they are focused on how the stimulus automatically triggers a task, and thus fail to explicitly describe how the cue has a role in a task switching paradigm.

Cue priming theories also account for the context of a switch block and the role of a cue. Thus, cue priming theories account for all the trial types in a standard task switching and a double cuing paradigm. Non-switch trials are the fastest since a match is made in the first stage of compound encoding between the current cue-stimulus compound and the short-term memory representation, cue switch trials take longer as the current cue-stimulus compound must be matched to a long-term memory representation in the first stage of compound encoding, and task switch trials take the longest as a match is made with a long-term memory representation in the first stage of compound encoding, and then a task must be retrieved in the second stage of cue-task retrieval.

In summary, all three theories account for the role of block, but only task preparation and cue priming further account for the role of a cue. Task preparation theories predict that a cue is independent of block. However, the cue priming theory specifically proposes that the cue may be linked to the context of a switch block. Task priming does not propose a role of the cue.

2.2.3.3 The task switch cost and asymmetric switch cost

Past theories propose different effects for how interference from other tasks influences preparation of a current task. The effect of interference from other tasks can be measured by testing whether changes in task difficulty produce an asymmetric switch cost. The finding of asymmetric switch costs was originally used to support task priming accounts. Task priming accounts claim that a switch cost arises from interference when switching away from a past task.

If the tasks are of unequal difficulty, carryover of a difficult task causes more interference (and hence a greater switch cost) than carryover of an easy task.

In contrast, task preparation theories propose that a preparation process can resolve interference from a previous task when switching to a new task. If the tasks are of unequal difficulty preparation is biased toward the difficult task, since the easy task already has a high base level of activation (Yeung & Monsell, 2003). Task preparation accounts are supported by evidence that interference from a past task can be reduced, and this also removes or reverses the asymmetric switch cost (Arbuthnott, 2008; Monsell et al., 2000; Yeung & Monsell, 2003).

We propose that the cue priming account can also be used to explain asymmetric switch costs, by using learned cue associations to automatically resolve interference when switching to a new task. Similar to other theories, cue priming suggests that asymmetry arises from the differential strength of task associations, but cue priming specifically proposes differential strength of cue-task associations. With tasks of unequal difficulty, cue-task associations for the easy task are stronger (i.e., have more priming) than associations for the difficult task. When switching from a difficult to an easy task, the priming of the prior difficult task is automatically counteracted by the greater priming of the current easy task. The stronger association with the easy task produces a reverse asymmetric switch cost.

Our predictions are speculative, since the asymmetric switch cost from task difficulty has not been previously measured with the double cuing paradigm. However, the backward effect of interference when switching away from a past task has been measured with the double cuing paradigm. One set of evidence from the double cuing paradigm fails to support our prediction, as it indicates that a cue switch cost is not influenced by task interference, but a task switch cost is influenced by task interference (Altmann, 2006, 2007; Gade & Koch, 2008; Horoufchin et al., 2011; Koch et al., 2010; Mayr, 2006; Mayr & Kliegl, 2003; Monsell & Mizon, 2006). However, another set of evidence does suggest that a cue switch cost is influenced by task interference, and that the cue can even be used to resolve interference by inhibiting an irrelevant task (Nicholson et al., 2006).

Further support of a cue priming explanation is seen in that increasing the strength of cue-task mappings reduces a switch cost, and conversely, decreasing the strength of the cue-task mappings increases a switch cost. The strength of cue-task mappings can be increased by familiarity, recency, transparency, or saliency of the mappings (Schneider, 2016; Schneider & Logan, 2011). For example, the switch cost is lower for meaningful or direct cues that have pre-existing associations with the task that they signal (such as the word 'color' in a color task). The strength of cue-task mappings can be decreased within an experiment by reversing cue-task mappings (compared to providing new cue-task mappings) or by informing participants about cue-task mappings (Forrest, Monsell, & McLaren, 2014; Gade and Koch, 2007).

2.2.3.4 Aims

The current study measured processes that have been shown to contribute to a switch cost: the cue change (cue switch cost), task change (task switch cost), and context of a switch block (global switch cost). The study then made the novel contribution of measuring how a cue switch cost is influenced by a global switch cost. Finally, the study measured how changes in a control factor of task difficulty influence global and task switch costs (asymmetric switch costs). These manipulations enabled us to test the assumptions of previous theories. The setup also enabled examining the magnitude of cue switch cost, global switch cost, and asymmetry of individual task-related switch cost in a single experiment.

Global switch cost has not been previously measured with the double cuing paradigm, but evidence from the standard task switching paradigm indicates that the role of the cue is influenced by the context of a switch block. The asymmetry of switch costs has also not been previously measured with the double cuing paradigm, but evidence from both paradigms indicates that a cue may be used to resolve interference from changes in task difficulty.

We manipulated conditions of the combined paradigm to produce a set of trial types that each reflect a different combination of components that contributes to a task switch cost. We then subtracted the effect of each manipulation to fractionate the empirical components that produce a switch cost. Following this, we investigated interactions between manipulations to examine the nature of the control processes that may underlie the observed components. Manipulating experimental conditions allowed us to examine theories for the processes proposed to underlie a switch cost. Thus, we aim to gain insights into the control processes for task switching, by linking observed components to theoretical processes.

Our specific aims are outlined below.

A. Examine the mechanism for cue processing (i.e., cue changes). To achieve this, measurements were combined from the double cuing and standard task switching paradigm, to test whether a cue change (cue switch cost) is influenced by the possibility of a task change (global switch cost). We predict an interaction, with a cue change having a large effect size only under the possibility of a task change, and a small effect size with no possibility of a task change.
B. Examine the mechanism for task processing (i.e., actual and potential task changes) after accounting for cue processing. To achieve this, measurements accounted for the specific task, to test whether a task change (task switch cost) and possibility of a task change (global

switch cost) is influenced by task difficulty (asymmetric switch cost). We predict an interaction between task type and a task change, and between block and task change. It is uncertain whether switch costs will be larger for switching away from a difficult task (asymmetric switch cost) or switching to a difficult task (reverse asymmetric switch cost).

To investigate proposed mechanisms for a cue change, we tested whether the cue change was influenced by the context of a switch block. Existing theories differ on whether there will be a main effect of a cue change or block and whether these effects interact (Table 2.2). Task priming accounts propose a main effect of block but not a main effect of a cue change, since a process linked to the task set occurs over trials in a switch block. Task preparation accounts would predict that a main effect of a cue change for an updating process related to the cue takes place on cue switch trials in which a cue changes. Preparation accounts do not predict an interaction between cue change and block, since the updating process is not influenced by concurrently active representations. The cue priming account predicts a main effect of cue change for an encoding process related to the cue as well as an interaction between cue change and block, since compound cue encoding is influenced by other available task representations on non-switch and cue switch trials in a switch block.

Table 2.2: Theoretical predictions for current study.

Theory	Test 1: Cue change x Block	Test 2a: Block x Task difficulty	Test 2b: Task change x Task difficulty
Task preparation	Significant main effects	Significant main effects and interaction (symmetric)	Significant main effects and interaction (symmetric)
Task priming	Significant main effect of block	Significant main effects and interaction (asymmetric)	Significant main effects and interaction (asymmetric)

Cue priming	Significant main effect of block and interaction	Significant main effects and interaction (asymmetric)	Significant main effects and interaction (asymmetric)

To investigate proposed mechanisms for an actual and potential task change, we tested whether local and global task changes were influenced by interference from a more difficult task. Existing theories propose there will be main effects of a task change (local switch cost), block (global switch cost), and task difficulty, and that both task change and block will interact with task difficulty. However, theories differ on the direction of the interaction. Task priming accounts predict that a task change will take longer when switching from a difficult to an easy task (a local asymmetric switch cost), due to having to inhibit the more difficult task on a switch trial. Similarly, trials in a switch block will be longer for an easy task than a difficult task (a global asymmetric switch cost), due to having to inhibit the more difficult task across trials in a switch block. Task preparation and cue priming models predict that a task change will be faster when switching to an easy task (a reverse asymmetric local switch cost), due to a stronger association with the easier task. Similarly, trials in a switch block will be faster for an easy task (a reverse asymmetric global switch cost), due to a stronger association with the easier task.

The paradigm used in the current study had tasks of unequal difficulty levels. Past studies have shown that it is much easier to for individuals to categorize faces according to gender than to emotion, possibly because individuals use different mechanisms for the tasks of emotion and gender categorization in faces (Bruce & Young, 1986; Haxby, Hoffman, & Gobbini, 2001). Since the tasks were of unequal difficulty, we were able to introduce task type as a control factor.

2.3 Methods

2.3.1 Participants

The study was conducted online, via a task on the website of one of the research collaborators (Dr. Stian Reimers). Implementation was identical to Reimers and Maylor (2005). Sessions were brief (< 10 minutes) to encourage participation and task completion. The task was completed 29,242 times. Some completions were excluded (25 where participants who reported an age below 10; 12,629 with an error rate over 35% in at least one experimental condition, 1,346 with no age reported, 485 where participants indicated that they had completed the task before, and 272 other completions that were not suitable for data analysis). The final sample after exclusions consisted of 14,757 individuals (4139 identifications as male, 10,536 identifications as female, and 82 no response). Included participants had an age range of 10 to 66+ [4]years, with a median age of 23 (*interquartile range* = 16). Age, gender, and education were self-reported. Participants were given information about the task before commencing the study. Our obtained sample size was sufficient to detect an effect size of $\eta_p^2 = 0.001$, giving us power to detect even a tiny effect.

2.3.2 Materials

The task switching paradigm used in the current study was very similar to Reimers and Maylor (2005). It consisted of two task sets with the addition of two cues per task ("emotion" or "feeling", and "gender" or "sex"). Two stimuli were used: either a happy female face and a sad male face, or a sad female face and a happy male face. Stimulus set was randomly allocated between subjects.

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[4] Participants reported their actual age, but individuals over 65 were grouped into a single age of '66+'.

2.3.3 Design and procedure

The experiment consisted of three blocks: Two single-task blocks, and a switching block. All tasks were choice reaction time measures, in which participants pressed a keyboard button ('D' or 'K') to select one of two responses (happy/sad or male/female).

Key mappings were made at the start of the experiment, and then remained consistent across blocks. After key mappings were made, the two stimuli to be used were selected to create incongruent mappings of the two response options, so that the participant would have to give a different response to each stimulus depending on which task was cued. Key mappings were randomized for each participant.

The single task blocks consisted of 12 trials. The cue changed every two trials but was redundant in these blocks. In the single task blocks, participants categorized each face according to gender (male/female) or emotion (happy/sad), with the order of single task blocks randomized across participants. The two face stimuli were presented equal numbers of times in random order.

The switching block consisted of 50 trials (two filler trials at the start, 48 experimental trials). As in Reimers and Maylor (2005), trials were paired, with repetitions of the same cue, meaning that trials were always cue/task switch followed by non-switch, followed by cue/task switch followed by non-switch. For example:

c_1t_1 - c_1t_1 - c_2t_1 - c_2t_1- c_1t_1 - c_1t_1 - c_3t_2 - c_3t_2 - c_1t_1 - c_1t_1 - c_4t_2 - c_4t_2 - c_3t_2 - c_3t_2

NS CS NS CS NS TS NS TS NS TS NS CS NS

where c1 and c2 are separate cues for the task t1 (e.g., Emotion, Feeling), and c3 and c4 are separate cues for the task t2 (e.g., Gender, Sex). Trial type indicated as non-switch (NS), cue-only switch (CS) and task switch (TS). Order of switches (CS or TS) was randomized subject to the constraint that there were exactly 12 cue-switch trials and 12 task-switch trials (as well as 24 non-switch trials), and no more than three consecutive switches of the same type.

The sequence of stimuli was constrained so that one of the two face stimuli was chosen with 50% probability for each trial. The exception was when the previous three stimuli were all the same face, in which case the other face was used.

At the start of a trial, a cue appeared, which remained on the screen throughout the trial. After 250ms[5], one of the two face stimuli for that participant was presented for 250ms. As soon as the face was presented, participants could respond using the keyboard. Immediately after a response, the cue disappeared, and there was a 1,500ms inter-trial interval (ITI) before the next trial began. Following an incorrect response, a box with the word 'OOPS!' appeared on the screen for 1,000ms, after which there was an ITI of 1,750ms and the next trial started.

The paradigm had five trial types in total: two in the single-task block (non-switches and cue-only switches) and three in the switch block (non-switches[6], cue-only switches, and cue plus task switches). Reaction times and percent error were measured for each trial type. Incorrect responses and reaction times under 200 ms were excluded from analysis. Data were collected between April 2006 and May 2011.

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[5] The times given here are those that were specified in the code. In practice, as the code has no control over monitor synchronization or other processes on the user's computer, they are likely to be imprecise. For a discussion of presentation duration accuracy under Adobe Flash, see Reimers & Stewart (2015).

[6] Technically, there were two types of non-switch trials in the switch block: non-switch after cue switch, and non-switch after cue plus task switches. Both fall under the broad category of non-switch trials. In calculating processes for switch cost, only one non-switch trial type was used (non-switch after cue plus task switches) to provide a purer baseline for process subtraction. However, analyses were also run on the second type of non-switch trials (non-switch after cue switch) and compared for differences, but no significant change was observed when adding the additional trial type.

2.3.4 Analyses

2.3.4.1 Analysis of variance (ANOVA)

The combined paradigm contains three trial types and two types of trial block, producing five trial classifications in total (Figure 2.6). Non-switch blocks consist of a single task in which the cue changes (cue switch trials) or remains the same (non-switch trials). Switch blocks consist of no cue or task change (non-switch trials), a cue change but no task change (cue switch trials), or task changes (task switch trials).

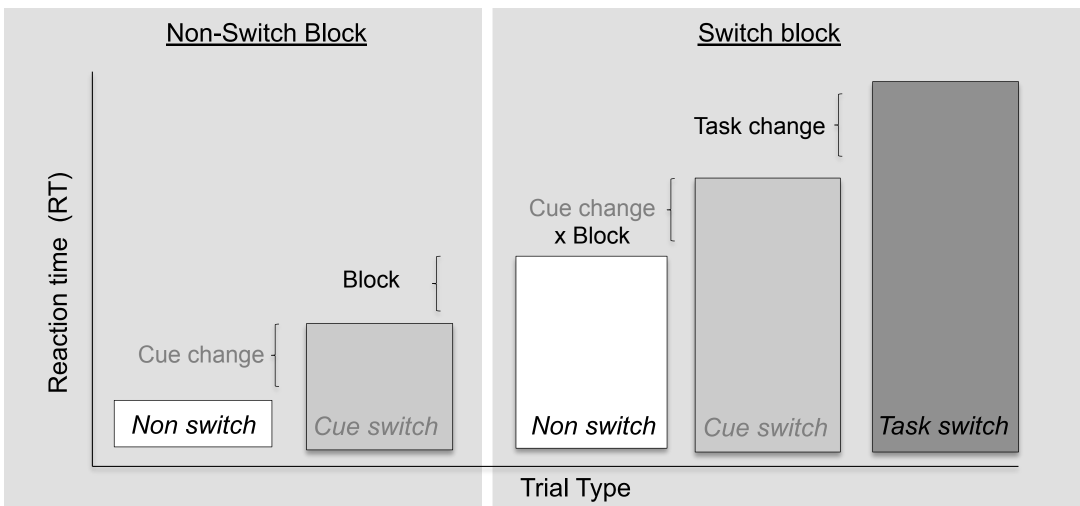

Figure 2.6: Trial types in a combined paradigm

A schematic diagram of trial types for the combined paradigm arranged in order of complexity. The combined paradigm in the current study manipulated a cue change, block, and a task change. We also manipulated task difficulty (not shown). Each task manipulation leads to a further increase in reaction time. The image shows how trial types are subtracted to create components of a switch cost.
Note. Image based on Jost et al. (2015, Figures 1C and 2C)

Trial types were classified into factors and measured using an ANOVA. Based on the literature for local and global switch cost, the factor of a task change was measured by comparing trials in the same block to measure the process for within-block or local switch cost. A between-block or global switch cost was measured using a factor of block to compare the non-switch trials in switch and non-switch blocks. A pure local switch cost was measured using a factor of task change to compare task switch and cue switch trials in a switch block. A cue switch cost was measured using a factor of cue change to compare cue switch trials to non-switch trials, in both a switch block and a non-switch block. An asymmetric switch cost was measured using a task difficulty factor to compare the specific task for each trial type in each block.

It is logically impossible with the current experimental design to have task switch trials in a non-switch block, or to have a task change without a cue change (refer Figure 2.6). Due to the unbalanced design, a single ANOVA with all the manipulations for trial types does not produce a complete factorial design since all possible combinations of each level of each factor were not measured. Hence, trial types were classified into two separate ANOVAs (refer Analyses below). The ANOVAs divided effects into within and between blocks.

To summarize, the factors tested were as follows:

- block: non-switch trials in a non-switch block versus non-switch trials in a switch block
- task change: task switch trials versus cue switch trials (in a switch block)
- cue change: cue switch trials versus non-switch trials (in both blocks)
- task type: gender-sex trials versus emotion-feeling trials

These factors were used to test the two goals of the current study: (1) the cue switch mechanism via the interaction between cue change and block, and (2) the task switch mechanism, via the (2a) interaction between block and task type and (2b) the interaction between task change and task type.

2.3.4.2 Effect sizes

Simple (unstandardized) effect sizes are reported using the units of the measurement instrument, in this case reaction times in milliseconds. The effect size for each factor describes the increase in baseline reaction time as a result of that factor. Using past studies and our understanding of reaction time effects (refer discussion section for details), we interpreted effects above 10 ms as small, above 50 ms as medium, above 100 ms as large, and above 200 ms as very large. As a second measure of unstandardized effect size, we report the percentage increase in reaction time for each effect. The percentage increase is calculated as

$$\%\ increase = \left(\frac{increase}{original\ value}\right) \text{ x } 100, \qquad [1]$$

where,

$$increase = new\ value - original\ value \qquad [2].$$

2.4 Results

Analyses were conducted using the R language and environment for statistical computing. Before analysis, each participant's reaction times were trimmed using a recursive trimming script to remove data that were greater than 4 standard deviations above the mean for each condition. An across-participant recursive trimming procedure was then applied, with the criterion changing as more trials were removed (technique described in van Selst & Jolicoeur, 1994). Trimming was done per age per condition using the R package trimr (Grange, 2015). When an extreme reaction time was found, that subject was excluded from the sample. The final sample size after trimming was 13,718 (*n*=1039 removed). Means for each trial type are presented in Figure 2.7.

Before conducting the main ANOVA-based analysis to classify trial types according to different factors, we used a repeated measures ANOVA to confirm that there were differences between all the trial types. The repeated measures ANOVA compared reaction times across trial types: non-switch trials in non-switch and switch blocks, rt_{nsns} and $rt_{nss,}$ respectively, cue switch trials in non-switch and switch blocks, rt_{csns} and $rt_{css,}$ respectively, and task switch trials in switch blocks, rt_{ctss}). Each trial type was predicted to measure a different aspect of task switching performance. Trial types were further broken down into task type (emotion and gender). A significant test statistic was found, $F(9,125320) = 15683$, $p < .001$, indicating that all trial types were significant predictors of reaction time on task switch trials. On emotion trials, effect sizes were 225 ms for rt_{nsns}, 198 ms for rt_{csns}, 6.5 ms for rt_{nss}, 182 ms for rt_{css}, and 385 ms for rt_{ctss}. On gender trials, effect sizes were 261 ms for rt_{nsns}, 237 ms for rt_{csns}, 53.8 ms for rt_{nss}, 119 ms for rt_{css}, and 282 ms for rt_{ctss}.

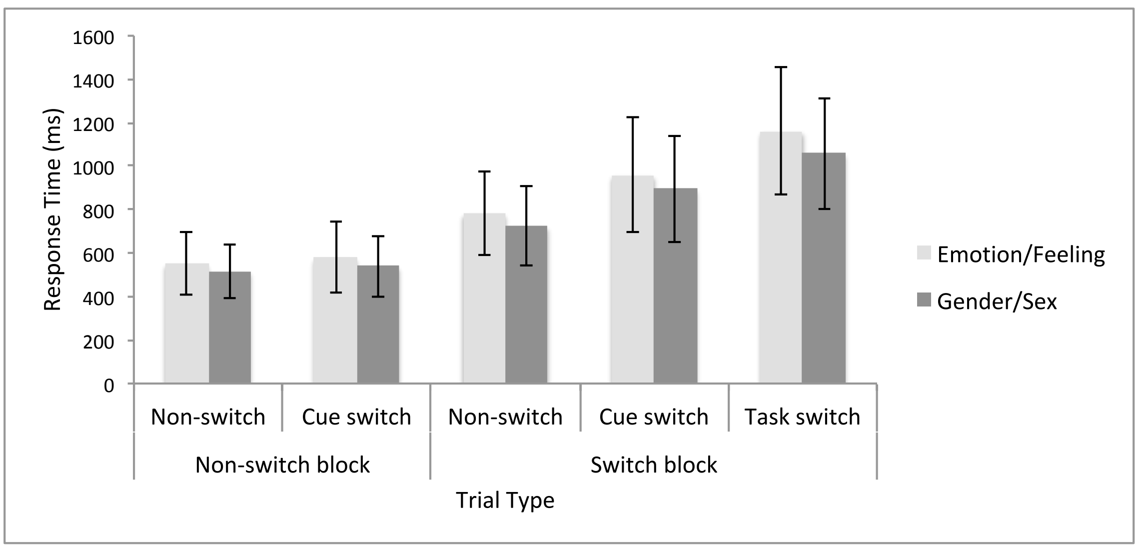

Figure 2.7: Reaction times for each trial type

Mean (+/- 1 SD) reaction times per trial type, broken down into the two task types. The reaction time for each trial type increased as the trials became more complex. The more difficult task type (emotion/feeling) took slightly longer than the less difficult task (gender/sex) across trial types.

Next, trial types were coded into factors and measured for significant main effects and interactions. Coding trials into factors allowed us to examine the different categorizations between trial types. For example, between trials in the same block (a main effect of block) and between non-switch and cue switch trials (a main effect of a cue change).

2.4.1 Initial models (all factors included)

2.4.1.1 Between-blocks ANOVA

For the first ANOVA, trials between blocks were used to produce a 2 x 2 x 2 ANOVA (task type: gender-sex, emotion-feeling; cue change: non-switch, cue switch; block: non-switch, switch).

<u>Test 1: Cue change and block</u>

The factor of block was significant (Table 2.3). Trials in a switch block were slower than those in a non-switch block. This confirms past studies on a global switch cost or between-block effect, since it takes longer to respond to trials on which there is a possibility that a task might change, compared to trials on which there is no possibility of a task change. Block had a very large unstandardized effect size of 206.7 ms, indicating that there was a substantial increase in processing time with the possibility of a switch.

Cue change was significant, and there was a significant two-way interaction of block and cue change (Table 2.3). There was an overall small main effect of cue change, 23.2 ms. Thus, we do not interpret this effect further. There was a large interaction between cue change and block, 149.2 ms.

Post-hoc tests of the interaction indicated that cue change trials took significantly longer than non-switch trials in a non-switch block, $F(1, 100256) = 222$, $p < .001$, and non-switch trials in a switch block, $F(1, 100256) = 10675$, $p < .001$ (Figure 2.8A). However, in a non-switch block, the difference between these trial types was minimal, with an effect size of 25.1 ms. Thus, we do not interpret this effect further. In a switch block, the difference was notable, with an effect size of 174 ms.

Test 2a: Block and task type

The factor of task type also had a significant effect. Participants took slightly longer to perform the emotion/feeling task than the sex/gender task, which confirms past studies that emotion/feeling is the more difficult task. There was a small effect size of 35.9 ms.

Table 2.3: Regression results for the between-block ANOVA.

	Initial Model (all factors)	Final Model (without Task Type)
Factor	*B* (*SE*)	*B* (*SE*)
Constant	516.12*** (1.68)	534.06 *** (1.20)
Block	206.74*** (2.38)	218.92 *** (1.70)
Cue Change	23.16 *** (2.38)	25.12 *** (1.70)
Task Type	35.89 *** (2.38)	
Block x Cue Change	149.20 *** (3.37)	148.95 *** (2.40)
Block x Task Type	24.36 *** (3.37)	
Cue Change x Task Type	3.91 (3.37)	
Block x Cue Change x Task Type	0.51 (4.76)	
R^2	0.42	0.41
F	1.049e+04***df(7,100256)	2.34e+04***df(7,100260)

Note. The table displays unstandardized regression coefficients (*B*), fit indices, and significance tests. The dependent variable was reaction time, measured in ms. ** $p < 0.01$*** $p < 0.001$

Table 2.4: Regression results for the within-block ANOVA.

	Initial Model (all factors)	Final Model (without Task Type)
Factor	*B* (*SE*)	*B* (*SE*)
Constant	895.23 *** (2.37)	927.05 *** (1.70)
Task Change	163.08 *** (3.35)	182.73 *** (2.40)
Task Type	63.64 *** (3.35)	
Task Change x Task Type	39.31 *** (4.73)	
R^2	0.13	0.10
F	2425*** df(3,50128)	5814*** df(1,50130)

Note. The dependent variable was reaction time, measured in ms. ** $p < 0.01$*** $p < 0.001$

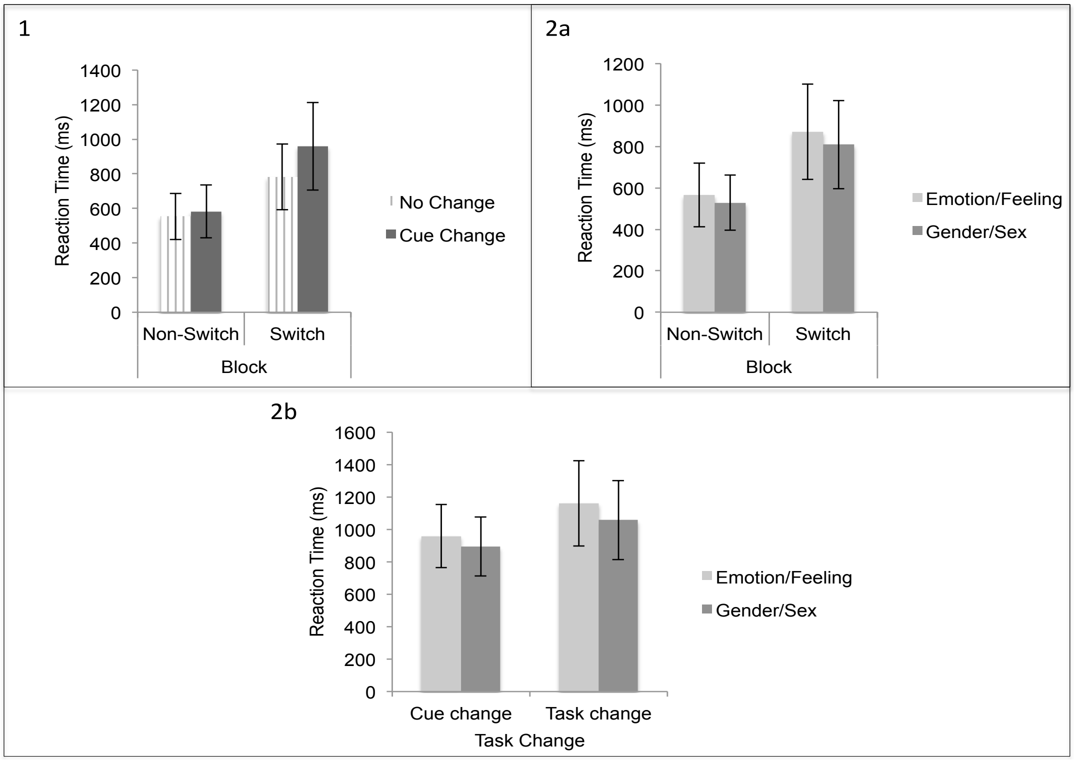

Figure 2.8: Reaction times for interactions

Mean reaction times (+/- 1 SD) for each of the three interaction effects. (1) The factor of block interacted with cue change, (2a) the factor of block interacted with task type, and (2b) the factor of task change interacted with task type.

There was a significant two-way interaction between block and task type, but with a small effect size of 24.4 ms. Although small, the interaction was over half the size of the main effect. The interaction showed that the longer processing time for a switch block was even longer for the difficult task (Figure 2.8B). This suggests a reverse asymmetric effect of task difficulty on global switch cost.

There was no significant two-way interaction of task type and cue change. This indicates that unlike global switch cost, the longer processing time for a cue was not dependent on the type of task. There was no significant three-way interaction of task type, block, and cue change.

2.4.1.2 Within-block ANOVA

For the second ANOVA, trials within a switch block were used to produce a 2 x 2 ANOVA (task type: gender-sex, emotion-feeling; trial type: cue switch, task switch).

Test 2b: Task change and task type

The factor of task change was significant (Table 2.4). Task switch trials took longer than cue switch trials, indicating that changing a task had an additional slowing compared to only changing a cue. Task change had a large effect size of 163.1 ms, indicating that there was a substantial increase in processing time for a task switch relative to a cue switch.

Task type had a significant effect, with a medium effect size of 63.6 ms (Table 2.4). Similar to the between-block ANOVA, it took longer to perform the difficult task (emotion/feeling) than the easy task (sex/gender) across trial types. There was a significant two-way interaction between task change and task type, with a small effect size of 39.3 ms. The interaction showed that the longer processing time for a task switch was even longer for the difficult task (Figure 2.8C). The demonstration of reverse asymmetry fails to confirm past studies demonstrating an asymmetric local switch cost.

2.4.2 Final models (removing the factor of task type)

To investigate the specific contribution of each factor to the total switch cost, the factor of task type was removed since it was not a notable effect size. Additional regression models were fitted for each of the ANOVAs described above. Block had a significant and very large effect size of 218.9 ms. Cue change had a significant but small effect size of 25.1 ms. The two-way interaction between block and cue change was significant and had a large effect size of 149.0 ms. On the second ANOVA, task change had a significant and large effect size of 182.7 ms.

The final regression equation combining both ANOVAs and ignoring task type is

$$rt_{cts} = 534.1 + 218.9\ rt_{Block} + 25.1\ rt_{CueChange} + 149.0\ rt_{BlockXCue} + 182.7\ rt_{TaskChange}, \quad [1]$$

where rt_{cts} is the reaction time on cue plus task switch trials (a task plus cue change) in switch blocks. A graph dividing the total reaction time per trial into the effects of the different factors is presented in Figure 2.9.

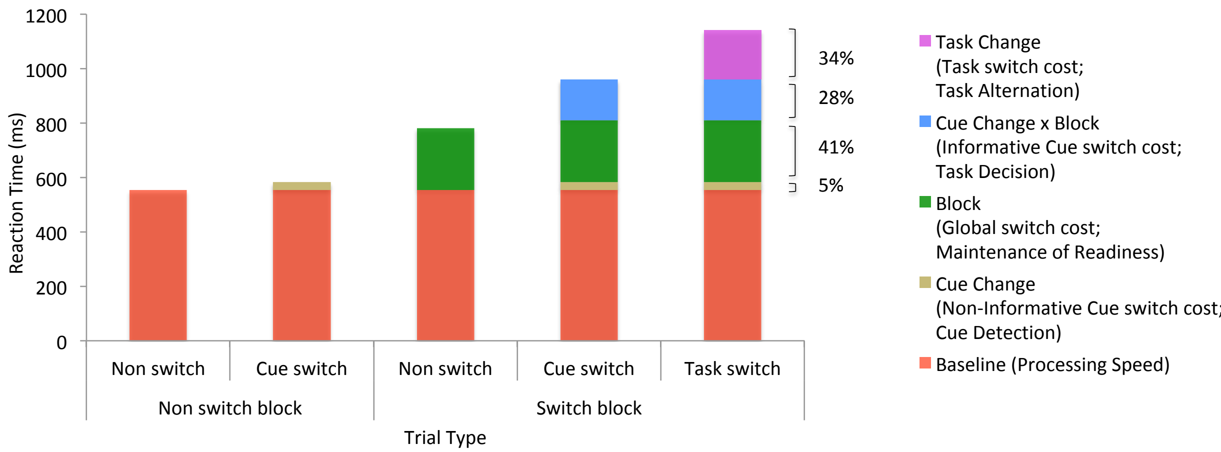

Figure 2.9: Trial types broken down into theorized processes

Mean reaction times (in ms) for each trial type, averaging across task type. The reaction time for each trial is divided into the control processes for that trial. Control processes are explained by the factor (i.e., experimental manipulation) and the theorized underlying process (in parentheses). The percentage of increase in time compared to the baseline is shown for each process.

2.5 Discussion

There is a considerable cost when individuals shift rapidly between tasks. The task switching paradigm has been used to fractionate the switch cost into a task change (local switch cost) and readiness in case of a change (global switch cost). Local and global switch costs can also include effects of switching away from a previous task, seen in a greater switch cost for shifting away from a difficult task than an easy task (asymmetric switch costs). A local switch cost can be further fractionated into a cue change (cue switch cost) and a pure task change (task switch cost). The current study measured these effects to gain novel insights into the components that contribute to a switch cost. In line with many previous studies, we did not find an asymmetric switch cost (Arbuthnott, 2008; Lupker, Kinoshita, Coltheart, & Taylor, 2003; Monsell et al., 2000; Rubinstein et al., 2001; Ruthruff et al., 2001; Yeung & Monsell, 2003). We replicated a cue switch cost for local switch cost and extended it to the parallel finding that a cue switch cost depends on the context of a switch block. Past findings have highlighted the role of the cue in task switching. We add to these findings to show that the role of the cue is dependent on the possibility of a task change (in a switch block), possibly since a cue has an effect only in circumstances where the cue can signal a potential task change. This finding explicitly confirms what was previously only an implicit assumption in the task cuing literature—that the cue is used specifically to signal a new task.

Our findings failed to confirm asymmetric local and global switch costs. Instead, we found symmetric local and global switch costs, demonstrating forward effects for shifting to a current task, with a greater switch cost for shifting to a difficult task than shifting to an easy task. The asymmetric switch cost has been inconsistently found in past studies. Our finding adds to the studies that fail to observe an asymmetric switch cost. We extend this observation by using a double cuing paradigm to more clearly measure asymmetric changes in task difficulty, by parsing the task switch cost from the cue switch cost.

We replicated local, global, and cue switch costs. Our findings support past insights that cue switch costs may be separate from task switch costs. Our findings provide the novel insight that cue switch cost should be measured in the context of a switch block, since cue switch cost is not independent of a switch block. These findings offer an important clarification on two effects that have been widely supported but had not been tested in combination with each other.

2.5.1 Value of fractionating cue switch cost

The current study achieves the goal of fractionating cue switch cost, to account for previously demonstrated effects of block and task difficulty. The double cuing paradigm has provided a unique means to isolate a cue change from a pure task switch. The paradigm has paid considerable attention to the source of task switching effects. The paradigm has offered compelling evidence that the cue plays a major role in task switching, but also that a task switch cannot be completely accounted for by a cue. In contrast, the source of a cue switch has received considerably less attention. The current study addressed this gap.

Fractionating cue switch cost to account for effects of block is theoretically useful, since task preparation and cue priming accounts make contrasting predictions on whether cue-related processing is influenced by the presence of other tasks. Accounting for cue switches in a non-switch block is empirically useful, since it has the benefit of completeness in accounting for all the conditions in a double cuing paradigm. Task switching studies have found an effect of switching a task within and between blocks, but double cuing studies have been limited to the effect of switching a cue within a switch block only.

Researchers have failed to explicitly clarify whether or not they expect a cue change to be influenced by block. We expect this oversight is built on the assumption that a cue change is only of interest in a switch block—that is, under the context of a possible task switch. Intuitively, this makes sense. Without the possibility of a switch, the cue has no utility and may even be distracting. However, the intuitive assumption that a cue change is not informative in a non-switch block had yet to be empirically demonstrated. If a cue change also had an effect in a non-switch block, then this finding could be used to calculate a purer measure of the cue switch cost, which was not confounded by the presence of switch trials.

Only one study to date has attempted to further fractionate a cue switch cost (Schneider, 2016). The comparison process that occurs during a cue change was further parsed into perceptual comparison to assess the visual form of the cue, and conceptual comparison to assess the meaning of the cue. Separate processes were found for each, which further supports the use of a cue to automatically compare between past learned associations. The fractionation of a cue change in the current study measures a different aspect of cue-related processing, but Schneider's findings are useful in highlighting that cue-related processing in task switching is more complex than was previously thought.

2.5.2 Framework for components of task switching

Going by the standards of reaction time effects, the switch cost is extremely large (hundreds, instead of tens, of milliseconds; Monsell & Driver, 2000). The current study replicated the extremely large effect size of a switch cost. Further, we were able to quantify the time taken for the components that contribute to the overall switch cost, by using regression models (via ANOVAs) to partition the total switch cost into each of the contributing effects.

At the most general level of analysis, a switch cost represents the decrement in performance between a switch trial and a non-switch trial in a task switching paradigm. We measured reaction times on a non-switch trial in a non-switch block to account for this baseline reaction time. Baseline reaction time is considered to reflect *processing speed* or psychomotor speed (Salthouse, 1996, 2005). Processing speed reflects the time taken for processes that occur on all speeded reaction time tasks, such as identifying a stimulus, selecting a response, and executing a movement (Rubinstein et al., 2001). These processes occur across all trials in all blocks, and are not unique to task switching

Accounting for processing speed enabled us to isolate switch-specific processes from these general cognitive, motor, and perceptual processes. We found that processing speed was the largest contributor to the total reaction time on a task switch trial. Regression coefficients (unstandardized effect sizes) indicate that reaction times for processing speed accounted for around half of the total reaction time when a task changed (task switch trial). In other words, the time taken to switch a task was nearly as long as the time taken to perform the task on its own.

Being ready for a potential task change in a switch block (global switch cost) was the second largest contributor to the total reaction time, taking 219 ms or 41% longer than performing a single task. Global switch cost had an even larger effect than actually making a task change (task switch cost), which took 183 ms or 34% longer. Accounting for a cue change (cue switch cost) also had an effect of taking 148 ms or 28% longer than performing a single task. Importantly, the effect of a cue change was notable only when the cue signaled a potential task change, rather than when the cue changed but was not informative—the latter only took 25 ms or 5% longer.

Most of the global and local switch cost literature has confounded a task change (actual or potential) with a cue change. Similarly, the cue switch cost literature has confounded a cue change with a potential task change. The current study proposed a way of isolating these effects. Thus, we partitioned switch cost into a framework with all the previously demonstrated effects (Figure 2.5). Future studies should test this framework using experimental manipulations targeting each of the proposed components.

We suggest using new terms to avoid confusion when referring to our adapted measures of global, cue, and task switch cost. We propose terms to disambiguate the standard measures of a switch cost (Figure 2.9). The proposed terms link our results to previous findings on the nature of the underlying processes represented in each measure. Specifically, a switch cost can be fractionated into a *task alternation* process for a task change itself, a *maintenance of readiness* process to anticipate a potential task change, a *cue detection* process for a cue change with no potential task change, and a *task decision* process for a cue change with a potential task change.

2.5.3 Theoretical mechanisms for a switch cost

A longstanding issue in cognitive psychology has been the study of the control processes that produce goal-oriented behaviour. The task switching paradigm has been proposed and widely used as a representative measure of executive control (Brown et al., 2007; Rogers & Monsell, 1995; Rubinstein et al., 2001; Monsell, 2003; Monsell & Driver, 2000; Sohn & Anderson, 2001). However, a constellation of automatic processes has been supported in the task switching paradigm, leading some researchers to question the need for executive control in task switching (Allport & Whylie, 1999; Altmann, 2003; Logan & Bundensen, 2003). The current study provided insight on this debate by showing that an automatic control explanation may sufficiently account for the observed phenomena in a double cuing task switching paradigm. We also gained insights on the type of automatic control in task switching, since the findings supported the automatic control theory of cue priming but not of task priming.

2.5.3.1 Combining the task switching and double cuing paradigms

The question of cognitive control has been addressed using both the task switching paradigm and the double cuing paradigm. Independent findings from each paradigm have yielded different results on the role of executive and automatic control processes. The current study makes the novel contribution of combining these paradigms. We compared empirical effects and proposed theoretical explanations from each paradigm to gain insights into whether automatic or executive control processes contribute to task switching.

The general consensus from the task switching literature is that both automatic and executive control are involved. Early single component theories from the task switching paradigm debated whether a switch cost reflected an executive control process for preparing a current task and resolving interference from competing tasks or an automatic process of priming from carryover of a previous task (Rogers & Monsell, 1995; Allport et al., 1994). An additional executive control process was proposed for general preparation when anticipating a potential shift (Meiran et al., 2000; Rubinstein et al., 2001). The executive control process for task preparation was linked to the cue, while the automatic process for task priming was linked to the stimulus or carryover from a past task. Later multi-component theories proposed that task preparation and task priming are inextricably linked and that both contribute to a switch cost (Meiran et al., 2000; Sohn & Anderson, 2001). Similarly, reviews of the literature propose the need for both processes (Kiesel, Steinhauser, Wendt, Falkenstein, Jost, Philipp, & Koch, 2010; Meiran, 2010; Vandierendonck et al., 2010).

Theories from the double cuing paradigm have failed to reach a consensus on whether switch cost requires executive control. One theory built on past multi-component theories to propose a switch cost included both an executive control process for task preparation linked to the cue and an automatic process for task priming linked to the stimulus or carryover from a past task (Mayr & Kliegl, 2003). An opposing theory proposed only an automatic cue priming process to prepare a current task and resolve interference from competing tasks (Logan & Bundensen, 2003; Schneider, 2016). In summary, past theories debated whether switch costs reflected an executive control process for shifting to a task using a cue (task preparation), an automatic process for shifting away from a past task based on a stimulus (task priming), or an automatic process for shifting to a task using a cue (cue priming).

Early empirical findings from the task switching paradigm supported both task preparation and priming and suggested these processes were independent. Task preparation was linked to using the cue, while task priming was linked to the stimulus (Meiran, 2000; Meiran et al., 2000; Ruthruff et al., 2001; Sohn & Anderson, 2000). Later findings suggested that these processes were not independent and interacted with each other (Hsieh & Liu, 2005; Kiesel et al., 2010; Meiran, 2010; Vandierendonck et al., 2010; Yeung & Monsell, 2003). Further, as the effects of the cue in a task switching paradigm were more closely examined, it appeared that processes previously attributed to task preparation and priming may actually be linked and both use the cue (Forrest, Monsell, & McLaren, 2014; Gade and Koch, 2007; Nicholson et al., 2006; Schneider, 2016; Schneider & Logan, 2011).

The double cuing paradigm explicitly separated cue and task processes. Early findings with the double cuing paradigm supported separate components of task preparation and priming (Altmann, 2006, 2007; Gade & Koch, 2008; Horoufchin et al., 2011; Koch et al., 2010; Mayr, 2006; Mayr and Kliegl, 2003; Monsell & Mizon, 2006). Later evidence supported joint cue and task processes (Logan and Bundensen, 2003, 2004; Schneider & Logan, 2005; Logan & Schneider, 2006; Scheider, 2016). By combining effects from these paradigms, we were able to test the need for separate cue and task components.

Existing theories proposed mechanisms related to the cue, the task, or both. The theories differed on the nature of these mechanisms and whether they were distinct. The cue mechanism was thought to reflect either a top-down process (task preparation) or a bottom-up process (cue priming). The task mechanism was thought to reflect a bottom-up process that was either independent to the cue process (task priming) or an after-effect of the cue process (cue-task retrieval, a product of cue priming). Our results enabled us to more closely test predictions of past theories.

2.5.3.2 Testing the mechanism for a cue switch

To examine the mechanism for a cue switch, cue switch cost was measured in conjunction with a global switch cost (single task blocks versus mixed task blocks). Past findings with the double cuing paradigm focused on the role of the cue in local switch cost. We extended this to look at the role of the cue in global switch cost. The extension allowed us to measure a pure cue switch cost, to test whether the effect of a cue was dependent on whether there was the possibility of a switch.

The previously demonstrated role of the cue in local switch cost suggested a cue is used for a task switch, which supported both task preparation and cue priming accounts. However, the role of the cue in global switch cost cannot support both accounts. Measuring the interaction between a cue change and block specifically tested whether a cue was also used under the possibility that a task switch may occur, indicating that a cue was used for the organization of multiple mappings in working memory to generally prepare for a task change. This cannot be explained under task preparation accounts, which propose that the cue is only used to retrieve a single mapping into working memory.

The current study found an interaction between a cue change and block. The size of the effect for a cue switch cost was dependent on whether the cue change occurred in a switch block (i.e., with the possibility of a task switch). This finding indicates that a cue change takes longer in the context of multiple and interfering task representations, since a switch block involves holding several competing tasks in mind.

The finding fits with the cue priming account. The cue priming account proposes that the cue processing mechanism involves a race comparison process between cue and stimulus compounds, in which a dominant representation is selected (Logan and Bundensen, 2003, 2004; Schneider, 2016). The race comparison process accounts for simultaneously active task representations, and the selection of a dominant representation accounts for competing task representations.

The finding challenges task preparation accounts, which propose a cue processing mechanism that involves retrieval of a task from long-term memory into short-term memory (Mayr & Kliegl, 2000, 2003; Meiran, 2000; Meiran et al., 2000). The retrieval process assumes that only a single task representation is held in working memory at a time (Schneider, 2016). This assertion was not supported in the current study, since a cue change was dependent on the context of a switch block.

An alternate explanation exists for the cue change and block interaction that does fall in line with task preparation accounts. A revised version of the cue retrieval account of task preparation account proposes that the effect of the cue varies according to task switching probability (i.e., the likelihood of a task switch given a cue switch; Mayr, 2006; Monsell & Mizon, 2006). The cue could have a conditional effect that depends on the possibility of a switch. The proposed mechanism is that in the task application stage, individuals make a quick check of the cue from previous trial to decide whether or not to shift a task.

A counter mechanism from the cue priming account is that subjects learn all the cue-cue transitions (Schneider & Logan, 2006). This has been tested in studies that varied the probability of a task switch in a double cuing paradigm. Probability manipulations influenced patterns of cue and task switch cost, which supports our findings that cue switch effects may be influenced by whether or not a task switch may occur. The counter explanation of cue-cue transitions was not supported, indicating the need for a separate task-level process in addition to cue-level explanations. Although the revision that a cue is influenced by switch probability could be applied to the finding of an interaction of cue change with block, it still makes the assumption that the cue retrieval process is not influenced by multiple active task representations. In contrast, the revised cue priming account encompasses both a switch probability and simultaneously active task representations. Thus, this account fits best with our findings since it predicts that a cue change is dependent on the context of a switch block.

2.5.3.3 Testing the mechanism for a task switch

To examine the mechanism for a task switch, task switch cost (local and global) was measured in conjunction with changes in task difficulty (switching from an easy to a difficult task, and vice versa). An asymmetric switch cost has been found when using tasks of different difficulty, with a larger switch cost when switching to an easier task than the other way around (Allport et al., 1994; Los, 1999). However, attempts at replication have found that an asymmetric switch cost is far from universal (Monsell et al., 2000). It is possible that asymmetry may be masked by a control process that resolves interference from a previous task to switch to a new task. Such a control process has been proposed via task preparation but could also be explained by cue priming.

The current study failed to find a standard asymmetric switch cost and instead found a reverse asymmetric switch cost, with a larger switch cost when switching to a difficult task. This finding indicates that a task change takes longer for difficult tasks. The results imply that a task switch requires a forward-acting process. This process could be either an executive control task preparation process or an automatic cue priming process.

The finding fits with the cue priming account, which proposes that the task processing mechanism involves using the cue to retrieve a task representation. The cue-task retrieval process accounts for the strength of the cue-task association, with stronger associations being faster to retrieve. The finding also could fit with task preparation accounts, which account for the strength of the stimulus-task association. However, task preparation accounts require an executive control process linked to the cue, and this was not supported.

The finding that a switch cost did not take longer when switching away from a more difficult task challenges task priming accounts, which propose that task processing arises from automatic interference triggered by the stimulus or carryover of a past task. The role of inhibition in task priming makes the prediction that stronger task representations are harder to switch away from, an assertion that was not supported in the current study.

The finding of a reverse asymmetric switch cost may have been specific to the parameters of the paradigm used (e.g., a short cue-target interval, small number of trials, or semi-predictable experiment structure). However, past studies using other paradigms with differing parameters have also failed to find an asymmetric switch cost (Koch et al., 2010; Monsell et al., 2000). Future studies can examine the generalizability of the lack of an asymmetric switch cost.

2.5.3.4 Independence of cue and task switch mechanisms

Multi-component theories have proposed two independent processes: a cue processing mechanism for task preparation, and a task processing mechanism for task priming. Although cue priming proposes a single process, it does have two stages: a cue processing stage for compound encoding, and a task processing stage for cue-task retrieval. Hence, it could be argued that both accounts propose two processes, one for the cue and one for the task. Any distinctions between components and stages may be superficial.

Earlier versions of the cue priming account were clear that only process was involved, with the second stage of cue-task retrieval merely being a by-product of the earlier stage of compound cue encoding (e.g., Arrington et al., 2007). The recent version of cue priming also proposes that a single component exists in which the cue and task are inextricably linked. The product of the compound cue encoding stage is a representation of the task, and it is this representation that is used to retrieve a task in the following stage (Schneider, 2016). However, the recent version of cue priming does allude to the possibility of separate component. The recent theory separates compound cue encoding into perceptual and semantic encoding stages and proposes a third stage for cue-task retrieval. It acknowledges that the third stage of cue-task retrieval could be qualitatively distinct and independent to the first two stages of compound cue encoding ("the third stage of cue encoding - or a distinct stage following cue encoding", "one could argue that the retrieval stage is qualitatively distinct from the other two stages and reflects processing that is separate from cue encoding", Schneider, 2016, p. 1122). Further research is needed to empirically test the independence of these components.

2.5.4 Is the task switch process intentional?

We began this paper stating that the finding of a switch cost, a notable decrement when switching tasks, has been reliably established in the task switching literature. Yet whether a switch cost actually measures an intentional (executive control) process for switching a task has elicited considerable disagreement in the literature. The question of whether there is true task switching in the paradigm has faced considerable attention. The current study offers insights into this question.

Task preparation theories focus on switch costs as reflecting executive control processes specifically to set up a new task set when a task changes (task switch trials). There is intuitive appeal in the idea of a conscious control process to select and prepare a new task. Challenging this idea, numerous empirical demonstrations have shown that switch cost is pervasive despite attempts to help intentional preparation on task switch trials. Robust costs occur even with lots of practice, a long preparation time, prior knowledge of the task, and completely disambiguated stimuli. The original proponents of the task preparation theory acknowledged that part of the switch cost is externally triggered by a bottom-up process (exogenous reconfiguration) that resolves interference to shift away from a previous task (Rogers & Monsell, 1995)

We reviewed two alternatives to an intentional task process. Task and cue priming theories propose automatic processes from the carryover of shifting away from a past task, or the automatic set up to shift to a task using the cue. The crux of task priming and cue priming theories is that they move the focus away from an intentional process limited to a task change (i.e., on a task switch trial). Instead, they propose processes that occur even without a task change, extending the focus to trials when there is no task change (i.e., a non-switch trial). This strongly challenges the explanation of a switch cost from intentional shifting. Task priming proposes that an automatic carryover process produces a task repetition benefit when a task repeats, while cue priming proposes that an automatic cue-task associative retrieval process produces a cue repetition benefit when a cue repeats. General preparation theories also move the focus away from the actual task change, by proposing an intentional process for anticipating a potential task change.

Priming offers a parsimonious explanation that builds on a widely demonstrated effect in cognitive psychology. Cue and task priming theories apply priming to task switching to propose a succinct process that is not specific to task switching. Also included in these theories are simpler cases of automatic processing that could apply to task switching: proactive interference from carryover of associations with past stimuli in task priming theories, or perceptual encoding of environmental information in cue priming theories. In contrast, task preparation accounts are specific to the task switch.

Our findings did not support the automatic process of negative task priming but did support the automatic process of positive cue priming, in producing a switch cost. Cue priming replaces the need for the intentional task preparation process of a task set. Instead it proposes that task sets can be selected automatically, using a race comparison process of learned cue-stimulus associations.

Cue priming thus offers a parsimonious model in which a single process can encompass all the findings previously attributed to multiple components. This model has cast doubt on whether the task switching paradigm involves task switching at all. The model falls under the general framework of priming, an effect widely replicated across cognitive abilities. Priming research shows that learned associations between stimuli and tasks or responses can be retrieved on any trial, and that these associations can influence performance. The cue priming mechanism for a switch cost proposes an encoding process with joint cue-task mappings, with a shift occurring as an after effect of the compound cue encoding process, rather than from a process of actually switching to a new task.

Thus, it appears that a process for shifting to a new task is needed, but this process may a result of cue processing. Task preparation and cue priming theories both propose explanations for the shift to a new task (unlike task priming, which proposes an explanation for the shift away from a past task). Our findings failed to support task preparation, which is an executive control process, but are in line with cue encoding, which is an automatic process. Although it may seem intuitive to conceptualize task switching as intentionally shifting between tasks, our findings suggest that such a process may occur automatically. These results challenge the common referral to the task switching paradigm as a measure of executive control. Our findings add to a growing literature that a true task switch cost may occur from an underlying process that is not specifically for reconfiguring a task set for a shift.

2.5.5 Limitations and generalizability of the current study

2.5.5.1 Organization of components

We did not test how the observed components are organized, specifically, whether they occur in a parallel or serial manner. Previous fractionations of a switch cost have alluded to independent stages with serial organization (Sohn & Anderson, 2001; Rubinstein et al., 2001). More generally, complex cognitive abilities are often proposed to arise from the operation of several processing stages rather than a single undifferentiated one (Barrett & Kurzban, 2006; Fodor, 1983; Marr, 1976). Although parallel processing is possible for some cognitive abilities, serial processing is more common as it enables more flexible and efficient use of resources. Future studies can further look into the independence and organization of components.

2.5.5.2 Task difficulty changes

Asymmetric switch costs are not consistently replicated (Koch et al., 2010). We explored theoretical explanations for how a process that reduces interference from a previous task could mask asymmetry. In a similar vein, asymmetric switch costs may be visible under experimental conditions that increase the amount of interference from a previous task. Asymmetric switch costs have been found with a decrease in advance preparation time, and for extreme differences in task difficulty (Monsell et al., 2000).

A limitation with asymmetric switch cost measurements in a standard paradigm is that each time the difficulty changes in switch blocks, a task also changes. The confound between task and difficulty changes leaves it unclear whether asymmetric task switch effects are due to a change in task or a change in difficulty alone. Similar to cue deconfounding in the double cuing paradigm, a clever solution has been a difficulty deconfounding paradigm that introduces difficulty changes regardless of task changes (Schneider & Anderson, 2010).

When task changes and difficulty changes were isolated, asymmetry costs were due to difficulty changes rather than task changes. Asymmetry was attributed not to changes in task but to sequential changes in difficulty over trials (Schneider and Anderson, 2010). The finding that trial difficulty changes cause asymmetric costs independent of a task change supports this explanation. Sequential difficulty accounts succinctly explain all of the reported asymmetric switch costs, without the need to look for task-specific processes. Rather, such accounts predict that task changes with equal difficulty occur in parallel.

Similar to how the double cuing paradigm separates task and cue switches, the difficulty manipulation paradigm was designed to separate task and difficulty changes. Findings with this paradigm challenged the assumption of asymmetric switch theories that asymmetric switch costs are specific to task switching. However, the classification of a task in the difficulty manipulation paradigm is questionable. The authors examined primary changes in difficulty between two tasks —an addition task classified as easy, and a subtraction task classified as difficult. They contrasted these with secondary changes in difficulty within each task—easier and difficult processing within addition and subtraction.

It could be argued that easy and difficult addition tasks are in fact separate tasks. The authors defined tasks as involving nominal categories, allowing them to claim that secondary difficulty manipulations are not the same as separate tasks. However, other task switching studies have defined tasks at different levels of abstraction, and even used the same nominal category to define different tasks. For example, a task switching paradigm in which the two tasks were to respond with the compatible location (LEFT-LEFT) or incompatible location (LEFT-RIGHT; Crone, Bunge, van der Molen, & Ridderinkhof, 2006), or another paradigm where the two tasks were to respond to the vertical (UP-DOWN) or horizontal dimension (LEFT-RIGHT; Meiran, Gotler, & Perlman, 2001). Both examples would be considered secondary difficulty manipulations by Schneider and Anderson's classification since both tasks was the same nominal category of classifying spatial location.

The lack of consensus on how tasks are defined highlights a general issue with the task switching literature. In the original task switching paradigm, the authors acknowledged it is difficult to precisely define what constitutes a task, even in the narrow context of reaction time tasks. This difficulty continues today (Schneider & Logan, 2014). Although it seems intuitive that tasks of different categories are different tasks, it is less widely agreed whether different versions of the same task (with a parameter variant, such as a spatial location task differing in the spatial separation of the keys) are also tasks. Positively, it is not necessary to resolve the conceptual boundary of a task to gain insights into the control processes for switching.

Another limitation is that asymmetric switch costs from task difficulty changes may not always measure task priming (Koch et al., 2010). Alternate ways of measuring task priming include backward inhibition effects, which index carryover from two trials ago (*n*-2 task repetition costs; Dreisbach et al., 2002; Dreisbach, 2012; Mayr & Keele, 2000). However, backward inhibition effects have already been extensively measured in a double cuing paradigm, while asymmetric switch costs have not been (Mayr & Kliegl, 2003; Altmann, 2006, 2007; Gade & Koch, 2008; Horoufchin et al., 2011; Koch et al., 2010; Mayr, 2006; Monsell & Mizon, 2006).

2.5.5.3 Fractionations using other versions of the task switching paradigm

The current findings support a fractionation into multiple components of task switching using a combined task switching and double cuing paradigm. Other versions of the paradigm have different conditions and test different aspects of switching. A comparison of the standard task switching and double cuing paradigms suggested that both paradigms may provide similar results (Schneider & Logan, 2011; c.f., Altmann, 2006).

The current study used a semi-random[7] task switching paradigm, in which a task change was unpredictable and was explicitly signaled by a cue on each trial. Another version is a predictable task switching paradigm, in which a task change follows a set switch sequence (e.g., every second trial), without an explicit cue to signal a task change. Predictable task switching paradigms exhibit local and global switch costs even without the cue (Poljac, Koch, & Bekkering, 2009; Ruthruff et al., 2001) but cannot be used to gain insights into cue switches. Predictable paradigms indicate that a global switch cost from preparation for a switch occurs even without a cue (Poljac et al., 2009), which is in line with our findings that the general slowing during a switch block occurs regardless of a cue change. By deconfounding cue change cost and switch block, our findings show that the opposite effect of a cue change cost without the context of a switch block does not occur.

2.6 Conclusions

One of the most robust findings in the cognitive literature is that response latencies are longer when shifting a task than repeating a task. The ubiquitous finding of a switch cost has been assumed to imply fundamental constraints on control during shifting. Our findings confirm

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[7] Participants knew (or could readily learn) on non-switch trials that they would be non-switch. So non-switch trials were completely predictable. Switch trials were predictable to some degree – participants could learn that they would either involve a cue switch or a task-and-cue switch but wouldn't know which type until cued.

that switching enlists multiple control process in addition to executing a shift itself. Substantial costs were found when anticipating the possibility of a switch, and in using a cue to select a task. Importantly, both these effects occurred even on trials in which a shift did not occur and were even larger than the actual cost of shifting a task, suggesting that the control of cognition in task switching was not specific to a switch. By examining these effects in light of each other and of task difficulty changes, we were able to gain further insights into the mechanisms for each. We found that cue processing is dependent on the possibility of a switch. We also found that task processing is dependent on the difficulty of the task (the strength of the task representation). Our results show that the switch cost is a complex phenomenon that arises from a number of processes, many of which are not switch-specific.

Switch cost has been commonly described as an index of cognitive control. However, a number of compelling arguments have proposed that automatic processes completely account for performance when rapidly switching from one task to another. By combining measurements from the task switching paradigm with those from the double cuing paradigm, we tested the role of executive and automatic processes for task switching. Our results fit with theoretical frameworks of automatic cue priming rather than automatic task priming or executive control of task reconfiguration. Future studies should further test the experimental conditions that give rise to automatic and executive control in the task switching literature.

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3 Study 2A: Effects of age on task switching

3.1 Abstract

Performance on a variety of cognitive tasks is better in young adults than either children or older adults, but the precise way in which performance varies with age is relatively unexplored. The study reported here used an exceptionally large Internet-based sample (n = 13,718) to investigate fine-grained age-related differences in task switching performance (measured by reaction times, accuracy, and intra-individual variability). Performance was further split into components of task switching, including global switch cost (maintenance of readiness for a potential task change), local switch cost (task alternation for a task change), cue switch cost (task decision using a signal for a task change), and cue perception (detection of a signal without a task change). Segmented regression models were used to identify the gradient of change and age ranges for shifts in gradient for individual components.

Data demonstrated an overall improvement (faster response speed, fewer errors, reduced intra-individual variability) in task switching through adolescence to young adulthood, followed by a gradual decline through adulthood. Differential lifespan trajectories were found for different components, with different ages of peak performance and differences in whether aging through adulthood was linear or accelerated in middle age, suggesting differential effects of age on aspects of task switching. Processing speed accounted for some, but not all, of the between-subject and intra-individual variability across the lifespan. Age-related decline in performance was qualitatively different from developmental improvement, indicating that aging is not always a mirror of development.

Keywords: cognitive flexibility, executive function, development, aging, task switching

3.2 Introduction

Cognitive performance changes substantially across the lifespan (for reviews, see Drag & Bieliauskas, 2010; Craik & Bialystok, 2006; Craik & Salthouse, 2011; Greenwood, 2007; Kausler, 1991; Salthouse, 1996, 2010; Verhaeghen, & Salthouse, 1997). Two broad patterns of variation in ability with age are generally seen (Craik & Bialystok, 2006). Some abilities—including certain language skills (see Kemper, 2006), procedural skills such as musical performance (Krampe & Ericsson, 1996), and others related to crystallized intelligence—improve through childhood and remain relatively constant through adulthood. A larger set of abilities, often related to processing speed or fluid intelligence, show an inverted U-shaped curve, characterized by an improvement through childhood, a plateau or slow decline during adulthood, and then a later more pronounced decline in older age. This pattern has been observed in a wide range of abilities, including episodic memory (Shing & Lindenberger, 2011), working memory (Hasher & Zacks, 1988), planning and problem solving (de Luca, Wood, Anderson, Buchanan, Proffitt, Mahony et al., 2003), and linguistic complexity (Kemper, 2006).

One of the areas in which substantial research on age effects has been conducted is tasks involving executive control—particularly task switching (Allport, Styles, & Hsieh, 1994; Rogers & Monsell, 1995), the ability to flexibly shift between potential actions. Investigating this goal-directed behaviour helps understand executive control mechanisms that enable adaptive performance in dynamic environments. Task switching shows an inverted U-shaped trajectory with age.

Task switching is one the more frequently examined executive control tasks in cognitive aging and is of particular interest because the comparison of different trial types allows a fractionation of components of executive control (Meiran, 2010; Miyake, Friedman, Emerson, Witzki, Howerter, & Wager, 2000). However, with a few exceptions (e.g., Reimers & Maylor, 2005; Cepeda et al., 2001), studies examining the effects of age on task switching performance have tended either to compare at the broad categorical level—children vs. young adults vs. older adults—or have focused on either development through childhood and adolescence or aging through adulthood, but not both. As such, the precise trajectory of executive control abilities across the lifespan as a whole is unclear. The aim of the current investigation is therefore to measure overall performance and performance of underlying components of task switching across the lifespan in a single study, using a sample size large enough to model development and aging trajectories in a fine-grained way.

The manuscript proceeds as follows: First, we will give an overview of general research into task switching and its components, after which we will review the separate literatures on development and aging in task switching performance. Finally, we will discuss the few studies examining both development and aging together and present the rationale for our study.

3.2.1 Task switching

Task switching is one of the most studied measures of executive control (e.g., Allport et al., 1994; Jersild, 1927; Rogers & Monsell, 1995; for overviews, see Monsell, 2003; Grange & Houghton, 2014). Task switching procedures capture the ability of participants to shift rapidly from one set of stimulus-response mappings to another. As the stimuli that participants see are not informative regarding which response mapping to use (though see Forrest, Monsell, & McLaren, 2014), task switching requires top-down control in selecting the appropriate response on a given trial.

In a task switching paradigm individuals perform one task at a time on a set of stimuli, then switch to another task on the same set of stimuli. For example, participants might switch from classifying a series of digits as odd or even to classifying them as greater or less than five, or switch from classifying shapes by color to classifying them by the number of sides they have. Across a variety of procedures, an incontrovertible finding is that individuals consistently perform worse when switching between tasks than when repeating a task (Jersild, 1927). This switch cost is typically reflected in decreased speed (slower responses) and accuracy (more incorrect responses).

There have been many variants within the basic task switching paradigm, with differing stimuli and response options, stimulus types, and preparation times (Meiran, 2010; Monsell, 2003). One of the major ways in which switching procedures can vary is in the predictability of the task switch. Some have a regular structure in which a task changes after a fixed and consistent number of trials (e.g., AABBAABB… across a switching block). In this kind of procedure, participants are either required to remember the task required on a given trial or presented with a cue to indicate task type. In the explicit cuing version of the paradigm, participants do not know until the start of a trial which task they will be completing. In these cases, a cue is used on every trial to signal which task is to be performed.

Switch costs can be fractionated into the underlying control processes associated with switching. The main fractionation in the task switching literature has been into local and global switch costs. A local switch cost (also known as specific switch cost) measures the slowing from a task change. A global switch cost (also known as mixing or general switch cost) represents the slowing from when a task change might occur, regardless of whether it does occur. A local switch cost measures the time to execute a task shift itself, whereas a global switch cost measures the time for maintaining readiness for a potential task shift. Global switch cost is measured as reaction time difference between blocks of trials—specifically, a block of trials in which one task is performed (non-switch blocks) and a block of trials in which the task switches (switch block). Local switch cost is measured as the latency difference between trials within a switch block—specifically, trials where the task changes (switch trials) and trials where the task repeats (non-switch trials).

3.2.3 Empirical research on the effects of age on task switching

Research on task switching has primarily focused on examining the processes involved in executive control. However, a growing body of research has examined how cognitive control capabilities are related to age. This has partly been to examine the cognitive capabilities that people possess at different points in the lifespan and their trajectory with age, which has implications for education, support, and social policy (see, e.g., Diamond, 2013; von Hippel, 2007), and partly to understand the sequence of development and decline as well as its neural correlates.

3.2.3.1 Development studies

Task switching studies with children often employ different tasks structures from typical adult task switching procedures to ensure young children can readily understand and perform the task (Peng, Kirkham, & Mareschal. 2018). This can make comparison across ages difficult, not least because task-switching tasks used for young children are generally designed to show switch costs from error rates rather than reaction times. That said, at a general level, a clear pattern of performance is seen. Children show improvement in task switching performance from early childhood through adolescence to adulthood.

Early development of switching is often examined using set shifting tasks. Set shifting differs from standard task switching in that participants shift to a different task over a new block of trials (Dajani & Uddin 2015), rather than repeatedly shift between tasks in a single block.

Children as young as six years old are able to alternate between rules on card sorting tasks of set shifting (Blackwell, Cepeda, & Munakata, 2009; Cepeda & Munakata, 2007; Blackwell, Chatham, Wiseheart, & Munakata, 2014). Performance continues to improve through later childhood into adolescence (Anderson, 2002; Anderson, Anderson, Northam, Jacobs, & Catroppa, 2001).

On reaction time-based task switching procedures, developmental improvement in local switch cost is observed through childhood and adolescence. Crone, Bunge, van der Molen, and Ridderinkhof (2006) found a monotonic reduction in both global and local switch costs with age, across their groups of 7-8, 10-12, and 20-25 year-olds in a speeded two-choice task. Performance may plateau by age 15. Huizinga, Dolan, & van der Molen (2006) found that 15-year-olds and 21-year-olds performed equally well on three predictable switching paradigms. No effects of age were seen on reaction time for global switch cost or on accuracy for local and global switch costs (Crone et al., 2006).

Another investigation found both local and global switch cost accuracy[8] improved between the ages of 4 and 13 years, with performance at 13 years still inferior to that of young adults (Davidson, Amso, Anderson, & Diamond, 2006). Conversely, there was no effect on reaction times, and the authors noted a potential age difference in speed-accuracy trade-off.

Similar findings have been obtained across a range of tasks and procedures (Crone, Ridderinkhof, Worm, Somsen, & van der Molen, 2004; Dibbets & Jolles, 2006; Zelazo, Craik, & Booth, 2004), with adult switch costs lower than those of children, and an improvement in

[8] Davidson and colleagues used univalent stimuli and a different duration for the response window, which may explain the findings on local switch cost differences in accuracy rather than reaction time. However, they report similar results from another study (Cohen, Bixenman, Meiran, & Diamond, 2001) that used a standard task-switching paradigm adapted for children.

performance observed through childhood and into teenage years. Methodological variations across studies may produce different results on whether switch costs can be demonstrated on reaction time or accuracy. In particular, when using a narrower response window, developmental effects may be seen on accuracy instead of reaction times.

3.2.3.2 Aging studies

A large majority of studies examining age effects in task switching have focused on older adults, often comparing the performance of young adults with that of people past retirement age. It is in older age that non-clinical deficits in executive control become more obvious, and their implications for everyday life more significant. A general pattern of findings is that older people show age-related slowing in RTs overall, and higher switch costs, with the evidence stronger for global switch cost than local switch cost. For example, Mayr and Liebscher (2001) found effects of age on global but not local switch cost, but another study found effects on both measures (Meiran, Gotler, & Perlman, 2001). When both measures were influenced by age, some studies found that effects on global switch cost may be larger than local switch cost (Kray & Lindenberger, 2000; Mayr, 2001). Others found that increasing interference from potentially relevant task sets—using four tasks instead of the standard two—produced age-related effects on local switch cost that were even larger than global switch cost (Kray, Li, & Lindenberger, 2002).

Task manipulations across studies suggest that local and global switch cost effects can be attenuated by experimental manipulations of task difficulty. Van Asselen and Ridderinkhof (2000) found larger local switch costs for old adults compared to young adults on unpredictable but not predictable[9] task switches. Others found local switch costs in older adults on predictable

[9] Their predictable condition also had more practice, so effects might be due to practice rather than switch predictability.

paradigms (Kray & Lindenberger, 2000) or regardless of whether switches were predictable or unpredictable (Kramer, Hahn, & Gopher, 1999). Local switch cost effects are found across a range of preparation intervals and at different levels of working memory load, although they can be reduced with practice to be equal to younger adults (Kramer et al, 1999). Similarly, global switch cost can be reduced on conditions with unambiguous stimulus, no response set overlap, or external task cues (Kray et al., 2002; Mayr, 2001), but others have found effects even under these conditions (Mayr & Liebscher, 2001; Meiran et al., 2001).

Error rates were low in all studies with older adults, with most less than five percent, hence error rates were not further investigated in most studies (Kray & Lindenberger, 2000; Kray et al., 2002; Meiran et al., 2001). When error rates were analyzed, older adults performed the task with fewer errors than younger adults, even though both groups had low error rates in all conditions (Kramer et al., 1999; Mayr, 2001; Mayr & Liebescher, 2001).

Meta-analyses of task switching in aging confirmed increases in global and local switch costs with age (Verhaeghen & Cerella, 2002; Wasylyshyn, Verhaeghen, & Sliwinski, 2011). However, some age-related effects on local switch cost effects disappear after accounting for general slowing in reaction time, while age-related effects on global switch cost persist even after accounting for age-related slowing. Overall, it appears that both global and local switch costs show a slowing in reaction time with aging.

3.2.3.3 Lifespan studies

Compared to studies that have focused on either childhood development or adult aging, relatively little research has examined executive control in both groups together. A small number of studies compared performance of children, young adults, and older adults (e.g., Kray, Eber, &

Lindenberger, 2004; Zelazo et al., 2004), and across a number of measures these studies found better performance among young adults relative to children and older adults. These are informative but the small number of groups means that they do not show age-related trajectories in executive control. For example, the age range over which improvement and decline occur, and whether decline accelerates in older age, and if so, how, cannot be explained using broad age categories. We know of two[10] previous studies on task switching that examined performance across the lifespan using a more detailed breakdown into age groups. Cepeda, Kramer, and Gonzalez de Sather (2001) ran a lab-based study with 152 individuals aged 7 to 82 years. Participants responded to four numerical stimuli, which could be classified by the total number of stimuli presented or the numerical value of the stimuli, which were manipulated orthogonally. Participants first completed single-task blocks in which they classified stimuli solely by quantity or identity, followed by eight switching blocks in which participants unpredictably switched between tasks every one to three trials, with a cue indicating which task to perform.

Local switch cost was calculated in the standard way, as the difference between RT on switch trials versus non-switch trials in a switching block. Global switch cost was not measured, but a between-blocks difference was calculated by subtracting mean reaction time across the single-task blocks from reaction time on the switch trials in the switch block. (Standard global switch cost uses non-switch trials in a switch block instead.) Both measures of switch cost followed a U-shaped curve across the lifespan, with improvement during childhood to young

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[10] A third lifespan study (Kray, Eber, & Lindenberger, 2004) also found a U-shaped curve on an embedded dual task when comparing children, younger adults, and older adults. Data from the no secondary task condition showed a change in global switch cost across the lifespan and a small reverse local switch cost for both development (-41 ms) and aging (-24 ms) but not in young adults (-4 ms). Changes in accuracy rates were consistent with those in reaction times, indicating no speed-accuracy tradeoff with age. However, the use of a dual task paradigm in this study means that findings are not directly relevant to the current study.

adulthood, a peak in young adulthood (21-30 years), followed by a plateau during mid-adulthood, and then a decline after the age of 60. Effects of age on global and local switch costs were maintained even after more than 1000 trials.

Reimers and Maylor (2005) used an Internet-based study to measure a large lifespan sample (N = 5,271) aged 10 to 66+ years. Participants responded to four face stimuli, which could be classified by gender (male-female) or emotion (happy-sad). Participants first completed single-task blocks in which they classified stimuli solely by gender or emotion, followed by a switching block in which they switched predictably between tasks, with two gender-classification trials followed by two emotion-classification trials, and so on.

A U-shaped curve was found for global switch cost, with a peak at age 16 (slightly earlier than Cepeda and colleagues found), after which performance declined through adulthood. Local switch cost showed a decline through adulthood and a small but non-significant improvement in adolescence based on raw reaction times, but these effects on local switch cost disappeared after controlling for overall reaction time.

Although our respective earlier findings were broadly similar in the effects of age, some differences were observed. Cepeda et al. (2001) found a small effect of age on error rates. Reimers and Maylor (2005) saw no effects of age on error rate for global switch cost, and a small effect of age on error rate for local switch cost. In both cases, effects of age on error rates were consistent with effects on reaction time latencies (i.e., error rates decreased as reaction times decreased). The similar pattern between error rates and reaction time latencies indicated that general age effects could not be accounted for by speed-accuracy tradeoff. More generally, Cepeda et al. (2001) found no significant effect of age on global switch cost through young adulthood, whereas Reimers and Maylor (2005) found a clear increase in global switch cost before middle age.

Differences in the results may be due to the methodological differences between the two studies, for example, the use of predictable (Reimers & Maylor, 2005) or unpredictable (Cepeda et al., 2001) switches, and the relative difficulty of the two tasks between which participants had to switch. They may also reflect the limited sample size of Cepeda et al.'s study or sampling effects in Reimers and Maylor's study.

3.2.4 Intra-individual variability across the lifespan

The findings reviewed so far have focused on average speed and accuracy in task switching across the lifespan. However, as well as looking at mean performance as a function of age, a smaller body of research has examined the variability in reaction times across trials for individuals.

Intra-individual variability is typically defined as the variation of the responses of one individual on repeated presentations of a single test in a single session, and time variability is psychologically significant not least because it is associated with other aspects of cognition such as intelligence (Deary, Der, & Ford, 2001), as well as being elevated in clinical disorders such as ADHD (Kofler et al., 2013) and dementia (Hultsch, MacDonald, Hunter, Levy-Bencheton, & Strauss, 2000). Furthermore, in older individuals intraindividual variability in reaction times has been associated with non-clinical deficits in working memory, episodic memory, and crystalized abilities (Hultsch, McDonald & Dixon, 2002), and is predictive of a diagnosis of cognitive impairment five years later (Bielak, Hultsch, Strauss, MacDonald, & Hunter, 2010).

Lifespan analyses show effects of age on intra-individual variability in reaction times. Similar to mean reaction times, the general pattern on intra-individual variability in reaction times is a U-shaped curve across the lifespan. Greater variability exists for children and older adults than younger adults (Deary & Der, 2005[11]; West, Murphy, Armilio, Craik, & Stuss 2002; Williams, Hultsch, Strauss, Hunter, & Tannock, 2005; Williams, Strauss, Hultsch, & Hunter, 2007). A gradation of change in intra-individual variability occurs over the lifespan, with the developmental slope much steeper than the slope for decline (Dykiert, Der, Starr, & Deary, 2012a). However, it may be that aging shows a smaller increase until age 70 years and then transitions to a steeper increase until age 90 years (Der & Deary, 2006).

The U-shaped relationship is independent of practice or fatigue effects (Williams et al., 2005). A meta-analysis of intra-individual variability in adulthood and aging confirmed the pattern across procedural variations (including the number of trials, response type, and number of possible choices; Dykiert, Der, Starr, & Deary, 2012b). The effects of age on reaction time intra-individual variability are greater for more complex tasks, with choice reaction time tasks showing larger increases in variability than simple reaction time tasks, and more complex measures such as a task of inhibitory control showing an even larger increase in variability (Williams et al., 2007).

Age effects were smaller when variability was adjusted for the mean reaction time, indicating that some variance is shared with mean reaction time. This finding is in line with a single processing speed factor that underlies age-related effects. However, larger variability in children and older individuals was still found after accounting for mean reaction time (Dykiert et

[11] Deary and Der (2005) also report an effect of gender on intraindividual variability after age 25. After choice reaction time was controlled for, the effect of age disappeared but the effect of gender remained. In a response to Deary and Der, Reimers and Maylor (2006) found that gender effects were a result of trial-to-trial effects rather than differences in variability per se.

al., 2012b; Williams et al, 2005; c.f., Myerson, Robertson, & Hale, 2007). Hence, not all of the effects are due to slowing with age.

As with the research on mean RTs, age-related findings from reaction time standard deviations (RTSDs) have been largely conducted at group level, comparing small groups of younger and older adults. As such, beyond establishing that young adults perform better than children and older adults, the fine-grained relationship between intraindividual variability and age had not yet been examined.

3.2.5 Single factor theories of whole-lifespan cognitive performance

Much of the research on task switching across the lifespan has separately examined development through childhood and decline through adulthood. Many theoretical accounts of these age-related changes have been developed separately for development (e.g., Crone et al., 2004; Davidson et al., 2006) and aging (e.g., Mayr & Liebescher, 2001; Meiran et al., 2001). The current study compared these different age groups in a single study. A commonality of theories developed for both age groups is that they are specific to task switching. However, some theories have been developed to account for these ages together, as well as extending to propose that a single mechanism may underlie age-related differences in performance across all cognitive tasks (Dempster, 1992; Craik & Bialystok, 2006).

3.2.5.1 Processing Speed hypothesis

One theory for a single mechanism is the processing speed hypothesis, which proposes speed of information processing as a general factor that explains age-related effects on various cognitive abilities, including task switching (Kail & Salthouse, 1994; Salthouse, 1996, 2005, 2009; Verhaeghen, & Salthouse, 1997). The reasoning for this hypothesis is that processing speed is considered to support other cognitive abilities and is susceptible to change with age.

The pattern of change of processing speed over the lifespan resembles an inverted U-curve. Proponents of the hypothesis supported their claims by indicating that task switching is correlated with processing speed across the lifespan (Salthouse, Hambrick, & McGuthry, 1998). However, subsequent studies directly tested the hypothesis subsequent by examining task switching performance over the lifespan after controlling for processing speed. These studies found effects of age attributable to switching beyond effects of age explained by processing speed alone, in childhood (Cepeda & Munakata, 2007) and aging (Verhaeghen & Cerella, 2002; Wasylyshyn et al., 2011).

3.2.5.2 Frontal Lobe hypothesis

A second theory is the frontal lobe hypothesis, which narrows down from a general factor for effects of age on all cognitive abilities to a specific class of cognitive abilities, namely executive functions. Executive functions are higher-order cognitive abilities that contribute to goal-directed behaviour. Executive functions are generally considered to reflect shared but distinct functions of task switching, working memory, response inhibition, and interference control (Miyake et al. 2000; Friedman & Miyake, 2017). The hypothesis proposes a frontal mechanism that explains age-related effects on executive functions, including task switching (West, Murphy, Armilio, Craik, & Stuss, 2002; Zelazo et al., 2004). The weaker performance on executive functions in development and aging has been attributed to neuronal changes in the frontal lobes (more specifically, the prefrontal cortex) with age. The reasoning for this hypothesis is that executive functions are considered to be supported by the frontal lobes, and the frontal lobes are much more prone to change with age than other brain regions (Band, Ridderinkhof, & Segalowitz, 2002). Hence, executive functions are more susceptible to age effects than cognitive abilities supported by posterior and subcortical areas.

The pattern of change in frontal regions resembles an inverted U-curve, with a gradual development into early adulthood and the earliest evidence of decline, compared to other regions in aging. Proponents for a frontal hypothesis supported their claims with evidence of an inverted U-shaped curve on inhibition, an executive function, across the lifespan (Dempster, 1992). However, subsequent studies directly tested the hypothesis by examining individual executive functions over the lifespan and found distinct patterns for each. Working memory measures follow a linear decline across the adult lifespan (ages 20 to 86 years), while a single inhibition measure showed a quadratic U-shaped curve (Borella, Carretti, & De Beni, 2008). Although there is some interdependence between working memory and inhibition, there remains unique variance in the developmental trajectory of each measure (Luna, Garver, Urban, Lazar, & Sweeney, 2004). Similar to behavioural findings, although neurological decay in the frontal cortex accounts for some variability in cognitive control, it does not completely capture all the age-related changes (Band et al., 2002; Reuter-Lorenz & Lustig, 2005).

The frontal hypothesis has been applied to task switching to suggest that the mechanisms for shifting in children are linked to simultaneously developing executive functions, namely, working memory and inhibition, both of which have a gradual development into young adulthood (Davidson et al., 2006; Diamond, 2002). However, direct tests of the frontal hypothesis for task switching confirm the results from studies of other cognitive abilities – that effects of age persist even after accounting for age-related change in other abilities related shifting (Cepeda et al., 2001). Further, the proportion of age-related variance on task switching explained by other cognitive abilities was greater in younger participants than older ones (89% versus 49%), suggesting more differentiation among abilities with aging. Task switching interacts differently with executive functions across the lifespan—task switching and working memory show positive associations, while task switching and inhibition are negatively associated (Blackwell et al., 2009, 2014; Blackwell & Munakata, 2014; Marcovitch, Boseovski, Knapp, & Kane, 2010). Together, these findings fail to support the frontal hypothesis of a single factor that produces age-related differences in all executive functions, since each (including task switching) shows differential performance with age.

3.2.5.3 Need for fractionation of whole-lifespan cognitive performance

The failure to support the processing speed and frontal hypotheses indicates that individual cognitive abilities and executive functions appear to develop independently. Recent research has taken this one step further. First, cognitive abilities were fractionated into underlying components and measured over the lifespan. Diverging trajectories were found for the components underlying sustained attention, inhibitory control, and working memory (Fortenbaugh et al., 2015; Nielson, Langenecker, & Garavan, 2002; Sander, Lindenberger, & Werkle-Bergner, 2012). For example, after fractionating inhibitory control, the ability to inhibit prepotent responses improved in childhood and declined slightly during aging, while the ability to execute prepotent responses showed a U-curve (Bedard, Nichols, Barbosa, Schachar, Logan, & Tannock, 2002; Williams, Ponesse, Schachar, Logan, & Tannock, 1999). These findings suggest that even the components that underlie each ability may develop independently.

Similarly, for task switching, the initially demonstrated U-shaped curve was not replicated after separating into local and global switch costs (Reimers & Maylor, 2005). Therefore, a single factor fails to capture the complexity of age-related differences on cognition. The present study builds on the need for lifespan measurement in task switching with a strongly supported additional fractionation of task switching that has not yet been measured with age.

3.2.6 Present study

Existing research has demonstrated clear effects of age in task switching performance both in development and through adulthood. However, these findings, understandably, tend to use relatively small numbers of different age group and limited sample sizes for a given age group, and very few examine the whole lifespan to allow direct comparison of age-related development and decline. Furthermore, most report a single overall measure of switch cost across the lifespan, meaning it is unclear which aspects of task switching are particularly impacted by the effects of age. The current study measures task switching across a wide range of ages from puberty to retirement. To complement mean analyses, we also measure intra-individual variability. Both raw and mean-adjusted measures of variability are reported, since were expected to provide slightly different results. For each of these measurements, task switching ability was parsed into underlying components, based on the existing theoretical literature.

3.2.6.1 Local switch cost dissociation: Cue and task change

A limitation of the standard task switching paradigm is that every time a task changes, a cue also changes. To separate the load associated with processing a change in cue from the load associated with changing the task itself, a double cuing paradigm was developed using two cues per stimulus, instead of one cue per stimulus in the standard paradigm (Logan & Bundesen, 2003; Mayr & Kliegl, 2003). Using two cues creates a new type of trial in which a cue changes but the task remained the same. This cue switch trial fixes the confound of task and cue switches in the standard paradigm.

Findings from the double cuing paradigm support a fractionation into cue and task switch costs (Jost, De Baene, Koch, & Brass, 2015). A cue switch cost measures the increase in reaction time that results solely from a cue change in the absence of a shift in task, while a task switch cost measures the increase in reaction time resulting from the complete process of changing task. Independent components have been proposed for each. A cue change involves a task decision process, by using the cue to retrieve the task from long-term memory. A task change involves a task alternation process, by applying a task set to select a response. Hence, local switch cost can be separated into a cue-related component for task decision, and a task-related component for task alternation.

3.2.6.2 Fractionation into task switching mechanisms

The experiment included two single task blocks to measure baseline performance, and a switch block. In the switch block, half the trials were non-switch repetitions of the task from the previous trial. The remaining half were a mix of task switches (in which the cue and task were both different relative to the previous trial), and cue switches (in which the cue changed, but the task did not). Three trial types were compared in two blocks, producing five trial types in total: non-switch trials ($rt_{ns,ns}$) and cue switch trials ($rt_{cs,ns}$) in non-switch blocks, and non-switch trials ($rt_{ns,s}$), cue switch trials ($rt_{cs,s}$), and task switch trials ($rt_{ts,s}$) in switch blocks. This allowed us to look at different components of task switching performance as a function of age.

We measured global and local switch costs in a similar manner to the existing literature. Maintenance of readiness (i.e., global switch cost) was calculated using trials between blocks, by subtracting non-switch trials on a non-switch block (i.e., a single task block) from non-switch trials on a switch block. Reaction times for all trial types are slower in a switch block, including trials on which no switching occurs. Local switch cost was calculated using trials within a switch block, by subtracting non-switch trials (i.e., in which a task is repeated) from task switch trials (i.e., in which a task changes).

Baseline processing speed was measured using non-switch trials in a non-switch block.

1. Processing speed ($rt_{ns,ns}$)
2. Maintenance of readiness (global switch cost; $r_{mrt} = rt_{ns,s} - rt_{ns,ns}$)
3. Local switch cost ($rt_{lsc} = rt_{ts,s} - rt_{ns,s}$)

Local switch cost was further dissociated to separate the effects of a switch of task and the processing of a new cue. We used the double cuing paradigm, with two cues for each task and trials on which the cue changed but the task remained the same. Although it has not yet been applied to age-related differences in task switching, accounting for the role of the cue has been strongly supported with the double cuing paradigm. Task decision (i.e., cue switch cost) was calculated by subtracting non-switch trials from cue switch trials. Task alternation (i.e., task switch cost) was calculated by subtracting cue switch trials from task switch trials. Both measurements were calculated in a similar manner to the existing literature, using trials within a switch block.

The additional components to isolate the effects of the cue are shown below,

4. Task decision (formerly cue switch cost in a switch block; $rt_{tdt} = rt_{cs,s} - rt_{ns,s}$)
5. Cue detection[12] (cue switch cost in a non-switch block; $rt_{cdt} = rt_{cs,ns} - rt_{ns,ns}$)
6. Task alternation (task switch cost; $rt_{tsc/tat} = rt_{ts,s} - rt_{cs,s}$)

3.2.6.3 Web based data collection

The current study used an internet-based sample, which allowed data collection from a large enough sample of participants across a range of ages, to examine fine-grained differences with age.

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[12] Although psychologically the effect of a cue change on a non-switch block (where the cue is non-predictive) is likely very different from that in a switch block (where it is predictive), we include this measure for completeness.

Reimers and Stewart (2007, 2015) examined the suitability of, among other things, Adobe Flash for measuring reaction times in online studies, and demonstrated that Flash allowed reasonably accurate estimates of reaction time to be made. Moreover, several studies have compared patterns of reaction times measured online with those in lab settings (including Stroop, flanker, Posner cueing, and attentional blink tasks; Crump et al., 2013), and have almost always found similar effects (see also Chetverikov & Upravitelev, 2015; de Leeuw & Motz, 2016; Enochson & Culbertson, 2015; Hilbig, 2016; Slote & Strand, 2015). There is a lot about task switching specifically that makes it robust to potential web-based data collection issues, such as within-subject comparisons of RTs, averaging across multiple trials for each measure (Reimers & Stewart, 2016). Finally, this web-based approach has been used in the past to examine age-related effects on task switching (Reimers & Maylor, 2005), with large sample sizes compensating for slightly reduced measurement accuracy.

3.2.6.4 Modelling continuous change

A large sample and broad range of ages enabled modelling variability over the lifespan with increased precision, which provides a more detailed index of age-related differences than previous studies that compared non-overlapping age groups at different points in the lifespan. In this way, we could investigate the age-related patterns of performance for components underlying task switching.

Segmented regression (also called piecewise regression) was used to estimate the rate of change in each component with age and demonstrate breakpoints and transition periods during which change occurs. Segmented regression was selected as it can identify the ages (and age ranges) that show a significant shift in performance, signifying a different phase of the lifespan.

The technique has been similarly used by other lifespan researchers to investigate other cognitive abilities over the lifespan (Hartshorne & Germine, 2015; Fortenbaugh et al., 2015).

We predicted we would see the standard U-shaped function on global switch cost across the lifespan as seen in most studies (e.g., Reimers & Maylor, 2005). Specifically, we expected improvement in adolescence, followed by decline in middle age and late adulthood. Existing lifespan data (Cepeda et al., 2001; Reimers & Maylor, 2005) gives an unclear picture on whether there is a plateau in adulthood followed by decline in older age, or whether there is a constant decline through adulthood. Using segmented regression allows us to test for whether a single shift or two fit the data better.

We predicted a much weaker effect of age on local switch cost. By using the double cuing paradigm and fractionation of task switching, we were able to examine the effects of age on the separate components of task switching. The results add to existing findings by allowing us to address issues of whether age-related decline and developmental improvement in switching are mirror images of each other or whether they have qualitative differences, and whether age effects are driven by a single or multiple mechanisms.

3.3 Method

3.3.1 Participants

Participants completed the study online. Most clicked through from a prominent link on the BBC Science website, related to a TV series with which one of the authors (SR) was involved. Sessions were kept short (< 10 minutes) in order to encourage individuals to participate and complete the task. The task was completed 29,242 times. The final sample was 14,757 individuals (4139 identifications as male; 10,536 identifications as female, and 82 no response) after participant exclusion, and 13,718 after stage-two outlier removal (described in the Analysis section below). Excluded were 25 completions by participants who reported their age as under 10, 12,629 completions with an error rate over 35% in one or more experimental conditions, 1,346 completions in which age was not indicated, 485 completions where participants indicated that they had completed the task before, and 272 other completions that were not suitable for data analysis.

Participants reported their age in one-year increments from age 10 to 65. There were also options of Under 10 and Over 65. Median age was 23 years (Interquartile range = 16 years). Age, gender, and education were self-reported. There were an insufficient number of younger participants (9 years and below) to create yearly bins, so their data were not included in the analysis, and participants who gave their age as Over 65 were treated as 66 years old for the analysis[13]. The study was left running online for five years. The final sample contained at least 30 subjects per year of age.

Different methods for estimating the minimum number of participants needed for a study of this nature gave values between 10 per year or 200 participants total [14]. For most ages, our

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[13] Ages in this category were (a) strongly positively skewed (meaning that most were close to 65), and (b) the category contained a small proportion of participants. Further discussion of the age distribution is in Study 2B (Tables 4.2 and 4.3).

[14] The exact number of participants required per age to adequately conduct a multiple regression is unclear. Previous researchers have suggested having at least 10 participants in each year of age (Hartshorne & Germine, 2015). This criterion was met in the current study. For a meaningful regression solution, is ideal to have a high ratio of cases to independent variables (Tabachnick, Fidell, & Ullman, 2007). One rule of thumb is $N > 50 + 8m$ (where m is the number of predictors) for testing the multiple correlation and $N > 104 + m$ for individual predictors. For the five components in the current study, the obtained sample size of $n = 13{,}718$ is much larger than the minimum requirements of 90 (50 + 40) and 109 (104 + 5). For a generalizable solution with data-driven regression (stepwise), the ideal sample of 200 (40 cases per variable) is also met. The obtained sample was also much larger than previous studies of lifespan task switching performance, which have used samples up to 5000 participants (Cepeda et al., 2001; Reimers & Maylor, 2005). Although the majority of the participants were young adults, the distribution of participants per component per age met assumptions of normality. To account for different sample sizes per age, alternative options would be (1) to place youngest and oldest participants into bins, grouping ages to get at least 100 participants in each bin (Fortenbaugh et al., 2015), or (2) to calculate a fixed set of age intervals (e.g., with a width of 5 or 10 years) and run a logistic regression. However, both options prevent measurement of continuous age-related change.

dataset greatly exceeds the number of participants needed for the analyses we ran. Even for ages where the obtained sample was at the lower end of the scale, it still met published recommendations and was larger than most existing datasets.

3.3.2 Materials

The task switching paradigm used in the current study was very similar to Reimers and Maylor (2005) and consisted of a choice reaction time measure with two task sets and two cues per task (“emotion” or “feeling”, and “gender” or “sex”). In this version of the task, there were only two stimuli: either a happy female face and a sad male face or a sad female face and a happy male face, with stimulus set allocated randomly between subjects.

3.3.3 Design and procedure

The experiment consisted of three blocks: Two single-task blocks for each of Emotion and Gender, and a switching block. All tasks were choice reaction time measures, in which participants had to select one of two responses (happy/sad or male/female) by pressing a keyboard button (‘D’ or ‘K’). The single task blocks consisted of 12 trials, with the cue (which was redundant in these blocks) alternating every two trials. Participants categorized each face either as male or female, or as happy or sad, depending on the block. Single-task block order was randomized across participants. Both face stimuli were presented equal numbers of times in random order.

The switching block consisted of 50 trials, including two filler trials at the start followed by 48 experimental trials. As in Reimers and Maylor (2005), trials were paired, with repetitions of the same cue, meaning that trials were always cue/task switch followed by non-switch, followed by cue/task switch followed by non-switch. This can be seen in Figure 1.3.

Order of switches (cue switch or task switch) was randomized subject to the constraint that there were exactly 12 cue-switch trials and 12 task-switch trials (as well as 24 non-switch trials) and no more than three consecutive switches of the same type.

The sequence of stimuli was constrained so that for each trial, one of the two face stimuli was chosen with 50% probability, except where the previous three stimuli were all the same face, in which case the other face was used.

Key mappings for happy-sad and male-female responses were consistent across blocks and randomized for each participant. Once key mappings were made at the start of the experiment, the two stimuli to be used in the study were selected such that mappings of the two attributes were incongruent. For example, if Happy and Female were mapped to the same response key, with Sad and Male mapped to the other response key, the stimuli selected for the experiment would be Happy-Male and Sad-Female, meaning that the participant would have to give a different response to each stimulus depending on whether they were cued to classify by emotion or gender.

At the start of a trial, there was a 1,500ms wait, after which a cue appeared, which remained on the screen throughout the trial. After 250ms[15], one of the two face stimuli for that participant was presented for 250ms. As soon as the face was presented, participants could respond using the keyboard. Immediately after a response, the cue disappeared, and the next trial began. Following an incorrect response, a box with the word 'OOPS!' appeared on the screen for 1,000 ms, after which there was an ITI of 250 ms and the next trial started with a further 1,500ms wait. See Figure 3.1 for an overview.

[15] The times given here are those that were specified in the code. In practice, as the code has no control over monitor synchronization or other components on the user's computer, they are likely to be imprecise. For a discussion of presentation duration accuracy under Adobe Flash, see Reimers & Stewart (2015).

The paradigm had five trial types: non-switches (6) and cue-only switches (5) in the non-switch blocks, and non-switches (25), cue-only switches (12), and cue plus task switches (12) in the switch block. Reaction times and percent error were recorded for each trial. Trials were arranged in order of complexity based on the response speed and the subtraction method was used to create five component measures of performance for each participant, namely, processing speed, cue detection, task decision, maintenance of readiness, and task alternation (Figure 3.2). The first two trials from each block were excluded in the calculations. Data were collected between April 2006 and May 2011.

3.3.4 Analyses

3.3.4.1 Data trimming

First, within-subject within-condition iterative (recursive) trimming was conducted, whereby reaction times greater than four standard deviations above or below the mean of other reaction times in that condition for that subject were excluded, iteratively, until no additional reaction times met the exclusion criterion. Trial-level trimming per subject enabled removal of extremely fast and slow responses, which could result from unwanted influences such as accidental key presses, distraction, or lapses in concentration. Second, between-subject within-age iterative (recursive) trimming was conducted using the R package trimr (Grange, 2015). The trimr package changed the cutoff criterion based on the number of trials (in this case, based on the number of participants in each age bin). The cutoff technique is described in van Selst and Jolicoeur (1994). A total of 1,039 participants were excluded during stage two of trimming, due to removal of one or more mean RTs. The final sample size after stage-two trimming was 13,718.

Secondary analyses were conducted on reaction time standard deviations and coefficients of variability to assess intra-individual variability, and percentage of errors to assess accuracy for each measure. Standard deviation of each participants responses was calculated using trimmed reaction times[16]. The standard deviation was selected for within-subject variability as it is typically used in studies to describe the amount of variability between subjects. To control for differences in mean response, we also calculated the coefficient of variation, which is the ratio of reaction time intra-individual standard deviation to mean reaction time for each individual. Using the coefficient of variation allows us to check for bias from within-subject variability deviations with age being confounded by mean changes with change[17].

3.3.4.2 Locally weighted Regression

Loess (locally estimated scatterplot smoothing; Cleveland, & Devlin, 1988; Jacoby, 2000) curves were fitted to qualitatively examine trends over age in the data and are shown in Figures 3.3–3.5. Loess enables data exploration as it does not require an a priori specification of relationships. Loess was used to smooth means for each age using a three-year moving window. Means are shown with a 95% confidence interval envelope. The fitting was done using the *loess* function in the *R* statistical software (Shyu, Grosse, & Cleveland, 2017).

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[16] Trimmed means were used to obtain normally distributed data. Without trimming, reaction times and standard deviations failed to meet normality. The criterion of four standard deviations was selected as it met normality and provided a compromise between removing noise and still leaving valuable information in the dataset. A more liberal criterion (5 SD) resulted in a lot of noise remaining in the dataset, while a more conservative criterion resulted in loss of a large portion of the dataset, which could have led to biased results from loss of genuine variability in the data. An alternate trimming option would have been to use cutoffs (e.g., 5000 ms), although this was statistically weaker (cutoffs still lead to non-normality) and theoretically weaker (some individuals may have been dropped for one lapse in attention, while other individuals who were erratic could be kept in the analysis).

[17] The coefficient of variability was calculated using the most common method in previous studies: dividing individual standard deviations by the mean and multiplying by 100. Some studies have used a partial regression procedure instead of the coefficient of variation. Regression is used to partial out the effects of potential confounding factors (age, practice, gender) on individual trial RTs before calculating individual SDs (termed "purified" residuals). However, the coefficient of variation offers a more precise measure of mean-adjusted intra-individual variability than purified residuals (Dykiert et al., 2012b).

3.3.4.3 Segmented Regression

Segmented regression was run to quantitatively determine the gradient of change, and the age of onset and offset of transitions. Analyses were conducted by looking at the effect of age on reaction time means per component, and on accuracy and reaction time intra-individual variability per trial type. Several models were fitted for each measure, increasing in complexity. First a linear function was fitted to estimate a single slope over the ages measured. Next, a model was fitted with one breakpoint (i.e., one shift) in the linear function, that is, with two periods of performance. Following this, models were fit with two breakpoints, and then three breakpoints.

Analyses were run using the *segmented* package in the *R* statistical software (Muggeo, 2003, 2008). The package fits linear regressions to data where the slope is allowed to change at a specified number of breakpoints[18]. Starting values to estimate breakpoints were obtained by a Davies test (Davies, 2002), which finds a non-constant regression parameter in the linear predictor of age—that is, a non-zero difference-in-slope parameter of a segmented relationship. Each model with set initial estimates was compared to an alternative model with no initial estimates (the alternative model fit *k* quantiles—that is, equally spaced values where *k* was the number of breakpoints to be fit). There was no significant difference in the model fit by either technique, ps > .1.

Hierarchical regressions were conducted to compare the different models. Models were selected based on whether the fit improved significantly (as measured by the *F* statistic) by adding additional breakpoints (from a linear model to a one-break model, and from a one-break

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[18] To ensure robust fitted estimates, we used 50 bootstrap samples (with n=1,000 per sample) in the starting algorithm, a convergence tolerance of 0.0001, and a maximum of 20 iterations. For the task decision time process, some of these parameters had to be adjusted for a model to be fitted when no initial estimates were provided, however it provided the same results as the model with pre-specified initial estimates using a Davies test.

to a two-break, or a three-break model). Final selection was made based on the model that provided a significantly better fit than simpler alternatives. The Akaike information criterion (AIC; Akaike, 1957) and Bayes information criterion (BIC[19]) are presented as measures of parsimony in model fitting.

In addition to the results from null hypothesis testing, effect sizes were interpreted to provide an indicator of the magnitude of the effect. Effect sizes are particularly informative in the current study since raw effect sizes provide intuitively useful information. The slope estimates (i.e., regression coefficients) predict the exact amount of change in reaction times (milliseconds) or accuracy (percentage of errors), and the breakpoint estimates provide the age at which performance shifts. For example, the coefficient for the first slope of processing speed reaction times is -41.8, which should be interpreted as an improvement of 41.8 ms per year. The first breakpoint estimate is 14.5, which is should be interpreted as an improvement until the age of 14.5 years. Finally, confidence intervals are reported to indicate the range of performance and ages measured. For example, in the previous scenario, the confidence intervals indicate an improvement of 31.6 to 52.1 ms per year from ages 14 to 14.9 years.

Since the expected task switching ability as a function of age changes in direction, a straight line regression model likely would not be adequate to capture effects of age. Residual plots indicated non-linearity in the reaction time distributions. Significant curvature was indicated in the model by quadratic tests, *p*s < .001, and a Tukey 1-*df* test, $p < .001$. Non-

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[19] AIC aims to select a model that best describes an unknown, high dimensional reality. BIC aims to select a true model, using the assumption that there was a true model independent of n, that generated the data; and that it was a model in the model set. Hence the true model is not in the set of candidate models for AIC, while it is for BIC. BIC is also more conservative when penalizing for extra parameters for AIC. Since initial estimates for our model were calculated a priori based on the data, several iterations were used before the model was estimated, and the aim of the model is prediction as well as explanation, we think that the BIC criterion is relevant in this case. However, the AIC criterion accounts for sample size (Burnham & Anderson, 2002), which also makes it suitable for the current investigation.

linearity is likely, since previous researchers have shown that RT performance across the lifespan follows an inverted U-shape curve (Salthouse, 1996), with a similar pattern reported for task switching performance (Cepeda et al., 2001; Reimers & Maylor, 2005). Although a standard polynomial approach has been previously used to model lifespan changes in performance on processing speed and sustained attention (Fortenbaugh et al., 2015), task switching performance may not meet the assumption of symmetry required when using quadratic functions[20]. Hence, the selected segmented technique that tests for asymmetrical patterns is ideal. To ensure that we were not fitting constantly accelerating data with segmented linear functions, we examined the loess curves for confirmation that observed data patterns were asymmetrical. Further, the hierarchical regression statistically tests for a single linear function (i.e., continuously accelerating data) compared to multiple breakpoints.

Using segmented linear functions accounts for performance changes at different ages but without the assumption of symmetry with polynomial regression. A further benefit of using segmented regression is that estimating the change point between linear segments and the confidence intervals around the point allows estimation of a transition zone, indicating an age range in which transitions are likely to occur.

3.4 Results

3.4.1 Locally weighted Regression

3.4.1.1 Mean reaction times

Qualitative patterns from the loess curve indicated an inverted U-shaped curve of

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[20] Since previous evidence indicates a quadratic relationship for processing speed (Salthouse, 1996; Reimers & Maylor, 2005), an alternative model was fit replacing processing speed with a quadratic term. The updated model was significant, $p < .05$, but had a 0.14% decrease in the total variance explained and an increase in the AIC criterion from 195184 to 195703.

development and decline per trial type (Figure 3.3). After dissociating into components, differential average reaction time patterns and timings of change were observed for each. Processing speed showed the largest change in performance, with considerably faster reaction times during adolescence, a gradual slowing in young adulthood, followed by a more accelerated slowing later in life. The remaining components showed much smaller rates of change, but there were still indications of shifts in early adulthood and late adulthood, which indicate maturation after development and the start of aging, respectively.

3.4.1.2 Accuracy

Average accuracy performance appeared to follow a roughly similar pattern and timing across trial types (Figure 3.4). A notable improvement (fewer errors) was seen until the late 20s, with a relatively stable performance after. Task switch trials in switch blocks had the largest change in performance, indicating that most errors are made when actually shifting compared to other components of task switching. Error rates were extremely low for the remaining trial types.

3.4.1.3 Reaction time intra-individual variability

As with accuracy, intra-individual variability in reaction times appeared to follow a roughly similar pattern and timing across trial types (Figure 3.5). Intra-individual variability decreased until the 20s, was mostly stable through adulthood, and started to increase again in mid to late adulthood. After accounting for mean reaction times, the developmental pattern was still visible, but the aging pattern disappeared, indicating that a notable portion of the increase in intra-individual variability later in life may be due to an overall slowing.

3.4.2 Segmented Regression

3.4.2.1 Mean reaction times

The results of each model fit with segmented regression are shown in Table 3.1.

Breakpoint estimates and rates of changes are shown in Table 3.2. For the components of processing speed and maintenance of readiness, the best fitting model had two breakpoints, that is, three phases of change (development, gradual decline, less gradual decline). For the components of task decision and task alternation, the best fitting model had one breakpoint, that is, two phases of change (Figure 3.6). For the component of cue detection, the best fitting model was a linear function with no breakpoints. Both the one and two breakpoint models followed the expected pattern of rapid developmental improvement followed by gradual decline. The exception was task alternation, which showed a decline but no developmental change.

Processing speed rapidly improved (faster reaction times) from the start of measurement at 10 years until 15 years of age by 41.8 ms (*SE* = 5.24) per year, followed by a slowing until 36 years of age of 1.23 ms (*SE* = 0.22) per year, and then a further slowing of 2.53 ms (*SE* = 0.31) per year. Maintenance of readiness improved from the start of measurement until 18 years of age by 6.63 ms (*SE* = 2.32) per year, followed by a slowing of 2.68 ms (*SE* = 0.25) per year, and then a further slowing of 4.51 ms (*SE* = 0.85) per year. Task decision improved from the start of measurement until 16 years of age by 7.32 ms (*SE* = 2.71) per year, followed by a slowing of 1.16 ms (*SE* = 0.13) per year. Task alternation, the best fitting model showed no significant change in reaction times from the start of measurement at 10 years until 34 years of age, followed by a significant slowing in reaction times of 2.92 ms (*SE* = 0.44) per year. Cue detection had no significant shifts in performance across the lifespan. Reaction times changed at a steady rate of 0.30 (*SE* = 0.13) ms per year through all the ages measured.

The age range at which development ended was earlier for processing speed (between 14 and 15) than maintenance of readiness and task decision (between 15 and 19). The age at which a less gradual decline began was earliest for processing speed (after 36 years) and later for maintenance of readiness (after 43 years). Overall, the range of ages in which development ends was much smaller than the range of ages in which decline begins. The overlap between confidence intervals for the age transitions indicates that some components develop and decline in parallel, while others do not.

Since sample sizes were not consistent for all ages, with much sparser groups at both ends of the lifespan, a manipulation check was run with balanced samples to test whether results would change. The additional analysis was run for the smallest possible group size. However, similar breakpoints were estimated for all components, confirming the validity of our current findings. A further analysis was run using samples of 100 individuals per age (with bootstrap resampling for smaller groups), but this analysis also did not change the pattern of results. Finally, our obtained sample size met recommendations of at least 10 participants in each year of age (Hartshorne & Germine, 2015).

Since reaction time distributions tend to be skewed, analyses on reaction time medians were conducted as an alternative measure of central tendency. However, medians are less appropriate as they cannot be combined with iterative trimming or reliably used in parametric analyses. Nevertheless, the overall pattern of results across components for median analyses was nearly identical to the mean analyses, including the number and estimate of breakpoints.

3.4.2.2 Accuracy

On accuracy, two trial types were best fit by a one-breakpoint model, all ps < .001, and three trial types were best fit by a two-breakpoint model, all ps < .01 (Table 3). The best fitting one-breakpoint models showed a small but significant decrease in percentage of errors from the start of measurement at 10 years until young adulthood (ages 22 to 29 years), followed by little to no change errors until the end of measurement (Table 4; Figure 3.7). The best fitting two-breakpoint models also showed a small but significant decrease in percentage of errors from the start of measurement at 10 years until young adulthood (ages 23 to 28 years), followed by a trivial shift until the end of measurement (ages 43 to 55 years). The exception was cue switch trials in non-switch blocks, which showed a trivial increase in errors from the start of measurement until adolescence (ages 11 to 15 years), followed by the typical pattern of a decrease in errors until young adulthood (ages 24 to 19 years). The rate of change in accuracy measures was trivial. The largest change in slope was 0.27 (*SE*=0.02) percent errors per year on task switch trials.

3.4.2.3 Reaction time intra-individual variability

For intra-individual variability, across all trial types the best fitting models had two breakpoints, all *p*s <0.001. The exception was cue switch trials in the non-switch block, which were best fit with one breakpoint (Table 3.5). Variability decreased significantly until mid to late adolescence (ages 15 to 19 years), followed by a trivial but significant increase until mid to late adulthood (ages 37 to 65 years), and then a larger increase until the end of measurement (Table 3.6; Figure 3.8).

After accounting for mean changes in reaction time using the coefficient of variability, the pattern of change moved from two breakpoints to one breakpoint, except for cue switch trials in a switch block which still had two breakpoints (Table 3.7). Across all trial types, mean-adjusted variability decreased significantly until late adolescence and the start of young adulthood (ages 16 to 21 years), followed by no notable change (Table 3.8; Figure 3.9). The exception was task switch trials, for which mean-adjusted variability slightly decreased until mid-adulthood (ages 37 to 49 years).

Tables and Figures

Table 3.1: Hierarchical regression results for mean reaction times

Block	Component	*Straight-line model vs. one-break model*	*One-break model vs. two-break model*	*Two-break model vs. three-break model*
Non-switch block	Processing Speed	*F*(2, 13714) =83.5***, ΔAIC = -162, ΔBIC = -147	***F*(2, 13712) = 6.17**, ΔAIC = -8.27, ΔBIC = 6.78**	*F*(2, 13710) = 0.67, ΔAIC = -2.66, ΔBIC = 17.7
	Cue Detection	*F*(2, 13714) =2.38, ΔAIC = -0.73, ΔBIC =14.3	*F*(2, 13712) =1.31, ΔAIC = 1.46, ΔBIC = 16.5	*F*(2, 13710) =0.32 [a], ΔAIC = 4.18, ΔBIC = 19.2
Both blocks (Global switch cost)	Maintenance of Readiness	*F*(2, 13714) =20.6***, ΔAIC = -37.2, ΔBIC = -22.1	***F*(2, 13712) = 3.26*, ΔAIC = -2.52, ΔBIC = 12.5**	*F*(2, 13710) = 0.76, ΔAIC = 2.48, ΔBIC = 17.5
Switch block (Local switch cost)	Task Decision	***F*(2, 13714) =7.79***, ΔAIC = -11.6, ΔBIC = 3.49**	*F*(2, 13712) = 1.80, ΔAIC =0.39, ΔBIC = 15.4	*F*(2, 13710) = 2.91[a], ΔAIC = -3.30, ΔBIC = 11.9
	Task Alternation	***F(2, 13714) =10.8***,* ΔAIC = -17.6, ΔBIC = -2.50**	*F*(2, 13712) = 0.30, ΔAIC = 3.39, ΔBIC = 18.4	*F*(2, 13710) = 0.85, ΔAIC = 2.29, ΔBIC = 17.3

* $p \leq .05$, ** $p \leq .01$, *** $p \leq .001$.
Note. Each analysis determined whether the second, more complicated model (the alternative) explained significantly more variance than the first, null model. The final selected model is highlighted in bold.
[a] The model with initial estimates had difficulty converging, so reported results are from a model with no initial estimates.

Table 3.2: Ages and slopes of transitions for mean reaction times

		Development		Adulthood	Aging	
Block	Variable	Slope 1	Age (years)	Slope 2	Age (years)	Slope 3
Non-switch block	Processing Speed	-41.8 [-52.1, -31.6]	14.5 [14.0, 14.9]	1.23 [0.79, 1.66]	35.5 [27.9, 43.1]	2.53 [1.92, 3.14]
	Cue Detection	-	-	-0.30 [-0.43, -0.17]	-	-
Both blocks (Global switch cost)	Maintenance of Readiness	-6.63 [-11.2, -2.08]	17.6 [16.3, 18.9]	2.68 [2.17, 3.20]	43.4 [33.5, 53.3]	4.51 [2.99, 6.05]
Switch block (Local switch cost)	Task Decision	-7.32 [-12.6, -2.02]	16.3 [15.1, 17.5]	1.16 [0.91, 1.41]	-	-
	Task Alternation	-	-	0.42 [-0.23, 1.07]	34.0 [28.1, 39.9]	2.92 [2.07, 3.77]

Note. 95% confidence intervals are shown in brackets. Values shown are for the best fitting model for each process.
Ages represent the estimated breakpoints, and slopes represent the regression coefficients.

Table 3.3: Hierarchical regression results for mean accuracy

Block	Trial	*Straight-line model vs. one-break model*	*One-break model vs. two-break model*	*Two-break model vs. three-break model*
Non-switch block	Non-switch trial	**F(2, 14728) =24.2***, ΔAIC = -44.4, ΔBIC = -29.2**	F(2, 14726) = 1.67, ΔAIC = 0.66, ΔBIC = 15.9	F(2, 14724) =0.16 ΔAIC = 3.69, ΔBIC = 18.9
	Cue switch trial	F(2, 14728) =34.2***, ΔAIC = -64.3, ΔBIC =-49.1	**F(2, 14726) = 5.77** , ΔAIC =-7.54, ΔBIC = 7.66**	F(2, 14724) = 0.95 ΔAIC =2.09, ΔBIC = 17.3
Switch block	Non-switch trial	F(2, 14728) =23.4***, ΔAIC = -42.8, ΔBIC = -27.6	**F(2, 14726) = 5.84**, ΔAIC = -7.73, ΔBIC = 7.46**	F(2, 14724) = 0.18 ΔAIC = 4.00, ΔBIC = 19.2
	Cue switch trial	**F(2, 14728) =28.4***, ΔAIC = -52.8, ΔBIC =-37.6**	F(2, 14726) = 2.40, ΔAIC =-0.80, ΔBIC =14.4	F(2, 14724) = 0.83 ΔAIC = 2.33, ΔBIC = 17.5
	Task switch trial	F(2, 14728) =45.9***, ΔAIC = -87.5, ΔBIC = -72.3	**F(2, 14726) = 3.28*, ΔAIC =-2.56, ΔBIC =12.6**	F(2, 14724) = 2.64 ΔAIC =-1.29, ΔBIC = 13.9

* $p \leq .05$** $p \leq .01$*** $p \leq .001$
Note. Each analysis determined whether the second, more complicated model (the alternative) explained significantly more variance than the first, null model. The final selected model is highlighted in bold.

Table 3.4: Ages and slopes of transitions for mean accuracy

		Development		Adulthood	Aging	
Block	Trial	Slope 1	Age (years)	Slope 2	Age (years)	Slope 3
Non-switch block	Non-switch trial	-0.11 [-0.15, -0.07]	25.6 [22.7, 28.5]	0.02 [0.002, 0.03]	-	-
	Cue switch trial	0.98 [-0.32, 2.28]	12.9 [11.1, 14.7]	-0.13 [-0.17, -0.09]	26.5 [24.1, 28.8]	0.03 [0.02, 0.05]
Switch block	Non-switch trial	-0.18 [-0.25, -0.11]	20.3 [22.9, 27.7]	-0.04 [-0.06, -0.02]	43.7 [47.9, 62.2]	0.04 [-0.001, 0.09]
	Cue switch trial	-0.16 [-0.20, -0.11]	24.1 [21.7, 26.4]	-0.001 [-0.02, -0.01]		
	Task switch trial	-0.29 [-0.35, -0.23]	25.3 [22.9, 27.7]	-0.05 [-0.07, -0.02]	55.0 [47.9, 62.2]	0.20 [-0.06, 0.46]

Note. 95% confidence intervals are shown in brackets. Values shown are for the best fitting model for each process.
Ages represent the estimated breakpoints, and slopes represent the regression coefficients.

Table 3.5: Hierarchical regression results for reaction time standard deviations

Block	Trial Type	*Straight-line model vs. one-break model*	*One-break model vs. two-break model*	*Two-break model vs. three-break model*
Non-switch block	Non-switch trial	$F(2, 12656) = 24.7^{***}$, ΔAIC = -45.3, ΔBIC = -30.4	**$F(2, 12654) = 3.42^{*}$, ΔAIC = -2.84, ΔBIC = 12.1**	$F(2, 12652) = 2.35$, ΔAIC = -0.70, ΔBIC = 14.2
	Cue switch trial	**$F(2, 12656) = 31.2^{***}$, ΔAIC = -58.3, ΔBIC =-43.4**	$F(2, 12654) = 0.20$, ΔAIC = 3.61, ΔBIC = 18.5	$F(2, 12652) = 0.27$, ΔAIC = 3.46, ΔBIC = 18.4
Switch block	Non-switch trial	$F(2, 12656) = 43.3^{***}$, ΔAIC = -82.3, ΔBIC = -67.4	**$F(2, 12654) = 10.5^{***}$, ΔAIC = -17.0, ΔBIC = 2.10**	$F(2, 12652) = 0.90$, ΔAIC = 2.19, ΔBIC = 17.1
	Cue switch trial	$F(2, 12656) = 45.9^{***}$, ΔAIC = -87.3, ΔBIC =-72.4	**$F(2, 12654) = 14.3^{***}$, ΔAIC =-24.7, ΔBIC =-9.77**	$F(2, 12652) = 0.54$, ΔAIC = 2.92, ΔBIC = 17.8
	Task switch trial	$F(2, 12656) = 25.7^{***}$, ΔAIC = -47.2, ΔBIC = -32.3	**$F(2, 12654) = 12.3^{***}$, ΔAIC =-20.6, ΔBIC =-5.71**	$F(2, 12652) = 2.87$, ΔAIC =-2.03, ΔBIC = 12.9

* $p \leq .05$ ** $p \leq .01$ *** $p \leq .001$

Note. Each analysis determined whether the second, more complicated model (the alternative) explained significantly more variance than the first, null model. The final selected model is highlighted in bold.

Table 3.6: Ages and slopes of transitions for reaction time standard deviations

		Development		Adulthood	Aging	
Block	Trial Type	Slope 1	Age (years)	Slope 2	Age (years)	Slope 3
Non-switch block	Non-switch trial[a]	-4.75 [-6.75, -2.75]	17.4 [16.5, 18.3]	0.46 [0.32, 0.60]	59.0 [52.8, 65.3]	3.87 [-0.73, 8.46]
	Cue switch trial	-8.36 [-10.9, -5.78]	17.6 [16.4, 18.7]	0.37 [0.20, 0.53]	-	-
Switch block	Non-switch trial	-16.2 [-22.1, -10.2]	15.5 [14.8, 16.2]	0.85 [0.59, 1.10]	43.0 [37.0, 49.0]	2.67 [1.79, 3.56]
	Cue switch trial	-15.5 [-20.3, -10.7]	16.3 [15.8, 16.9]	1.07 [0.80, 1.35]	50.2 [45.7, 54.8]	5.31 [3.10, 7.51]
	Task switch trial	-5.97 [-9.34, -2.60]	17.3 [16.2, 18.5]	0.90 [0.57, 1.22]	46.6 [42.3, 50.9]	4.20 [2.83, 5.58]

Note. 95% confidence intervals are shown in brackets. Values shown are for the best fitting model for each process.
Ages represent the estimated breakpoints, and slopes represent the regression coefficients.
[a] The model with initial estimates had difficulty converging, so reported results are from a model with no initial estimates

Table 3.7: Hierarchical regression results for reaction time coefficient of variability

Block	Trial	*Straight-line model vs. one-break model*	*One-break model vs. two-break model*	*Two-break model vs. three-break model*
Non-switch block	Non- switch trial	***F*(2, 12656) =13.3***, ΔAIC = -22.6, ΔBIC = -7.69**	*F*(2, 12654) = 1.24, ΔAIC = 1.51, ΔBIC = 16.4	*F*(2, 12652) = 0.37, ΔAIC = 3.26, ΔBIC = 18.2
	Cue switch trial	***F*(2, 12656) =17.3***, ΔAIC = -30.5, ΔBIC =-15.6**	*F*(2, 12654) = 0.003, ΔAIC = 3.99, ΔBIC = 18.9	*F*(2, 12652) = 1.90, ΔAIC = 0.19, ΔBIC = 15.1
Switch block	Non-switch trial	***F*(2, 12656) =9.29***, ΔAIC = -14.6, ΔBIC = 0.32**	*F*(2, 12654) = 2.86, ΔAIC = -1.73, ΔBIC = 13.2	*F*(2, 12652) = 0.36, ΔAIC = 3.28, ΔBIC = 18.2
	Cue switch trial	*F*(2, 12656) =12.5***, ΔAIC = -21.1, ΔBIC =-6.15	***F*(2, 12654) = 4.32*, ΔAIC =-4.63, ΔBIC =-10.3**	*F*(2, 12652) = 1.84, ΔAIC = 0.31, ΔBIC = 15.2
	Task switch trial	***F*(2, 12656) =7.09***, ΔAIC = -10.2, ΔBIC = 4.73**	*F*(2, 12654) = 2.36, ΔAIC =-0.73, ΔBIC =14.2	*F*(2, 12652) = 0.30, ΔAIC =3.40, ΔBIC = 18.3

* $p \leq .05$** $p \leq .01$*** $p \leq .001$

Note. Each analysis determined whether the second, more complicated model (the alternative) explained significantly more variance than the first, null model. The final selected model is highlighted in bold.

Table 3.8: Ages and slopes of transitions for reaction time coefficient of variability

		Development		Adulthood	Aging	
Block	Trial	Slope 1	Age (years)	Slope 2	Age (years)	Slope 3
Non-switch block	Non-switch trial	-0.32 [-0.53, -0.12]	19.0 [16.9, 21.1]	0.02 [0.003, 0.04]	-	-
	Cue switch trial	-0.66 [-0.97, -0.36]	17.6 [16.4, 18.7]	-0.009 [-0.03, 0.01]	-	-
Switch block	Non-switch trial	-0.34 [-0.55, -0.15]	18.0 [16.4, 19.6]	0.0017 [-0.015, 0.019]	-	-
	Cue switch trial	-0.42 [-0.68, -0.17]	17.7 [15.9, 19.5]	-0.04 [-0.07, -0.02]	48.9 [42.3, 55.4]	0.11 [-0.01, 0.24]
	Task switch trial	-0.0694 [-0.089, -0.05]	-	-	43.0 [36.8, 49.2]	0.043 [-0.02, 0.11]

Note. 95% confidence intervals are shown in brackets. Values shown are for the best fitting model for each process.
Ages represent the estimated breakpoints, and slopes represent the regression coefficients.

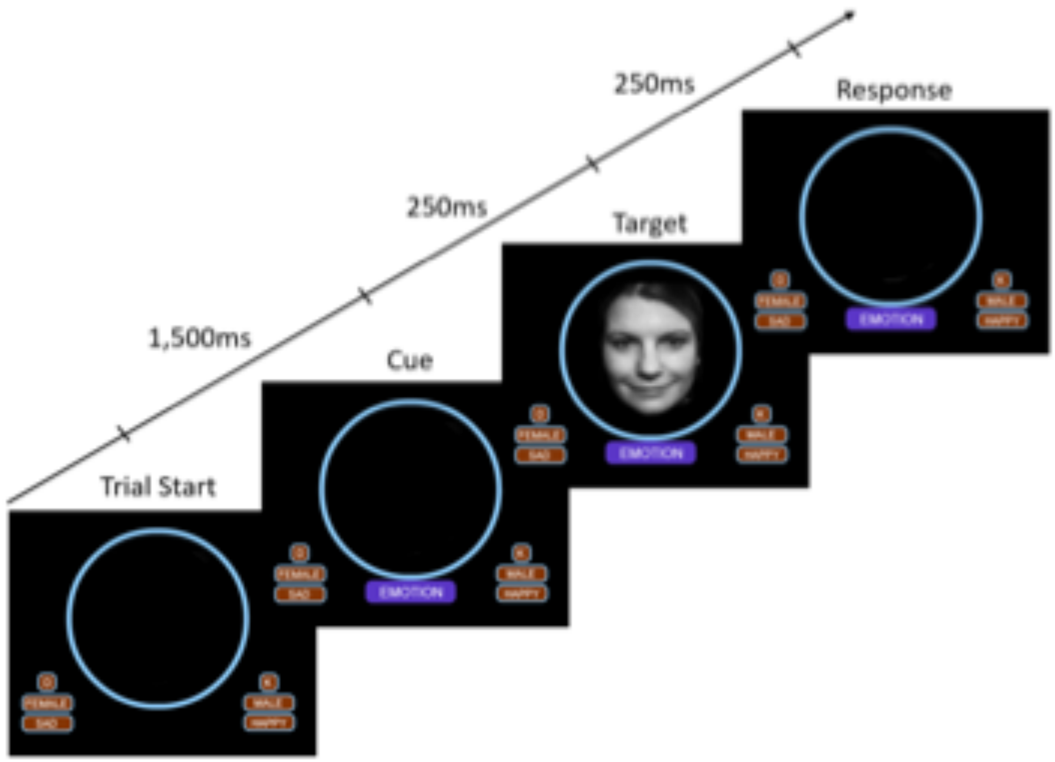

Figure 3.1: Timing of cue and target presentations in the double cuing paradigm

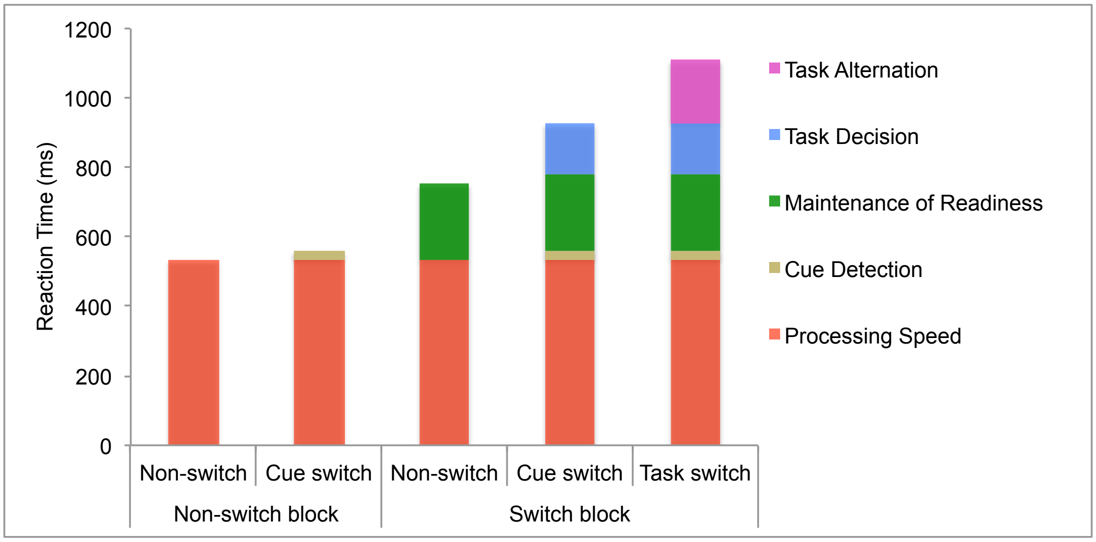

Figure 3.2: Mean reaction time per process

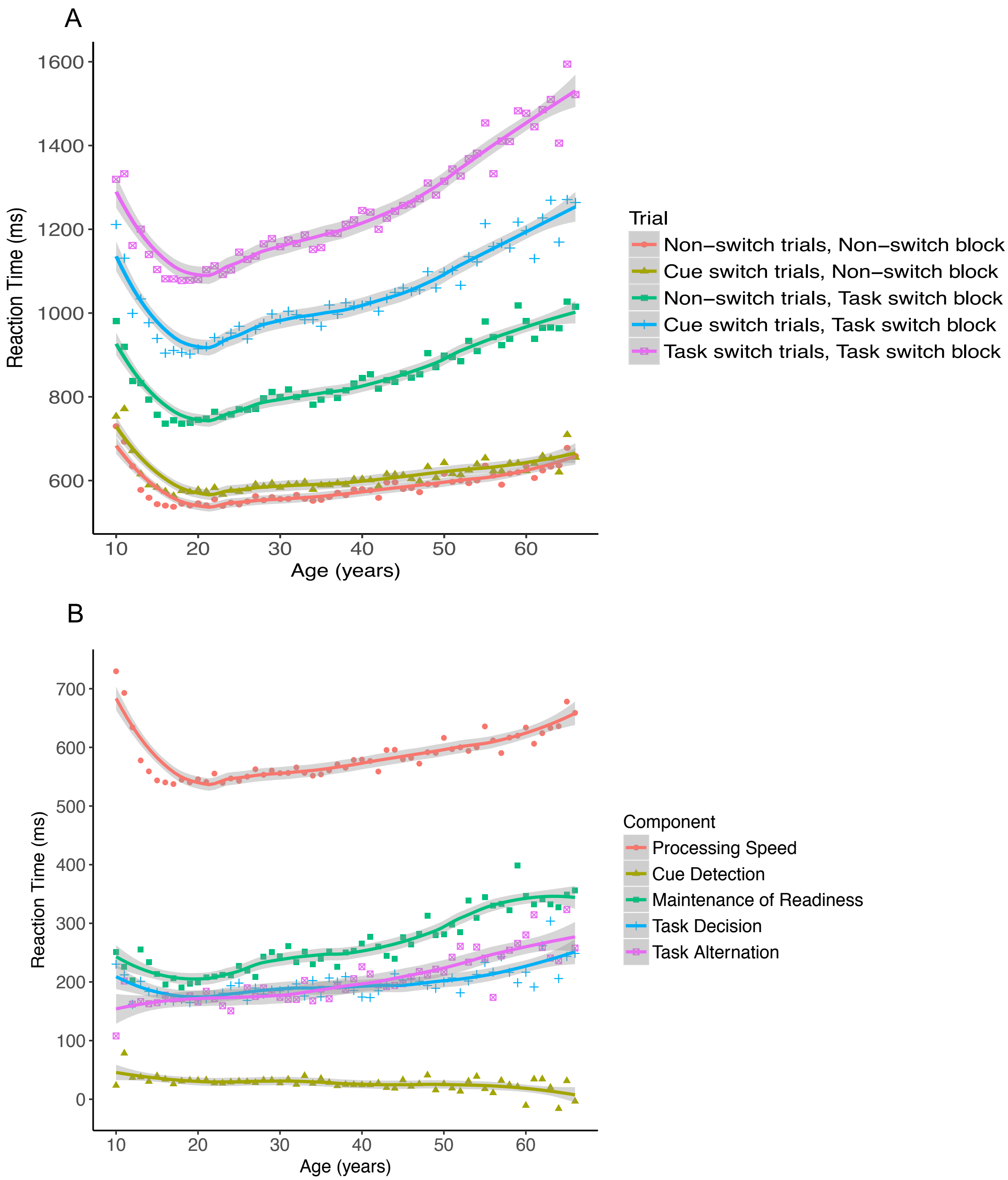

Figure 3.3: Loess curves of mean reaction time

Mean reaction times [95% CI] over age (A) per condition and (B) per component

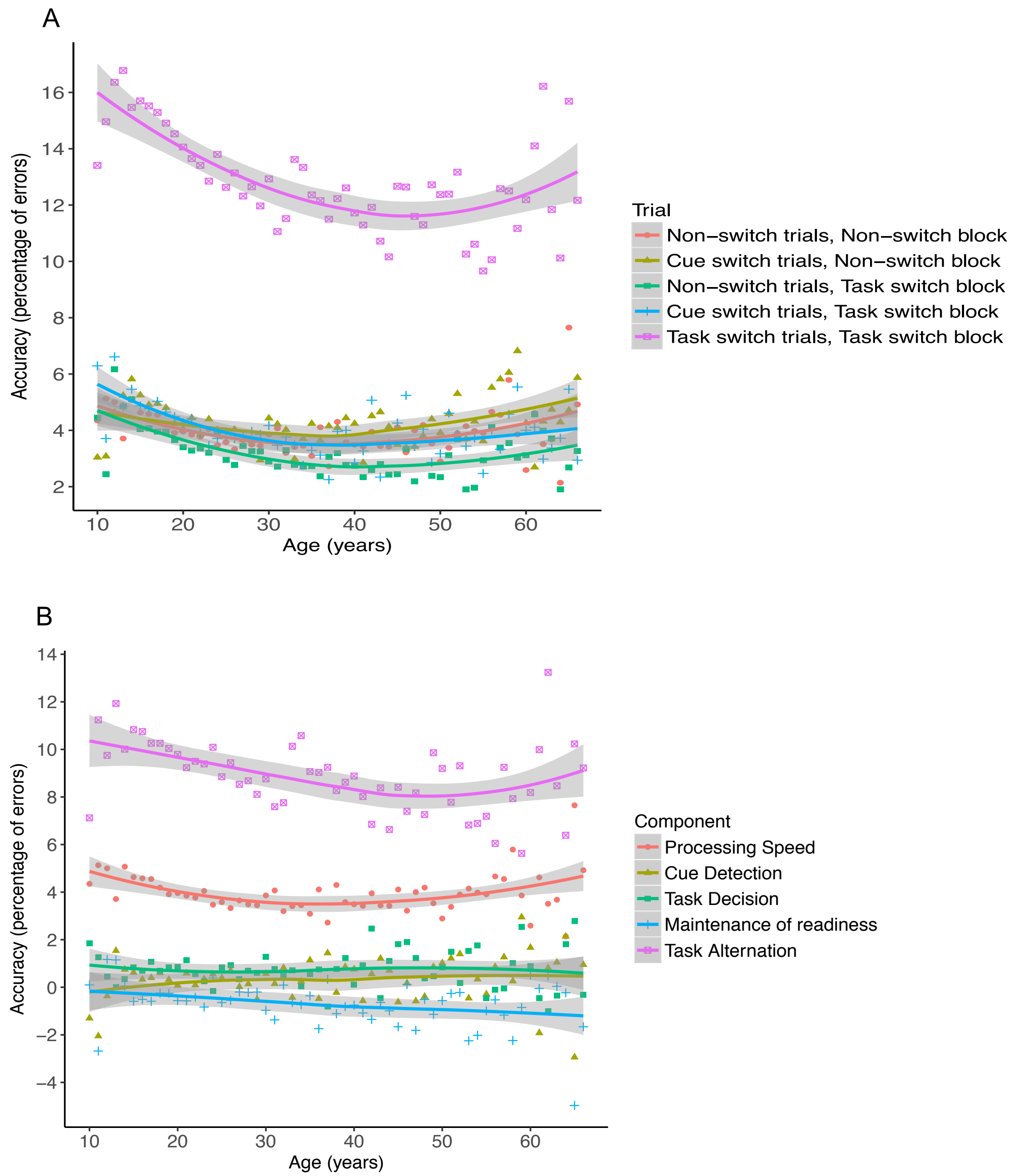

Figure 3.4: Loess curves of mean accuracy

Mean percent errors [95% CI] over age per condition.

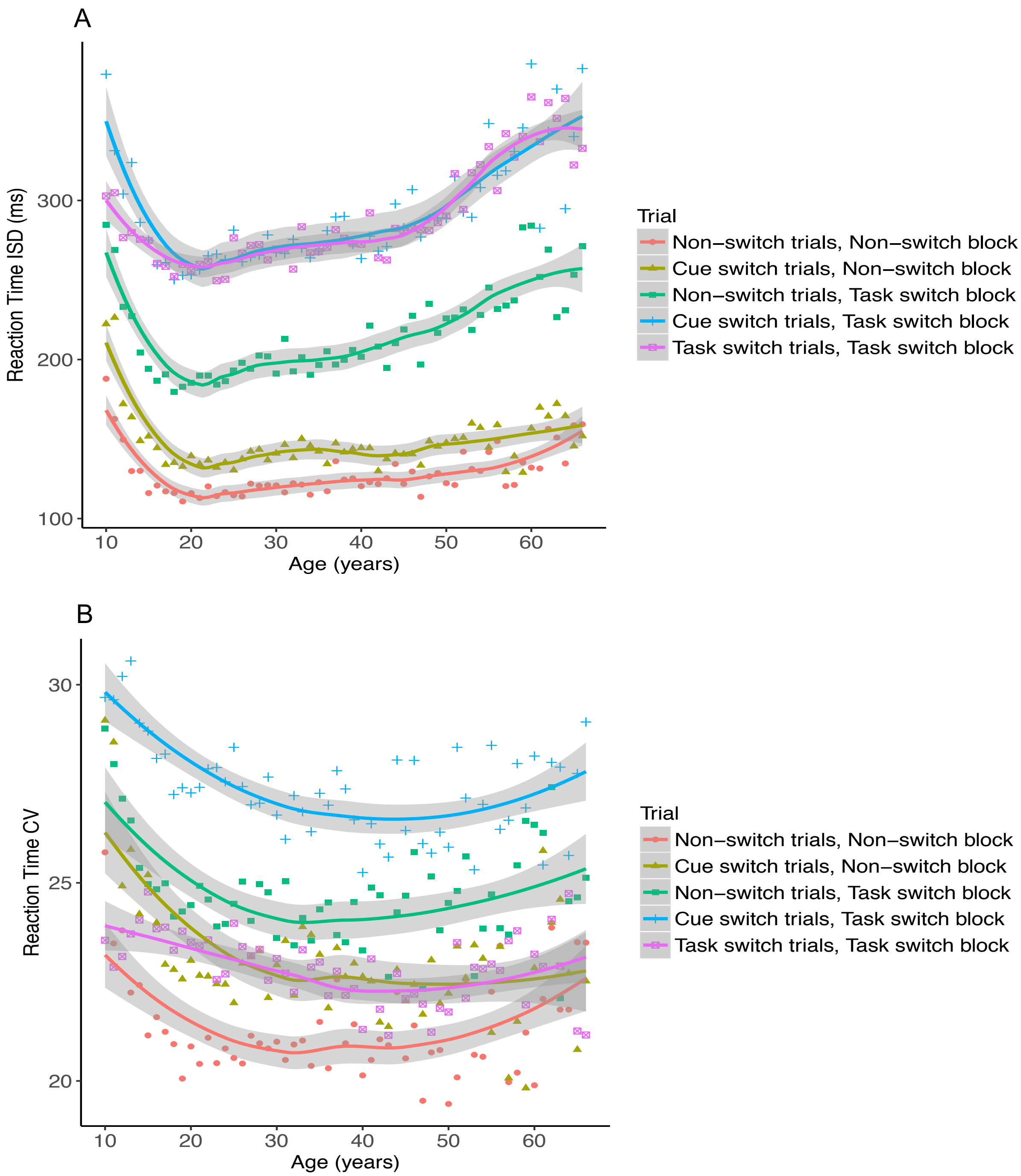

Figure 3.5: Loess curves of intra-individual variability in reaction time

Mean [95% CI] (A) intra-individual standard deviation, and (B) coefficient of variability (CV) over age per condition.

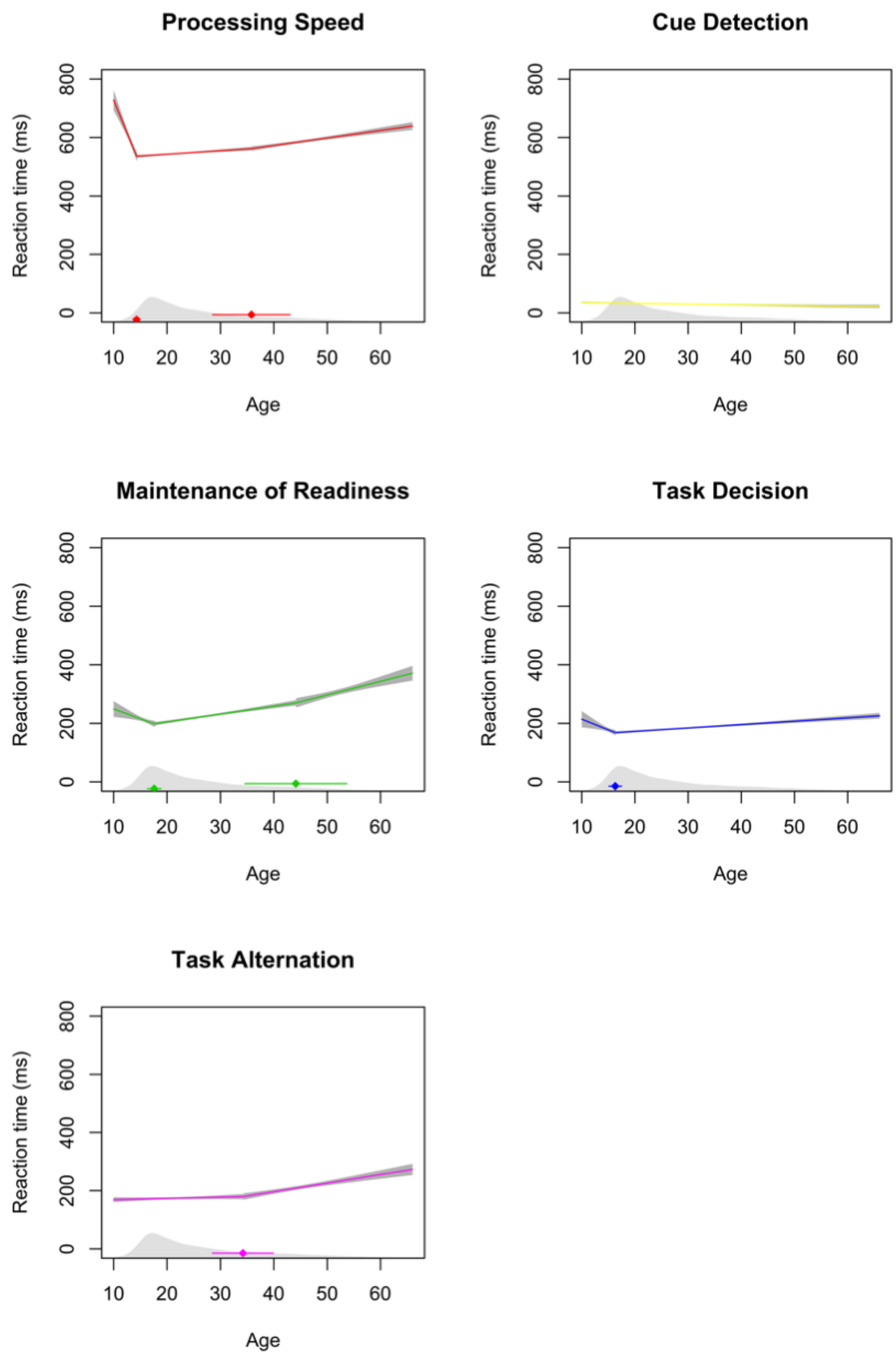

Figure 3.6: Segmented regression models of mean reaction time

Segmented linear regression models of mean reaction times per component. Breakpoints [95% CI] and population density curves are shown along the horizontal axis.

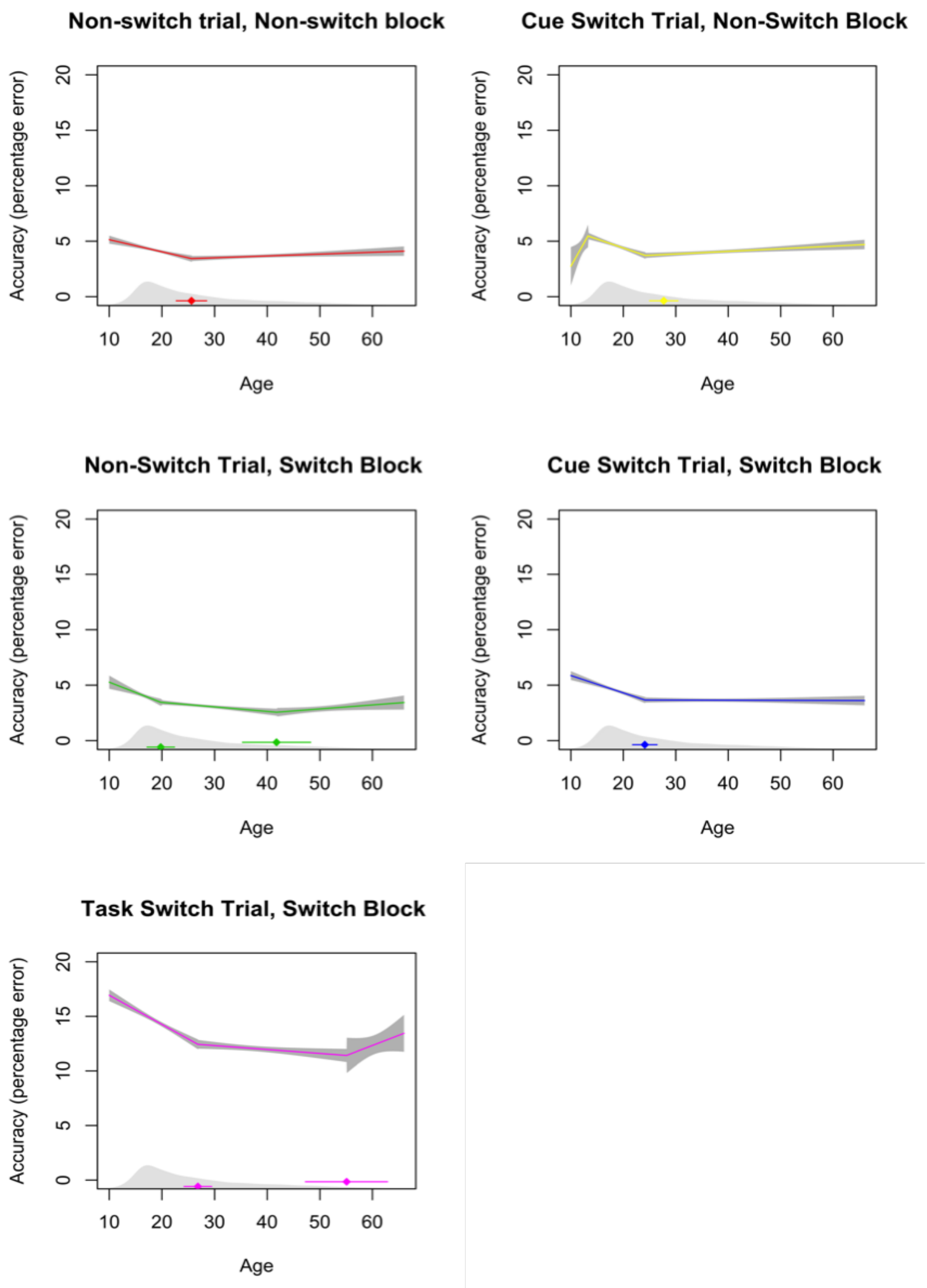

Figure 3.7: Segmented regression models of mean accuracy

Segmented linear regression models of mean percent error per component. Breakpoints [95% CI] and population density curves are shown along the horizontal axis.

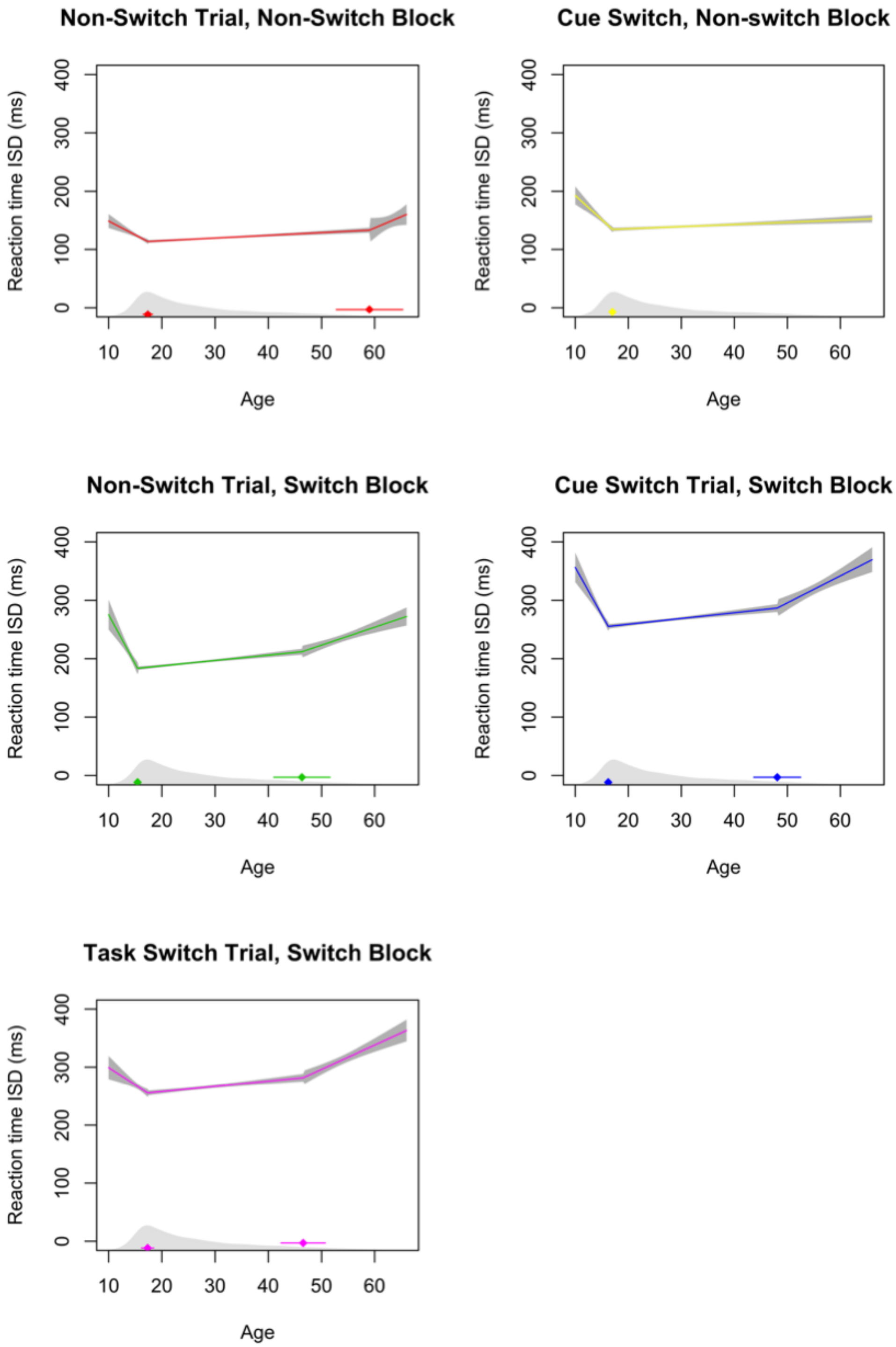

Figure 3.8: Segmented regression models of reaction time standard deviations

Segmented linear regression models of mean intra-individual standard deviation (ISD) in reaction times per condition. Breakpoints [95% CI] and population density curves are shown along the horizontal axis.

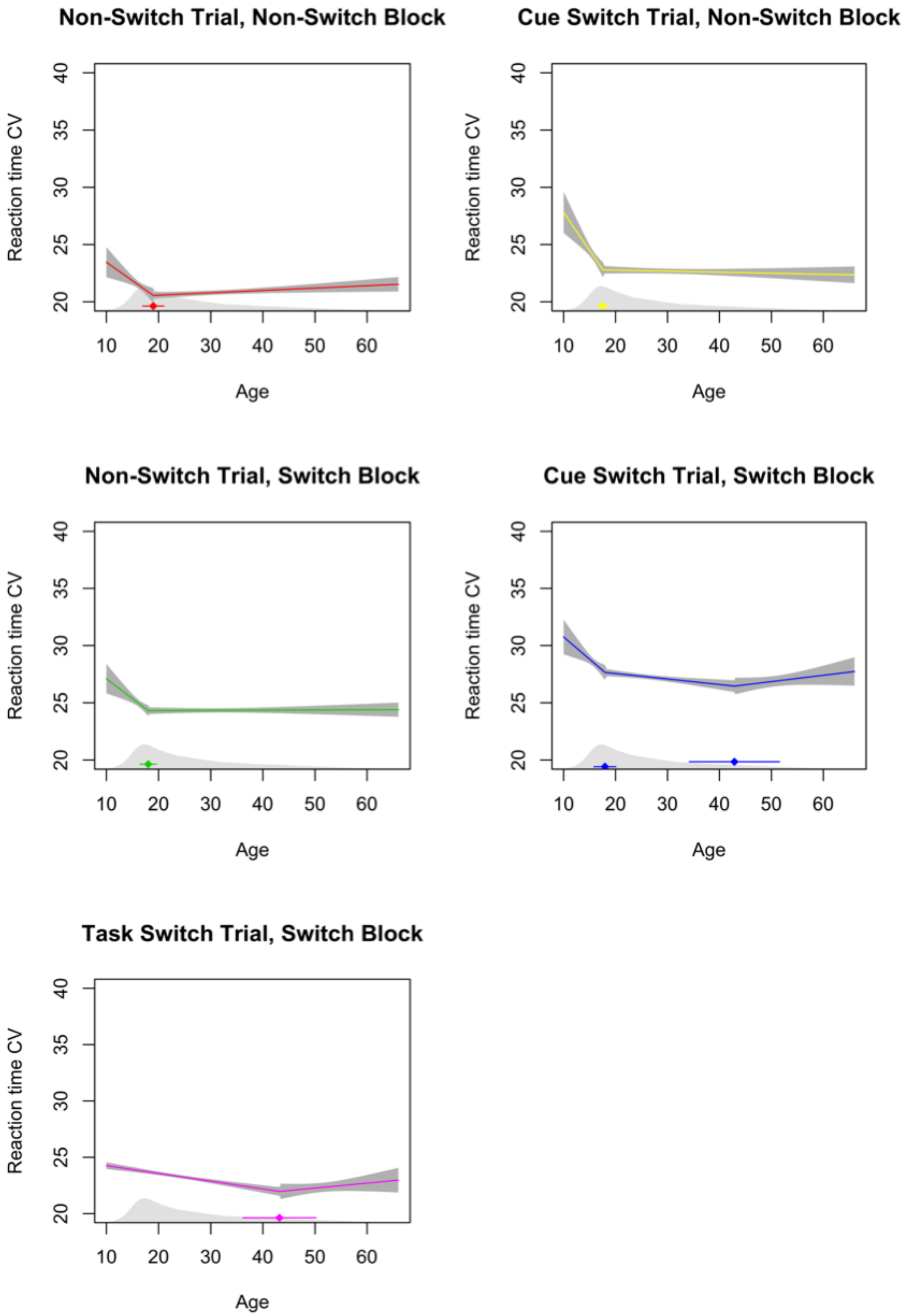

Figure 3.9: Segmented regression models of reaction time coefficient of variability

Segmented linear regression models of mean coefficient of variability (CV) in reaction times per condition. Breakpoints [95% CI] and population density curves are shown along the horizontal axis.

3.5 Discussion

Differences in task switching with age were measured using a large sample of over 13,000 individuals aged between 10 and 65 years old. Online data collection enabled collection of a much larger sample than past studies, allowing modeling of performance with age in a more fine-grained way than has been done previously. Overall performance demonstrated a U-shaped curve over age, characterized by a rapid developmental improvement from adolescence until young adulthood, followed by a gradual decline through young adulthood and middle age.

These findings provide a number of novel insights into aging and task switching performance. Most saliently, by examining the task switching performance of participants with a wide range of ages, we provide a very fine-grained, comprehensive—albeit cross-sectional—mapping of task switching performance to age, in a way that has never been achieved before. By comparing different trial types and using a design that deconfounds changes in cue and changes in task, we were able to break down overall performance into a set of hypothesized components and examine their differences in trajectory with age. By using segmented regression to examine the rates of change across the lifespan and identify breakpoints, we could quantify differences between the trajectories of different components of task switching. Finally, by examining adolescent development and middle-aged decline together using the same task and stimuli, we have been able to address issues of the similarity between development and decline in task switching performance, with different patterns of developmental improvement and age-related decline.

3.5.1 Patterns of task switching performance across the lifespan

Although past task switching research has supported the role of multiple components for task switching, the development and aging profiles for each has not been investigated in detail. Our findings largely replicate and extend those of Reimers and Maylor (2005), whose experimental design was most similar to ours. For general reaction times both studies found a similar pattern of developmental improvement through adolescence, with fastest performance among participants in late adolescence and young adulthood. Both studies observed a decline in aspects of task switching performance starting early in young adulthood. Previous research has tended to use a small number of groups—modally, comparing young adults with older adults—or has been understandably limited in the number of participants of a given age who could be tested (Cepeda et al., 2001). The present findings provide support—using a different experiment design and a larger number of participants—for the notion that both general age-related slowing and aspects of executive control show decline throughout adulthood, not just in older age.

Examining different types of switch cost in isolation, one difference in findings was the developmental trajectory of global switch cost (i.e., maintenance of readiness). Reimers and Maylor (2005) found a clear U-shaped relationship between age and RT in global switch cost, with a strong trajectory of developmental improvement between 10 and 17 years, but weaker effects of age on local switch costs. In the present study we found a small developmental reduction in global switch cost in RTs, and clear developmental improvements in local switch cost, seen in error rates. This difference in patterns of results is unsurprising given the difference in designs across the two experiments: The inclusion of a cue switch condition in the current study meant that participants could not anticipate whether a switch trial was going to be a cue-switch or full task-switch, unlike Reimers and Maylor, who alternated between full switch and non-switch trials predictably. Making switches unpredictable tends to reduce age effects on global switch cost and increase them on local switch cost (e.g., Kray et al., 2001; Cepeda et al., 2001; see Davidson et al., 2006).

Early maturity in local switch cost (i.e., task alternation time) is supported by previous studies that children can successfully shift in early childhood on simple tasks and by adolescence on complex tasks (Blackwell et al, 2009; Cepeda & Munakata, 2007; Davidson et al., 2006). While set shifting is not synonymous with task alternation, both involve the ability to switch from one task to another. Age-related differences on task decision time have not been measured in previous studies, despite this component being strongly supported in the cue switching literature. The current study offers a novel contribution to how an informative cue change (i.e., task decision) is influenced by age.

Unlike past studies in this area, the present study included a condition in which the cue changed but the task remained the same. This allowed further fractionation of the processes involved in task switching between identifying the task that needs to be completed and shifting to a new task.

In general terms, our results mirror those of Mayr and Kliegl (2003). Participants were slower on cue switch trials than on non-switch trials, and slower still on task switch trials relative to cue switch trials. Like Mayr and Kliegl, we found minimal differences in error rate between non-switch and cue switch trials but substantial differences between cue switch and task switch trials. We were, for the first time, able to separately examine the effect of age on cue and task switch costs. It was possible that the majority of the age effects in local switch cost would be attributed to retrieving task rules from long-term memory (and hence primarily reflected in the cue switch cost) or for reconfiguring of response mappings during a shift of task (and hence primarily reflected in the task switch costs). We actually found similar effects of age on both effects, suggesting a more general decrement to performance across the multiple components of task switching.

Both studies saw a speed accuracy trade-off in young adulthood. From age 17-18 years where performance was best to around age 40 years, RTs increased with age, whereas error rates decreased. The developmental performance improvements on reaction times may extend further beyond adolescence than it may initially appear but be seen in accuracy rather than speed. One of the implications of this finding is that some of the cognitive decline observed in the RTs may in part be a shift in preference towards giving slower, more accurate responses. It may be possible to separate genuine cognitive decline from shifts in response threshold by modelling both errors and reaction time distributions with a drift diffusion model (Ratcliff, Thapar, & McKoon, 2001; Ratcliff & McKoon, 2013), but this analysis is beyond the scope of the current paper.

3.5.2 Age of change in task switching components

As well as looking at the general age-related trends in task switching performance, we used segmented regression to examine more quantitatively the differences in age-related trajectory for different components of task switching. These analyses revealed distinct patterns of performance with age across the different components of task switching. Processing speed was fastest in mid adolescence around age 14 years, whereas more executive processes such as maintenance of readiness and task decision showed best performance at the end of adolescence around ages 17-18 years. Switching between tasks showed limited developmental improvement (similar to the findings of Reimers & Maylor, 2005) but showed slowing from early middle age.

3.5.3 Comparisons between development and aging

One of the aims of our experiment was to examine the similarities between developmental improvement and age-related decline in performance. Given performance on many cognitive tasks improves through childhood and adolescence and declines through adulthood, a parsimonious account would be that the two reflect common processes in opposite directions.

Clearly, at a superficial level there are differences in rate of change, which we were able to quantify in our study. Developmental improvement in overall switching RT between the ages of 11 and 16 years occurred at 31.6 ms per year [95% *CI,* -44.7, -29.5], which was 2.7 times faster than decline between the ages of 43 and 65 years, which occurred at 11.5 ms per year [95% *CI,* 9.50, 13.4]. The notably asymmetrical lifespan pattern demonstrates the value of segmented regression to account for the different rates of change and the peaks in performance at non-identical time points. Our results help clarify previous lifespan studies, which have been limited to polynomial functions, despite such functions assuming a symmetrical pattern that peaks around the middle of the lifespan (McAvinue, Habekost, Johnson, Kyllingsbaek, Vangkilde, et al., 2012; Sommers, Hale, Myerson, Rose, Tye-Murray, & Spehar, 2011; Westerhausen, Bless, Passow, Kompus, & Hugdahl, 2015; Yang, Goh, Chen, & Qiu, 2013; Yeatman, Wandell, & Mezer, 2014). The need for more advanced modeling of lifespan change has been highlighted (Lövdén, Ghisletta, & Lindenberger, 2004). Our findings indicate the exact age periods at which transitions occur, which is useful for understanding normal cognitive maturation and developmental change.

Moreover, by examining the different components of switching as a function of age, we observed qualitative differences in the contributions to changes in performance. Our results indicate that seemingly identical performance at both ends of the lifespan in switching RTs may arise from a different pattern in components that contribute to the switch cost but vary differentially with age. For example, Figure 4 suggests that developmental improvement in task switching performance is largely similar across different trial types and appears primarily driven by improvements in processing speed. On the other hand, decline in performance through young adulthood and middle age is relatively modest for RTs in non-switching blocks but is more pronounced in switch block RTs. One tentative account for this is that developmental improvement in task switching is more driven by general improvements in processing speed, whereas decline through young adulthood and middle age is more driven by decline in executive processes involved in maintenance of readiness and set shifting.

Early studies on effects of age on changes in cognitive ability suggested a symmetrical trajectory over the lifespan, with developmental improvement mirroring aging decline (Dempster, 1992; West et al., 2002; Zelazo et al., 2004). The inverted U-pattern gave rise to theories that a single cognitive factor may underlie performance over cognitive abilities. However, the pattern was not maintained after dissociating into individual cognitive abilities, or components underlying cognitive abilities (Band et al., 2002; Craik & Bialystok, 2006; Luna et al., 2004; Reuter-Lorenz & Lustig, 2005). Similarly, when lifespan change in task switching was compared to other cognitive abilities, effects of age on task switching were found to be switching-specific and could not be explained by other cognitive abilities (Cepeda et al., 2001).

The data from the current study helps clarify theories on the mechanisms that produce lifespan change. On one hand, research suggests that cognitive performance across various tasks and ages can be explained by a single factor. Proposed general factors have been processing speed (Salthouse, 1996, 2005) or a frontal factor (West et al., 2002; Zelazo et al., 2004), both of which are linked to task switching, vary with age, and have demonstrated a similar pattern in lifespan performance to task switching (an inverted U-shaped curve). Our findings support an alternate more complicated perspective in which multiple components contribute to cognitive performance and change across the lifespan.

However, our results offer some support for the theory on processing speed as a general mechanism. When measuring lifespan task switching performance, processing speed had the largest demonstrated amount of change in reaction times than all other components underlying task switching. Processing speed had the fastest rate of change during development (31.6 to 52.1 ms per year). Other components demonstrated a much slower rate of change (up to 12.6 ms per year) after accounting for baseline variance in speed. Our findings confirm the previous finding that processing speed accounts for a notable portion of mean reaction time performance on cognitive measures including task switching (Salthouse et al., 1998).

3.5.4 Intraindividual variability

This is the first time that a large dataset of this nature has been used to examine age-related differences in reaction time variability. Variability in individual performance times was large at the youngest ages, decreased in young adulthood, and increased again later in life. These findings map onto previous research on notable intra-variability in the range of performance across individuals at different ages (Dykiert et al., 2012a; Williams et al., 2005, 2007). Results indicated that processing efficiency is greatest in young adulthood and is sensitive to fluctuations in performance with age.

After accounting for differences in reaction times, the discrepancy across individuals was smaller but remained significant. In line with previous studies, our results demonstrate that a large amount of changes in intra-individual variability may in proportion to longer reaction times during development and aging (Dykiert et al., 2012b, Myerson et al., 2007). This again speaks to the argument for age related differences in cognitive performance being related to a single factor of general slowing. If general slowing were the only cause of age-related changes, we would predict that intraindividual variability would increase in proportion to mean reaction time. Our findings indicate that in adolescence and older middle age, performance is disproportionately variable. There could be several sources for this variability. The simplest would be basic perceptual and motor function; Young and old participants might have more noise in the perceptual pathways for identifying a target, or the motor pathways for executing a response. However, these factors would be expected to influence all trial types identically. The fact that harder (switch) trials showed larger age effects in absolute variability suggests that the noise is inherent in the decision process.

3.5.5 Strengths and limitations of the current study

Although the current study had some obvious strengths in the number and range of participants tested, there were some associated limitations. Some of these concerned the sample population. Participants were self-selecting. They had to have access to a computer and the internet in order to participate and had to have been on the BBC website to follow the link to the study. It is therefore possible that the middle-age adults were a self-selected subgroup of people with relatively unimpaired cognitive function, and as such the data reported here may underestimate the age effects on performance. The age range of participants who took part in the study was uneven and concentrated among young adults, meaning the study was unable to examine cognitive development in early childhood or old age. Although age-related decline was relatively slow in our sample, we expect that decline would accelerate later in life, as reported by other researchers (e.g., Nielson et al., 2002; Cepeda et al., 2001).

Our experimental design was cross-sectional, and is therefore susceptible to cohort effects, which might reflect current or cumulative experience with computers or electronic games that require speeded responses. As such, and as with any cross-sectional research, conclusions must be tentative. However, we note that the pattern of results is similar to Reimers and Maylor's (2005) findings, for example the age of peak performance being around the start of adulthood. As the data for these two studies were collected on average five years apart, we would expect to see any major cohort effects to be translated by five years in the current dataset. The observation that age-related patterns of performance were similar suggests that, at least at a gross level, the age-related differences do not appear to be primarily driven by cohort effect.

A second area of limitation is that model selection can be very sensitive to small differences in the data obtained. It is possible that a different sample would demonstrate slightly different numbers and positions of breakpoints. The sample size mitigates many of these effects. One further potential issue around model selection arises from using segmented linear fits where the data may be non-linear, which has the potential for introducing artifactual breakpoints where a trend is, for example, under constant acceleration. This is unlikely to be a substantial issue for the primary aims of this study, that is, the comparison of developmental and aging trajectories for different components, and the examination of the ages at which developmental improvement moved to age-related decline. However, we caution against interpreting breakpoints in middle age where the gradient of decline increases as being qualitative shifts in the aging process.

More generally, the observed results are linked to the specific features of the paradigm used. As discussed above, different experimental designs can lead to different age trajectories for different components of a task. For example, global switch cost showed relatively minor effects relative to local switch cost, which was the opposite pattern to that observed by Reimers and

Maylor (2005). This is primarily a limitation of the terminology used. Researchers use the same terms irrespective of whether switches were completely predictable or completely unpredictable, even though the cognitive processes isolated in the measures are rather different.

Different results may be obtained with especially easy or difficult paradigms due to floor or ceiling effects. Where tasks are excessively easy or excessively difficult, apparent age effects may be reduced, but away from the extremes. Task difficulty can lead to a shift from age effects primarily appearing in RTs to their appearance in error rates.

The appropriateness of our chosen paradigm may have varied across the lifespan. For example, processing speed measures recruit varying degrees of executive control demands at different points in the lifespan (Cepeda, Blackwell, & Munakata, 2013), so conclusions drawn on the role of processing speed should be cautioned. The components measured for the chosen paradigm are likely to develop and decline at different rates, and possibly interact with age, such that each stage of the lifespan is may recruit a given component in a different way. As an example, single task blocks, which usually serve as a measure of processing speed since they do not require higher-order cognitive control, may recruit executive control in older adults (DiGirolamo, Kramer, Barad, Cepeda, Weissman, Milham, et al., 2001). Task switching paradigms do not always demonstrate convergent validity across different measures or age groups (Cepeda et al., 2013). Depending on the task, developmental transitions in task switching have been observed in infancy, childhood, or adolescence (Munakata, Snyder, & Chatham, 2012). Hence, the observed patterns of development and decline are linked to the chosen measure and its variation across the lifespan.

3.5.6 Conclusion

The present study has used reaction time and error data from an exceptionally large task switching dataset to trace the trajectories of age-related differences in performance, indicating a rapid improvement in cognitive performance through adolescence, followed by a gradual, accelerating, decline through young adulthood and middle age. The differences in performance on different trial types lead us to tentatively conclude that the cognitive factors underlying developmental improvement are not identical to those underlying age-related decline, and as such, development and decline are not mirror images of each other. Although we do not claim to offer the final word on age-related change in task switching, we believe our web-based approach complements well the more traditional lab-based studies by sacrificing a degree of control for the opportunity to collect data from a large number of participants. We suggest that converging evidence from these two broad approaches can be fruitfully used to build a clearer picture of the way in which cognition and age are related.

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4 Study 2B: Effects of age on task switching: A replication study

4.1 Abstract

Cognitive ability develops and declines with age. Effects of age on task switching show a similar pattern, but past studies are limited by small samples and group comparisons of children or older adults to young adults. We previously addressed this gap with a massive web-based sample (*n*=13,718, ages 10 to above 65 years; Study 2A). The current study replicates this investigation (*n*=13,031) to finely model effects of age on components of task switching over the lifespan. Reaction time means and intraindividual variability developed rapidly in adolescence and declined gradually over adulthood. Accuracy developed into the twenties and had no decline. Individual components of task switching had differential rates and timings of age effects. The results provide novel extensions on age-continuous effects, intraindividual variability, and underlying processes. Findings show that decline over adulthood is not development in reverse: slowing is at a much smaller rate, and accuracy is maintained.

4.2 Introduction

The ability to respond adaptively and flexibly to a changing environment is a crucial aspect of human behavior. Individuals perform worse when shifting between tasks than when repeating a task (Rogers & Monsell, 1995). This *switch cost* consistently occurs on trials with a shift from one task to another (*local switch cost*), as well as on trials in a block where one must maintain readiness for the possibility of a shift (*global switch cost*).

4.2.1 Effects of age on task switching

Developmental studies indicate adolescents perform worse than young adults on local and global switch costs (Crone, Bunge, van der Molen, & Ridderinkhof, 2006; Davidson, Amso, Anderson, & Diamond, 2006; Huizinga, Dolan, & van der Molen, 2006). Aging studies indicate older adults perform worse than young adults on local and global switch costs (Eppinger, Kray, Mecklinger, & John, 2007; Friedman, Nessler, Johnson, Ritter, & Bersick, 2008; Kray & Lindenberger, 2000; Kray, Li, & Lindenberger, 2002; Mayr, 2001; Mayr & Liebscher, 2001; Meiran, Gotler, & Perlman, 2000). Aging effects are larger and more widely replicated for global switch cost than local switch cost (reviews by Verhaeghen & Cerella, 2002; Wasylyshyn, Verhaeghen, & Sliwinski, 2011).

Past development and aging studies have examined the start and end of the lifespan separately, making little contact with each other (Craik & Bialystok, 2006; c.f., Kray, Eber, & Karbach, 2008). A large lab lifespan investigation (*n*=152) found that task switching ability followed a U-curve from development to aging (Cepeda, Kramer, & Gonzalez de Sather, 2001). Local switch cost and a modified version of global switch cost improved until 20-30 years, was stable from 30-60 years, and declined after. A subsequent online lifespan investigation (*n*=5,271) found age-related improvement and decline for global, but not local, switch cost (Reimers and Maylor (2005).

4.2.2 Original study and gaps in previous research

Previous development and aging studies compared groups of children (up to 18 years) or older adults (above 65 years), to young adults (19–35 years). These cross-sectional comparisons left it unclear exactly when development ends, when aging begins, and what occurs in middle age (35–64 years). Our previous lifespan studies measured ability over the sweep of the lifespan. However, they divided the lifespan into age groups (e.g., every 10 years of age), leaving it unclear when shifts in ability occur—for example, adult levels were reached between 21 to 30 years in one study (Cepeda et al., 2001), and between 18 to 20 years in another (Reimers & Maylor, 2005).

Building on past studies (Table 4.1), we ran a massive online lifespan investigation over five years (n=13,718; Wiseheart, D'Souza, & Reimers, submitted, Study 2A). Our original study added to the existing literature in two key ways, with more precise measurement of (1) age, and (2) task switching ability. The current study directly replicated this investigation, using another massive sample collected online over the following five years (n=13,031).

Since age is continuous, we used segmented regression to model the rate of change per year and the exact age periods of shifts. Replicating previous literature, we fractionated task switching into components for global switch cost (*maintenance of readiness* for a potential task change) and local switch cost (an actual task change). We also fractionated baseline cognitive speed (*processing speed*) from switch costs.

Table 4.1: Summary of past studies on the effects of age on task switching

Switch costs are fractionated into global and local switch costs. Measurements are provided for reaction times and accuracy. Measurements that accounted for processing speed (*) or were atypical (^) are indicated.

Study				Effects of age			
				Reaction times (RTs)		Accuracy	
Author (Year)	***n***	**Ages (group comparisons)**	**Task**	**Global switch cost (GSC)**	**Local switch cost (LSC)**	**Global switch cost (GSC)**	**Local switch cost (LSC)**
Lifespan							
Cepeda, Kramer, and Gonzalez de Sather (2001)	*n*=152	7-82 years (10-12, 13-20, 21-30, 31-40,41-50, 51-60, 61-70, 71-82)	Quantity-Identity	rapid development (7-30), stable (30-60), decline (61-70)*[a]	same as GSC RTs	same as GSC RTs	same as GSC RTs
Reimers and Maylor (2005)	*n*=5,271	10-over 65 years (10–17, 18–30 , 31–45, 46–over 65 years)	Emotion-Gender	rapid development (10-17), gradual decline (18-over 65)	no age effect or small developmental improvement ^[b]	no effect	same as LSC RTs; small effect
Wiseheart, D'Souza, & Reimers (2019; Study 2A)	*n*=13,718	10-over 65 years (continuous)	Emotion-Gender; double cuing	rapid development (10-18), gradual decline (19-43), larger decline (44-over 65)	cue switch cost rapid development (10-16) and no decline; Task switch cost gradual decline (34-over 65)	rapid development (10-20), minimal development (21-44), stable (45-over 65)	cue switch trials development (10-24) and no decline; task switch trials rapid development (10-25), minimal development (21-55), stable (56-over 65)
Development							
Crone, Bunge, van der Molen, & Ridderinkhof (2006)	*n*=66	7–8, 10–12, and 20–25 years	Spatial compatibility	no effect^[c]	children > young adults^[c]	no effect^[d]	no effect[d]
Davidson, Amso, Anderson, & Diamond (2006)	*n*=314	4-13 years, and young adults (M=26.3 years, SD=5.4)	Arrows task, dots task	children > young adults	no age effects^[e]	children > young adults	children > young adults

Huizinga, Dolan, & van der Molen, 2006	*n*=384	6-8,10-12, 14-16, and 18-26 years	Local-Global, Dots-Triangles, Smiling Faces	-	children > young adults ^[c], *[f]	-	-
<u>*Aging*</u>							
Eppinger, Kray, Mecklinger, & John (2007)	*n*=26	young adults (M=21.3 years, SD=1.8), older adults (M =63.7 years, SD=2.6)	Colour-Word	no effect*[g]	older adults > young adults*[g]	no effect	no effect
Friedman, Nessler, Johnson, Ritter, & Bersick (2008)	*n*=40	young adults (M=23.1 years, SD=2.8), older adults (M=71.0 years, SD=6.9)	Magnitude-Parity	no effect*[g]	older adults > young adults*[g]	no effect	no effect
Kramer, Hahn, & Gopher (1999)	*n*=40	young adults (18-25 years, M=20.2), older adults (60-75 years, M=68.9)	Quantity-Identity	-	older adults > young adults	-	Older adults (5%) < younger adults (2%)
Kray, Li, Lindenberger (2002)	*n*=72	young adults (19-30 years, M=23.1. SD=2.99), older adults (59-72 years, M=66.8, SD=2.94)	Category-Number-Letter	no effect [h]	older adults > young adults *[g]	<3%, not analyzed	same as GSC accuracy
Kray & Lindenberger (2000)	*n*=118	young adults (20-40 years, M=29.6, SD=5.8), middle-aged (41-60 years, M=50.3, SD=6.2), older adults (61-80 years, M=69.5, SD=5.4)	Numerical, Figure, Words	older adults > young adults; older adults = middle adults	no effect	-	-
Mayr (2001), Study 1	*n*=48	young adults (M=20.1 years, SD=0.9), older adults (M=71.0 years, SD=3.3)	Colour-Shape	older adults > young adults; large effect	older adults > young adults; moderate effect	<4%, older adults < young adults	same as GSC accuracy
Mayr & Liebescher (2001)	*n*=48	young adults (M=18.3 years, SD=0.8), older adults (M=68.7 years, SD=2.6)	Colour-Form fadeout paradigm	older adults > young adults	no effect	<3%, older adults < young adults (not significant)	same as GSC accuracy
Meiran, Gotler, & Perlman (2001), Study 1	*n*=32	young adults (20-29 years, M=24.1, SD=2.3), older adults (64-76 years, M=68.3, SD=3.5)	Location task	older adults > young adults	older adults > young adults	<2%, no effect	same as GSC accuracy

Schapkin, Gajewski, Freude (2016)	*n*=93	young adults (21–35 years, M = 30.0, SD = 3.4), middle-aged adults (51–63 years, M = 55.0, SD = 3.2)	Magnitude-Parity	middle-aged adults > young adults *[g]	middle-aged adults > young adults *[g]	middle-aged adults > young adults	Middle-aged adults > young adults
Spieler, Mayr, LaGrone (2006), Study 1	*n*=48	young adults (M=19.3 years, SD=1.9), older adults (M=71.9 years, SD=4.5)	Colour-Form fadeout paradigm	older adults > young adults (not significant)	same as GSC RT	<5%, not analyzed but older adults < young adults	same as GSC accuracy
<u>*Development and Aging*</u>							
Kray, Eber, & Karbach (2008)	*n*=144	young children (7–9 years, M=8.1, SD=0.5), older children (11-13 years, M=11.7, SD=0.6), young adults (25-27 years, M=23.5, SD=1.9), older adults (66-77 years, M=69.5, SD=3.0)	Colour-Animal	young children > older children > young adults; older adults > young adults	same as GSC RT, but smaller	young and older children > young adults; older adults > young adults)	same as GSC accuracy, but smaller

[a] GSC calculated between-blocks, but with different trial types (switch trials in switch block compared with non-switch trials in non-switch block); [b] Small developmental improvement using raw reaction times instead of proportion switch cost; [c] Median RT; [d] Square roots of error percentages; [e] Very short response window may have caused long RTs and effects of age on accuracy; [f] Processing speed as a covariate; [g] Logarithm transformed reaction times; [h] Slightly lower reported rates for older adults

Note. Transforming reaction times by a logarithm corrects the exponential increase in processing speed with age (Kray & Lindenberger, 2000; Mayr, 2001).

Lifespan investigations found a U-curve of development and decline across cognitive abilities, and on processing speed (Craik & Bialystok, 2006; Hartshorne & Germine, 2015; Salthouse, Fristoe, McGuthry, & Hambrick, 1998). However, performance diverges on individual cognitive abilities, and even components of the same ability. Accounting for processing speed removes some, but not all, of the effects of age on task switching (Cepeda et al., 2001; Verhaeghen & Cerella, 2002; Wasylyshyn et al., 2011).

We further fractionated local switch cost into a task change (task switch cost, or *task alternation*), and a cue change (cue switch cost, or *task decision*). The standard local switch cost measure does not separate a cue change from a task change (Logan & Bundensen, 2003; Mayr & Kliegl, 2003). Cue switch costs have been widely supported (Jost, de Baene, Koch, & Brass, 2015), yet they have not been measured over the lifespan. Aging studies have suggested older adults may rely on the cue more (Kray, Eber, & Lindenberger, 2004; Schapkin, Gajewski, Freude, 2014; Spieler, Mayr, & LaGrone, 2006).

We further fractionated a cue switch cost into a cue change that could signal a potential task change (an informative cue switch cost, or *task decision* of using a cue to select a task), and a cue change with no potential task change (a non-informative cue switch cost, or *cue detection* of attending to a cue; D'Souza, Wiseheart, & Reimers, submitted, Study 1). Finally, we measured accuracy and within-participant (*intraindividual*) variability on reaction times for each trial type. Past studies have differed in whether effects of age were observed on task switching reaction times, accuracy, or both. The current study was a direct replication and expected a similar pattern of results.

4.3 Method

4.3.1 Participants

Participants were tested online on a website containing multiple online cognitive tasks (http://www.city-psychology-tests.co.uk/). Participants were free to complete some or all of the tasks. Referral to the website occurred via a link on the BBC Science website. Sessions were under 10 minutes to encourage task completion. Data were collected over five years.

The task was completed 29,959 times (19,410 identifications as female). Exclusions were made for completions with an error rate over 35% in one or more experimental conditions, participants whose age was not indicated, and where participants indicated that they had completed the task before. After exclusion, the sample size was n=14,042, with age 10 to over 66 years (median=20, interquartile range=8). Participants who indicated their age as below 10 years were dropped from the analysis (n=4), and those who indicated their age as over 65 years were treated as 66 years for the analysis (n=17).

Before analysis, reaction times were trimmed to remove extreme times, in two stages: 1) within-subject trimming (per participant per condition), and 2) between-subject trimming (per age per condition; Grange, 2015). A recursive trimming script returned data that were greater than a set standard deviation above the mean for each condition, with the criterion changing as more trials were removed. The final sample after trimming was n=13,031. Data were collected between 2011 and 2017.

4.3.2 Sample size calculation

Published recommendations for the minimum sample size per breakpoint period vary from 10 to 500 per breakpoint. Researchers have recommended that the number of breakpoints exceed the number of observations by a considerable amount, with k+1<<n, where k is the number of breakpoints, with 10-15 observations per breakpoint suggested as a rule of thumb (Chen, Chen, Gerlach, & Hsieh, 2011; Hartshorne & Germine, 2015). Direct testing of varying sample sizes with empirical and simulation data recommended sample sizes of n=80 per breakpoint (Ryan & Porth, 2006), and at least n=50 as the post-breakpoint metric for a sample size of n=500 (White, Muniz-Terrera, & Matthews, 2018). These metrics have been recommended to reliably detect and estimate breakpoints, with no additional benefit for larger samples.

Although the breakpoint itself does not depend on sample size, the precision of the estimate does. Samples of n=100 had breakpoints within the confidence intervals of a reference model 93% of the time, and both a breakpoint and model standard error within the interval 82% of the time (Ryan and Porth, 2006). In contrast, the acceptable metric of n=80 had values of 93% and 79%, respectively. A second benefit of a larger sample size is that it accounts for outliers in the data. The noisier the data, the larger the number of observations required. A sample of n=50 is the minimum to detect at all error precisions, while a sample of n=500 nearly guarantees detection across all error precision scenarios (White et al., 2018). Since data from individuals at both ends of the lifespan have more noise than young adults, more conservative sample size estimates are better.

It is often the case that sample sizes are uneven across changepoints, particularly with smaller samples post-changepoint. In addition, the data used for to calculate the metric by White and colleagues was based on longitudinal change in cognitive decline with age. Thus, we find the post-changepoint metric particularly relevant for the current study.

As illustrated in Table 4.2, using the most conservative metric of n=500 per changepoint, we were adequately powered to detect two breakpoints, with three periods of change: development (ages 10-19 years), young adulthood (ages 20-39 years), and middle adulthood (40-66 years). As illustrated in Table 4.3, the earlier development period could be further split into pre to mid-adolescence ages 10-15 years), and mid to late adolescence (ages 16-19 years). This is useful, since past studies on when development ends range from 13 to 21 years. In comparison, splitting the later adulthood period did not meet a metric of n=500.

For more liberal sample size estimates, we had n=73 individuals below age 12, n=84 above age 56, and n=246 above age 50. Thus, data reflect limited sampling of pre-adolescent performance and adequate sampling of adolescent performance. The data also reflect limited sampling of late-middle adult performance, but ideal sampling of early-middle to late-middle adult performance.

Table 4. 2 compares the spread over ages in the original sample to the replication sample. Although the total sample size was larger in the replication sample, the distribution of individuals across ages was less spread out than in the original sample. Therefore, the replication sample is less likely to be able to estimate change at very young and older ages.

Table 4.2: Sample sizes for three stages of lifespan change.

Effects of age were expected for three stages: development (childhood and adolescence), young adulthood, and early aging (middle adulthood). There is an inconsistency in the sample sizes for each age, with the lowest sample size at the end of measurement in middle age. All three age periods meet the minimum requirement of n=500.

	Original dataset (*n*=13,718)	**Replication dataset** (*n*=13,031)
Childhood and adolescence (ages 10-19 years)	*n*=4709 (34%)	*n*=6031 (46%)
Young adulthood (ages 20-39 years)	*n*=6863 (50%)	*n*=6328 (49%)
Middle adulthood (ages 40-66+ years)	*n*=2146 (16%)	*n*=672 (5%)

Table 4.3: Sample sizes for five stages of lifespan change.

Effects of age could be found for five stages, by further splitting the first stage of development and the last stage of early aging. The lowest sample sizes are at the start and end of the age ranges measured. The last two age periods do not meet the minimum requirement of n=500.

	Original dataset (*n*=13,718)	**Replication dataset** (*n*=13,031)
Pre to mid adolescence (ages 10-15 years)	*n*=964 (7%)	*n*=1,081 (8%)
Mid to late adolescence (ages 16-19 years)	*n*=3,745 (27%)	*n*=4,950 (38%)
Young adulthood (ages 20-39 years)	*n*=6,863 (50%)	*n*=6,328 (49%)
Early-middle adulthood (ages 40-49 years)	*n*=1,349 (10%)	*n*=426 (3%)
Late-middle adulthood (ages 50-66+ years)	*n*=797 (6%)	*n*=246 (2%)

4.3.3 Materials

An emotion-gender task switching paradigm was used (the same as reported in the original study; Wiseheart et al., submitted, Study 2A), consisting of two task sets with two cues per task (“emotion” or “feeling”, and “gender” or “sex”). The tasks were choice reaction time measures, in which participants had to select one of two responses (happy/sad or male/female) by pressing a keyboard button (‘D’ or ‘K’). Stimuli consisted of two photos of human faces: a happy female face and a sad male face, or a sad female face and a happy male face, with each set randomly allocated to participants.

The paradigm was divided into three blocks: Two non-switch blocks (one per task, 12 trials each), and a switching block (both tasks, 50 trials; 2 practice trials, 48 experimental trials). In each non-switch block, participants responded to one of the two tasks, with the order of the non-switch blocks randomized across participants. The cue changed every two trials in the non-switch blocks, but this was redundant. Stimuli were presented an equal number of times in a random order.

4.3.4 Design and Procedure

In the switch block, task changes occurred randomly, and were signaled by a cue indicating which task was to be performed. Trials were paired with repetitions of the same cue, allowing both types of switch trials (cue or task switch) to be followed by a non-switch trial, which was followed by a switch trial, etc.

Switches were randomized with the constraint that there were exactly 24 non-switch trials, 12 cue switch trials, and 12 task switch trials, and no more than three consecutive switches of the same type. The sequence of stimuli was constrained so that for each trial, one of the two face stimuli was chosen with 50% probability. The exception was if the previous three stimuli were all the same face, in which case the other face was used.

Key mappings were randomized per participant. Mappings were made at the start of the experiment and kept consistent across blocks. Once mappings were done, the two stimuli to be used were selected so that mappings of the two task attributes (happy/sad or male/female) were incongruent. In this way, participants had to make a different response for any given stimulus, based on the task.

On each trial a cue appeared and remained on the screen until a response was made. After 250 ms, a stimulus was presented for 250 ms. Participants could respond when the stimulus was presented. The cue disappeared after a response. On correct trials, there was an interval of 1.500 ms before the next trial. On incorrect trials, feedback (the word "OOPS!") was provided for 1000 ms, followed by an interval of 1,750 ms before the next trial. Reaction times and error rates were measured for each trial. Incorrect responses and reaction times under 200 ms were excluded from analysis.

The paradigm had five trial types in total: two in the single-task block (non-switches, $rt_{ns,ns}$ and cue-only switches, $rt_{cs,ns}$) and three in the switch block (non-switches $rt_{ns, s}$, cue-only switches, $rt_{cs,s}$, and cue plus task switches, $rt_{ts,s}$). Reaction time and error rate was measured for each trial.

Accuracy was calculated as the percentage of errors. The standard deviation of each person's responses was calculated to assess intraindividual variability. The coefficient of variation was also calculated to accounted for mean reaction time variability, using the ratio of reaction time standard deviations to mean reaction times per person.

Trials were arranged in order of complexity based on the response speed. Baseline processing speed was measured using non-switch trials on a non-switch block ($rt_{ns,ns}$). The subtraction method was used to calculate task switching components by comparing complex to less complex trials. A component for maintenance of readiness (global switch cost) was calculated by comparing trials between blocks, using non-switch trials. Components for local switch cost were calculated by comparing trials within a switch block. To account for the role of the cue, local switch cost was separated into task decision and task alternation components, by comparing non-switch trials to cue switch trials and task switch trials, respectively. For completeness, the role of the cue in a non-switch block (cue detection) was also calculated, by comparing non-switch trials to cue switch trials.

Calculations for each component are shown below.

1. Processing speed ($rt_{ns,ns}$)
2. Maintenance of readiness (global switch cost; $r_{mrt} = rt_{ns,s} - rt_{ns,ns}$)
3. Task decision (formerly cue switch cost in a switch block; $rt_{tdt} = rt_{cs,s} - rt_{ns,s}$)
4. Cue detection (cue switch cost in a non-switch block; $rt_{cdt} = rt_{cs,ns} - rt_{ns,ns}$)
5. Task alternation (task switch cost; $rt_{tsc/tat} = rt_{ts,s} - rt_{cs,s}$)

4.3.5 Analyses

Analyses were conducted using the R language and environment for statistical computing. Analyses were conducted per component for reaction time means, and per trial type for percent errors and intraindividual variability.

First, locally weighted regression curves were fit to the data to qualitatively examine the relationship between age and each component. A scatter-plot smoother with a span of 0.5 was used to foresee trends over the means for each age.

Next, segmented regression was calculated to quantitatively determine the timing and rate of age-related effects (Muggeo, 2008). Using age as a predictor, linear regression models were fit to the data. Separate models were fit for no breakpoints (a single line), one breakpoint (two lines), two breakpoints (three lines), and three breakpoints (four lines).

Starting values to estimate breakpoints were either pre-specified or fit using equally spaced values (with spaces determined by the number of breakpoints). Pre-specified estimates were obtained with a Davies test for a non-zero difference-in-slope

in age. There was no significant difference in the model fit by either technique, *p*s>0.05.

Hierarchical regression compared a straight-line model to a one-break model, followed by a one-break model to a two-breakpoint model, followed by a two-breakpoint model to a three-breakpoint model. Models were selected based on whether the fit significantly improved after including additional breakpoint. Change in the Akaike information criterion (AIC) and Bayes information criterion (BIC) assessed model parsimony.

4.4 Results

4.4.1 Local regression curves

4.4.1.1 Mean reaction times

Reaction times became faster until the end of adolescence on most trial types, then shifted to a gradual slowing throughout adulthood (Figure 4.1). The exception was cue switch trials in a non-switch block, which became faster until the end of adolescence but then shifted to stable performance. The longest reaction times and the largest change in performance with age on trial types were in order of complexity.

Separate patterns were found for each component. Processing speed and maintenance of readiness became faster through adolescence, then shifted to a gradual slowing throughout adulthood. Processing speed also showed a less gradual slowing later in life. Task decision and task alternation showed of a gradual slowing through adulthood, while cue detection showed no change.

4.4.1.2 Accuracy

The percentage of errors decreased until the late 20s, then remained stable across trial types (Figure 4.2). Task switch trials had the largest error rate. The remaining trial types had extremely low error rates.

4.4.1.3 Reaction time intra-individual variability

Individual standard deviations decreased until the end of adolescence, shifted to a gradual decline throughout adulthood, and shifted again to a steeper decline at the end of adulthood

(Figure 4.3). The coefficient of variability showed only the first shift. The most variable reaction times and the largest change in performance with age on trial types were in order of complexity.

4.4.2 Segmented Regression

4.4.2.1 Mean reaction times

The results of each model fit with segmented regression are shown in Table 4.4. Breakpoint estimates and rates of changes are shown in Table 4.5 and Figure 4.4. The best fitting model for processing speed, maintenance of readiness, and task decision mean reaction times had one breakpoint. The best fitting model for cue detection and task alternation has no breakpoints. The one-breakpoint models demonstrated a rapid improvement until mid to late adolescence, followed by a slowing through adulthood until the end of measurement. The rate of development (4 to 7 ms faster per year) was faster than the rate of decline (1 to 3 ms slower per year). The linear models indicated a steady change of 1 to 2 ms per year over the age range measured. The overlap between confidence intervals for the age transitions indicates that some components develop at around the same times.

4.4.2.2 Accuracy

The best fitting model across all trial types had one breakpoint (Table 4.6). The model showed a small but significant decrease in percent errors from the start of measurement at 10 years until young adulthood, followed by no change until the end of measurement (Table 4.7; Figure 4.5). The largest rate of development was on task switch trials (0.27% reduction in errors per year).

4.4.2.3 Reaction time intra-individual variability

The best fitting model for non-switch trials in each block had two breakpoints (Table 4.8). The best fitting model for the remaining trial types had one breakpoint. The two-breakpoint models showed a small but significant decrease in individual standard deviations from the start of measurement at 10 years until mid-adolescence, followed by no change until the 20s, then an increase till the end of measurement (Table 4.9; Figure 4.6). The rate of increase in middle age (7 ms per year) was faster than the rate of development (2 to 5 ms per year).

When using the coefficient of variability to control for mean changes in reaction time, the best fitting model moved to having one or no breakpoints (Table 4.10). No breakpoints were found for non-switch trials in switch blocks or task switch trials in switch blocks. The one-breakpoint models showed a small decrease in variability from the start of measurement at 10 years until mid-adolescence to the mid-20s, followed by no further change until the end of measurement (Table 4.11; Figure 4.7).

Table 4.4: Hierarchical regression results for mean reaction time

Block	Variable	*Straight-line model vs. one-break model*	*One-break model vs. two-break model*	*Two-break model vs. three-break model*
Non-switch block	Processing Speed	***F*(2, 13027) = 13.5***, ΔAIC = -23.0, ΔBIC = -8.01**	*F*(2, 13025) = 2.56, ΔAIC = -1.11, ΔBIC = 13.8	*F*(2, 13023) = 1.70, ΔAIC = 0.59, ΔBIC = 15.5
	Cue Detection	*F*(2, 13027) = 2.52, ΔAIC = -1.05, ΔBIC =13.9	*F*(2, 13025) = 3.46* [b], ΔAIC = -2.92, ΔBIC = 12.1	*F*(2, 13023) =0.25, ΔAIC = 3.51, ΔBIC = 18.5
Both blocks (Global switch cost)	Maintenance of Readiness	***F*(2, 13027) = 13.5***, ΔAIC = - 33.0, ΔBIC = -18.1**	*F*(2, 13025) = 2.56, ΔAIC = 0.72, ΔBIC = 15.7	*F*(2, 13023) = 1.70, ΔAIC = 5.56, ΔBIC = 20.5
Switch block (Local switch cost)	Task Decision	***F*(2, 13027) = 3.67*, ΔAIC = -3.35, ΔBIC = 11.6**	*F*(2, 13025) = 2.49, ΔAIC = -0.97, ΔBIC = 14.0	*F*(2, 13023) = 0.05, ΔAIC = 3.90, ΔBIC = 18.8
	Task Alternation	*F*(2, 13027) = 1.81, ΔAIC = 0.39, ΔBIC = 15.3	*F*(2, 13025) = 2.47, ΔAIC = -1.21, ΔBIC = 13.7	*A F*(2, 13023) = 1.91, ΔAIC = 0.19, ΔBIC = 15.1

* $p \leq .05$, ** $p \leq .01$, *** $p \leq .001$

Note. Each analysis determined whether the second, more complicated model (the alternative) explained significantly more variance than the first, null model. The final selected model is highlighted in bold.

[a] The model with initial estimates had difficulty converging, so results reported are from a model with no initial estimates

[b] A 2-breakpoint model was statistically better but appears to be modelling noise. Further, there should also have been a statistically better fit from the one to the two-breakpoint model, but this was not the case.

Table 4.5: Ages and slopes of transitions for mean reaction time

The slopes can be interpreted as the number of ms a component changes per year of age. Negative slopes depict an improvement in performance (faster reaction times), while positive slopes depict a decline (slower reaction times).

		Development		Adulthood
Block	Variable	Slope 1	Age (years)	Slope 2
Non switch block	Processing Speed	-7.63 [-12.1, -3.18]	16.3 [15.5, 17.1]	1.43 [1.16, 1.70]
	Cue Detection			-0.37 [-0.54, -0.20]
Both blocks (Global switch cost)	Maintenance of Readiness	-3.86 [-6.61, -1.11]	19.2 [17.8, 20.5]	3.17 [2.70, 3.64]
Switch block (Local switch cost)	Task Decision	-7.55 [-17.1, 1.98]	15.5 [13.7, 17.2]	1.17 [0.83, 1.50]
	Task Alternation			1.52 [1.14, 1.90]

Note. 95% confidence intervals are shown in brackets. Values shown are for the best fitting model for each process. Ages represent the estimated breakpoints, and slopes represent the regression coefficients.

Table 4.6: Hierarchical regression results for mean accuracy.

Block	Trial Type	*Straight-line model vs. one-break model*	*One-break model vs. two-break model*	*Two-break model vs. three-break model*
Non-switch block	Non-switch trial	**F(2, 14039) =13.0***, ΔAIC = -22.1, ΔBIC = -6.95**	F(2, 14037) = 0.74, ΔAIC = 2.52, ΔBIC = 17.6	F(2, 14035) =0.25, ΔAIC = 3.50, ΔBIC = 18.6
	Cue switch trial	**F(2, 14039) =17.3***, ΔAIC = -30.5, ΔBIC =-15.4**	F(2, 14037) = 0.79, ΔAIC =2.42, ΔBIC = 17.5	F(2, 14035) = 0.91, ΔAIC =2.18, ΔBIC = 17.3
Switch block	Non-switch trial	**F(2, 14039) =16.0***, ΔAIC = -28.0, ΔBIC =-12.9**	F(2, 14037) = 2.28, ΔAIC =-0.55, ΔBIC =14.5	F(2, 14035) =0.80, ΔAIC = 2.40, ΔBIC = 17.5
	Cue switch trial	**F(2, 14728) =17.7***, ΔAIC = -31.4, ΔBIC =-16.3**	F(2, 14726) = 1.49, ΔAIC =1.03, ΔBIC =16.1	F(2, 14724) = 1.27, ΔAIC = 1.46, ΔBIC = 16.6
	Task switch trial	**F(2, 14039) =35.4***, ΔAIC = -66.6, ΔBIC =-51.5**	F(2, 14037) = 1.39, ΔAIC = 1.22, ΔBIC = 16.3	F(2, 14035) = 1.29, ΔAIC = 1.42, ΔBIC = 16.5

* $p \leq .05$** $p \leq .01$*** $p \leq .001$

Note. Each analysis determined whether the second, more complicated model (the alternative) explained significantly more variance than the first, null model. The final selected model is highlighted in bold.

Table 4.7: Ages and slopes of transitions for mean accuracy

Block	Trial Type	Development Slope 1	Development Age (years)	Adulthood Slope 2
Non-switch block	Non-switch trial	-0.13 [-0.18, -0.08]	22.3 [19.7, 25.1]	-0.004 [-0.02, 0.01]
	Cue switch trial	-0.12 [-0.16, -0.09]	26.9 [23.3, 30.3]	0.01 [-0.03, 0.02]
Switch block	Non-switch trial	-0.12 [-0.16, -0.09]	25 [21.9, 28.1]	-0.003 [-0.02, 0.01]
	Cue switch trial	-0.10 [-0.12, -0.07]	31.2 [27.0, 35.3]	0.03 [-0.005, 0.06]
	Task switch trial	-0.27 [-0.32, -0.23]	28.0 [25.4, 30.5]	-0.006 [-0.05, 0.03]

Note. 95% confidence intervals are shown in brackets. Values shown are for the best fitting model for each process. Ages represent the estimated breakpoints, and slopes represent the regression coefficients.

Table 4.8: Hierarchical regression results for reaction time standard deviations.

Results of hierarchical regressions used for model selection for reaction time intra-individual standard deviations per trial.

Block	Trial Type	*Straight-line model vs. one-break model*	*One-break model vs. two-break model*	*Two-break model vs. three-break model*
Non-switch block	Non-switch trial	$F(2, 12016) = 6.39$**, ΔAIC = -8.77, ΔBIC = 6.02	**$F(2, 12014) = 3.88$*, ΔAIC = -3.77, ΔBIC = 11.0**	$F(2, 12012) = 0.73$, ΔAIC = 2.53, ΔBIC = 17.3
	Cue switch trial	**$F(2, 12016) = 7.88$***, ΔAIC = -11.7, ΔBIC =3.04**	$F(2, 12014) = 2.07$, ΔAIC = -0.14, ΔBIC = 14.6	$F(2, 12012) = 0.84$, ΔAIC = 2.31, ΔBIC = 17.1
Switch block	Non-switch trial	$F(2, 12016) = 10.2$***, ΔAIC = -16.5, ΔBIC = -1.69	**$F(2, 12014) = 3.59$*, ΔAIC = -3.17, ΔBIC = 11.6**	$F(2, 12012) = 2.35$, ΔAIC = -0.71, ΔBIC = 14.1
Switch block (Local switch cost)	Cue switch trial	**$F(2, 12016) = 16.8$***, ΔAIC = -29.5, ΔBIC = -14.7**	$F(2, 12014) = 2.50$, ΔAIC = -1.01, ΔBIC = 13.8	$F(2, 12012) = 0.96$, ΔAIC = 2.07, ΔBIC = 16.9
	Task switch trial	**$F(2, 12016) = 14.2$***, ΔAIC = -24.4, ΔBIC = -9.65**	$F(2, 12014) = 2.70$, ΔAIC = -1.39, ΔBIC = 13.4	$F(2, 12012) = 0.79$, ΔAIC = 2.41, ΔBIC = 17.2

* $p \leq .05$, ** $p \leq .01$, *** $p \leq .001$

Note. Each analysis determined whether the second, more complicated model (the alternative) explained significantly more variance than the first, null model. The final selected model is highlighted in bold

Table 4.9: Ages and slopes of transitions for reaction time standard deviations

		Development		Adulthood	Aging	
Block	Trial Type	Slope 1	Age (years)	Slope 2	Age (years)	Slope 3
Non switch block	Non switch trial	-5.02 [-9.56, 0.49]	15.4 [14.1, 16.8]	0.14 [-0.02, 0.30]	59.1 [53.9, 64.2]	7.2 [-1.73, 16.1]
	Cue switch trial	-7.85 [-13.5, -2.24]	15.3 [14.3, 16.4]	0.01 [-0.18, 0.19]		
Switch block	Non switch trial	-2.00 [-4.13, 0.14]	18.9 [16.7, 21.2]	1.05 [0.74, 1.36]	55.9 [49.7, 62.2]	7.10 [0.78, 13.4]
	Cue switch trial	-16.1 [-24.6, -7.66]	15.4 [14.6, 16.1]	0.96 [0.68, 1.24]		
	Task switch trial	-4.61 [-7.88, -1.33]	17.8 [16.5, 19.2]	1.38 [1.08, 1.67]		

Note. 95% confidence intervals are shown in brackets. Values shown are for the best fitting model for each process. Ages represent the estimated breakpoints, and slopes represent the regression coefficients.

Table 4.10: Hierarchical regression results for reaction time coefficient of variability

Block	Trial Type	*Straight-line model vs. one-break model*	*One-break model vs. two-break model*	*Two-break model vs. three-break model*
Non switch block	Non switch trial	***F*(2, 12016) = 4.18*, ΔAIC = -4.36, ΔBIC = 10.4**	*F*(2, 12014) = 2.51, ΔAIC = -1.03, ΔBIC = 13.8	*F*(2, 12012) = 0.49, ΔAIC = 3.03, ΔBIC = 17.8
	Cue switch trial	***F*(2, 12016) = 6.70**, ΔAIC = -9.40, ΔBIC = 5.39**	*F*(2, 12014) = 1.16, ΔAIC = 1.67, ΔBIC = 16.5	*F*(2, 12012) = 1.57, ΔAIC = 0.85, ΔBIC = 15.6
Switch block	Non switch trial	*F*(2, 12016) = 2.71, ΔAIC = -1.42, ΔBIC = 13.4	*F*(2, 12014) = 1.52, ΔAIC = 0.96, ΔBIC = 15.7	*F*(2, 12012) = 0.73, ΔAIC = 1.82, ΔBIC = 16.6
	Cue switch trial	***F*(2, 12016) = 4.11*, ΔAIC = -4.22, ΔBIC = 10.6**	*F*(2, 12014) = 1.73, ΔAIC = 0.54, ΔBIC = 15.3	*F*(2, 12012) = 0.44, ΔAIC = 3.12, ΔBIC = 17.9
	Task switch trial	*F*(2, 12016) = 2.89, ΔAIC = -1.75, ΔBIC = 13.0	*F*(2, 12014) = 2.36, ΔAIC = -0.72, ΔBIC =14.1	*F*(2, 12012) = 1.62, ΔAIC = 0.76, ΔBIC = 15.5

* $p \leq .05$** $p \leq .01$*** $p \leq .001$
Note. Each analysis determined whether the second, more complicated model (the alternative) explained significantly more variance than the first, null model.

Table 4.11: Ages and slopes of transitions for reaction time coefficient of variability.

		Development		Adulthood
Block	Trial Type	Slope 1	Age (years)	Slope 2
Non switch block	Non switch trial	-0.19 [-0.34, -0.04]	19.0 [16.3, 21.8]	-0.01 [-0.03, 0.02]
	Cue switch trial	-0.15 [-0.22, -0.07]	24.9 [20.1, 29.6]	0.001 [-0.04, 0.04]
Switch block	Non switch trial			0.02 [-0.04, 0.003]
	Cue switch trial	-0.50 [-0.89, -0.13]	16.0 [14.7, 17.3]	-0.05 [-0.07, -0.03]
	Task switch trial			-0.04 [-0.06, -0.03]

Note. 95% confidence intervals are shown in brackets. Values shown are for the best fitting model for each process. Ages represent the estimated breakpoints, and slopes represent the regression coefficients.

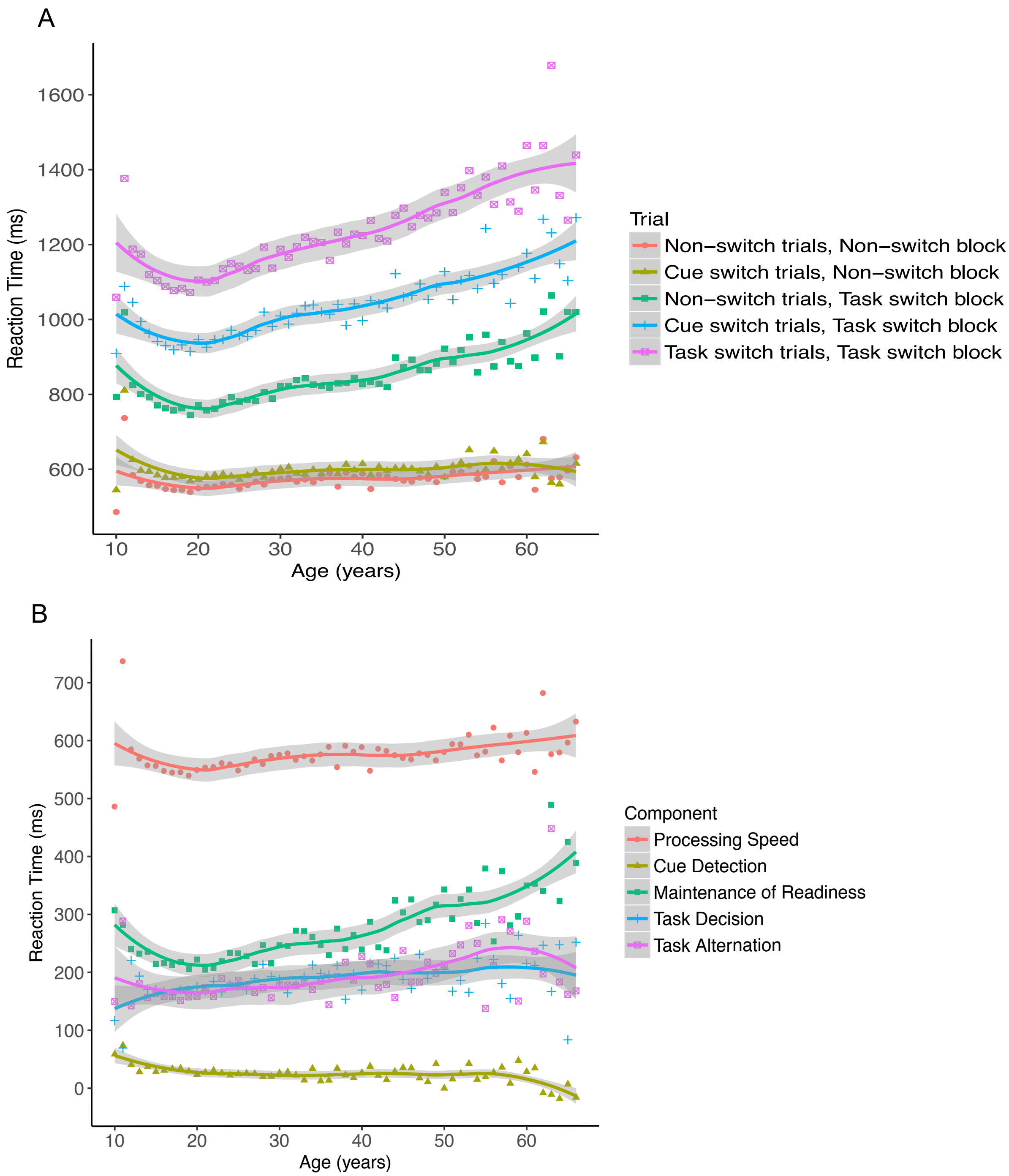

Figure 4.1: Loess curves of mean reaction time

Mean reaction times [95% CI] over age (A) per condition, and (B) per component.

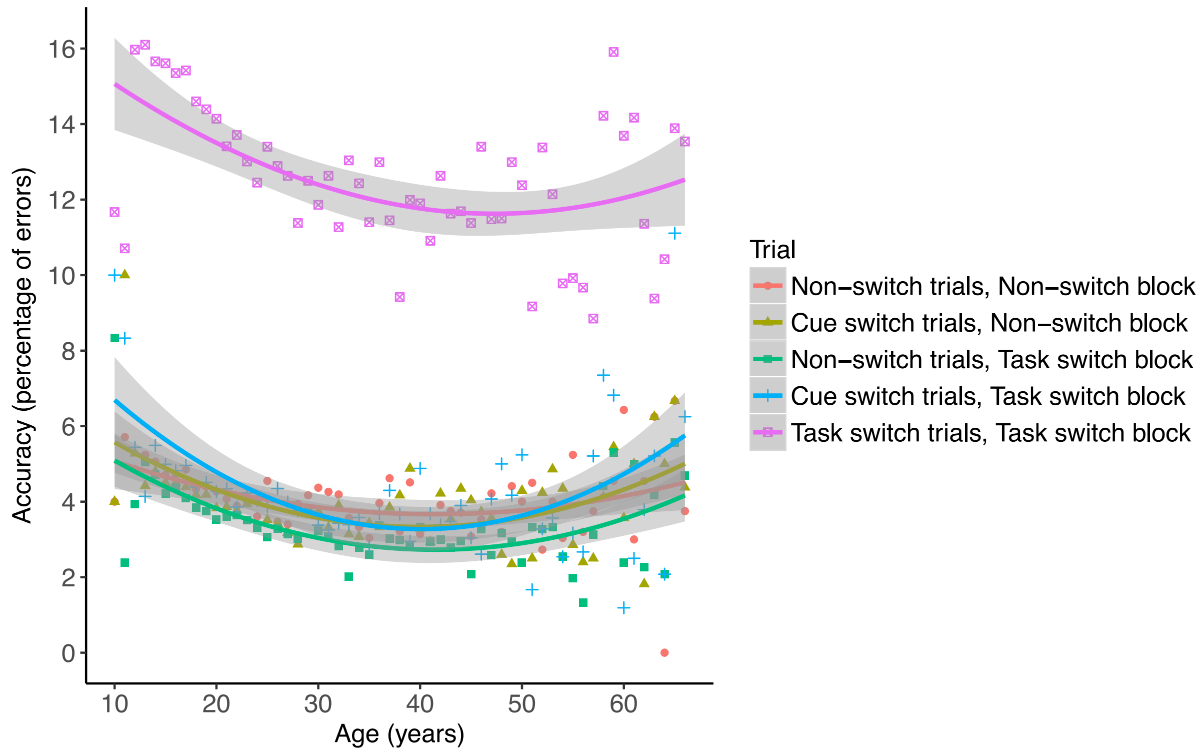

Figure 4.2: Loess curves of mean accuracy

Mean percent errors [95% CI] over age per condition.

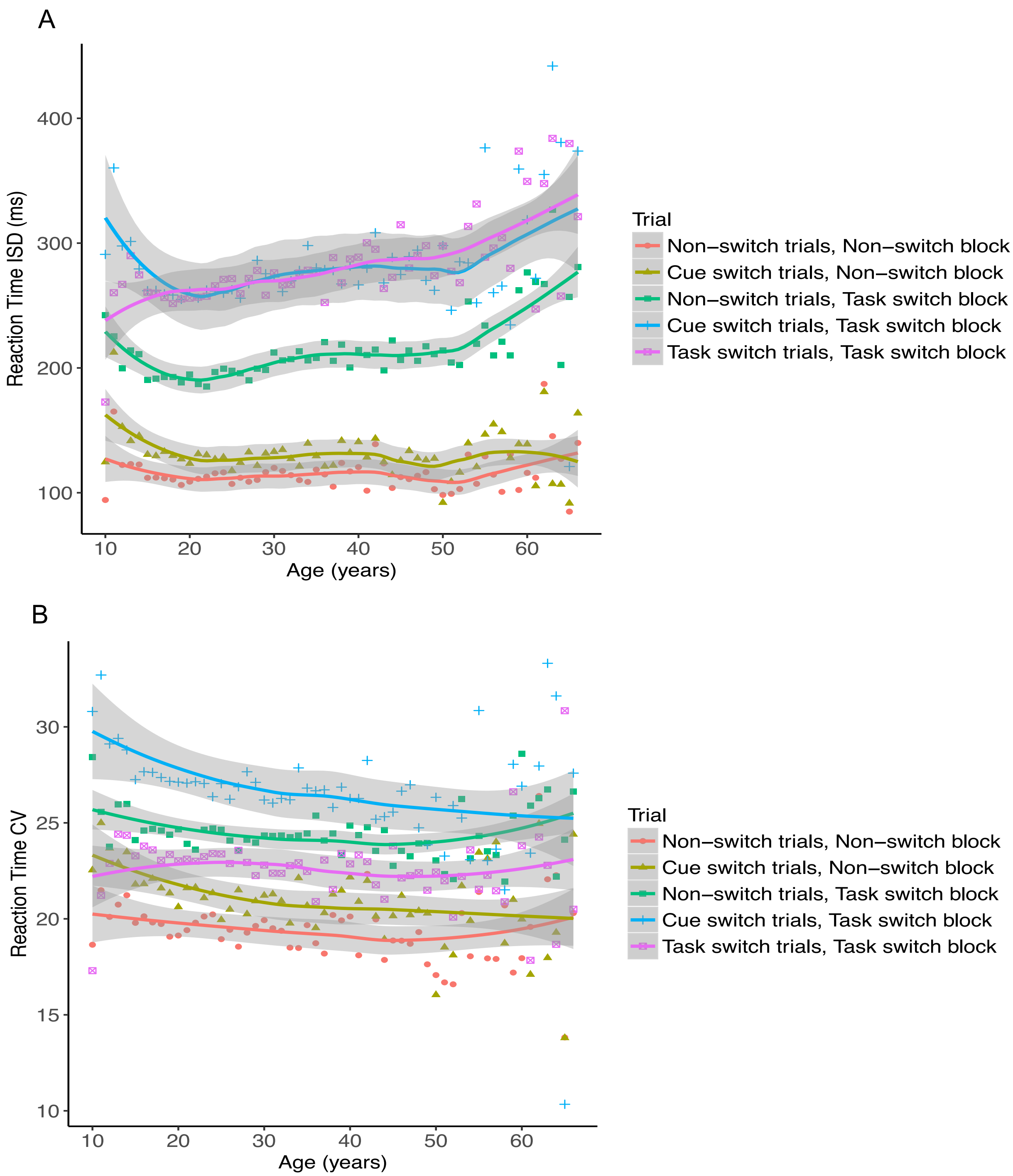

Figure 4.3: Loess curves of intra-individual variability in reaction time

Mean [95% CI] over age per condition on (A) intra-individual standard deviation (ISD) and (B) coefficient of variability (CV).

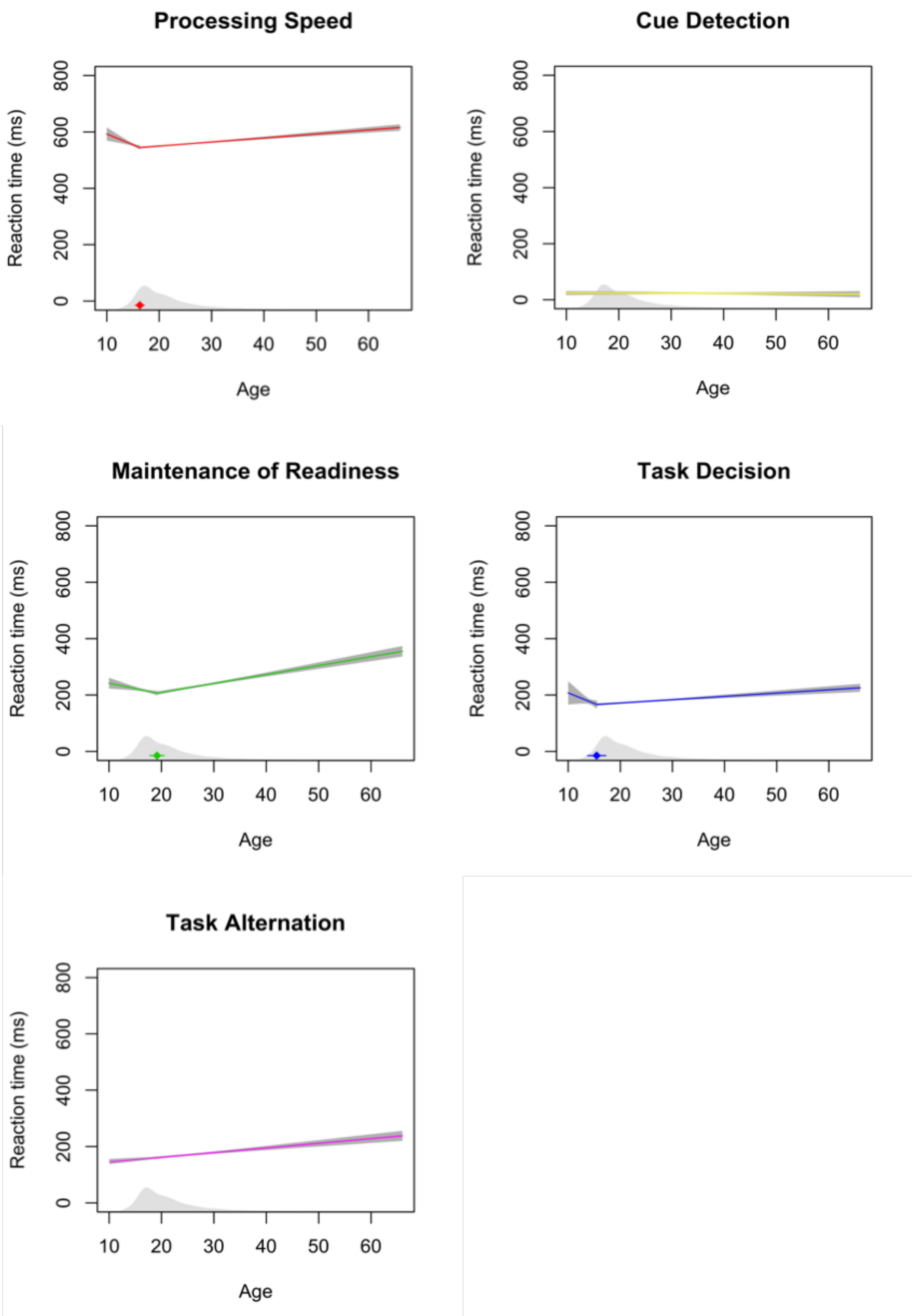

Figure 4.4: Segmented regression models of mean reaction times

Segmented linear regression models of mean reaction times per component. Breakpoints [95% CI] and population density curves are shown along the horizontal axis.

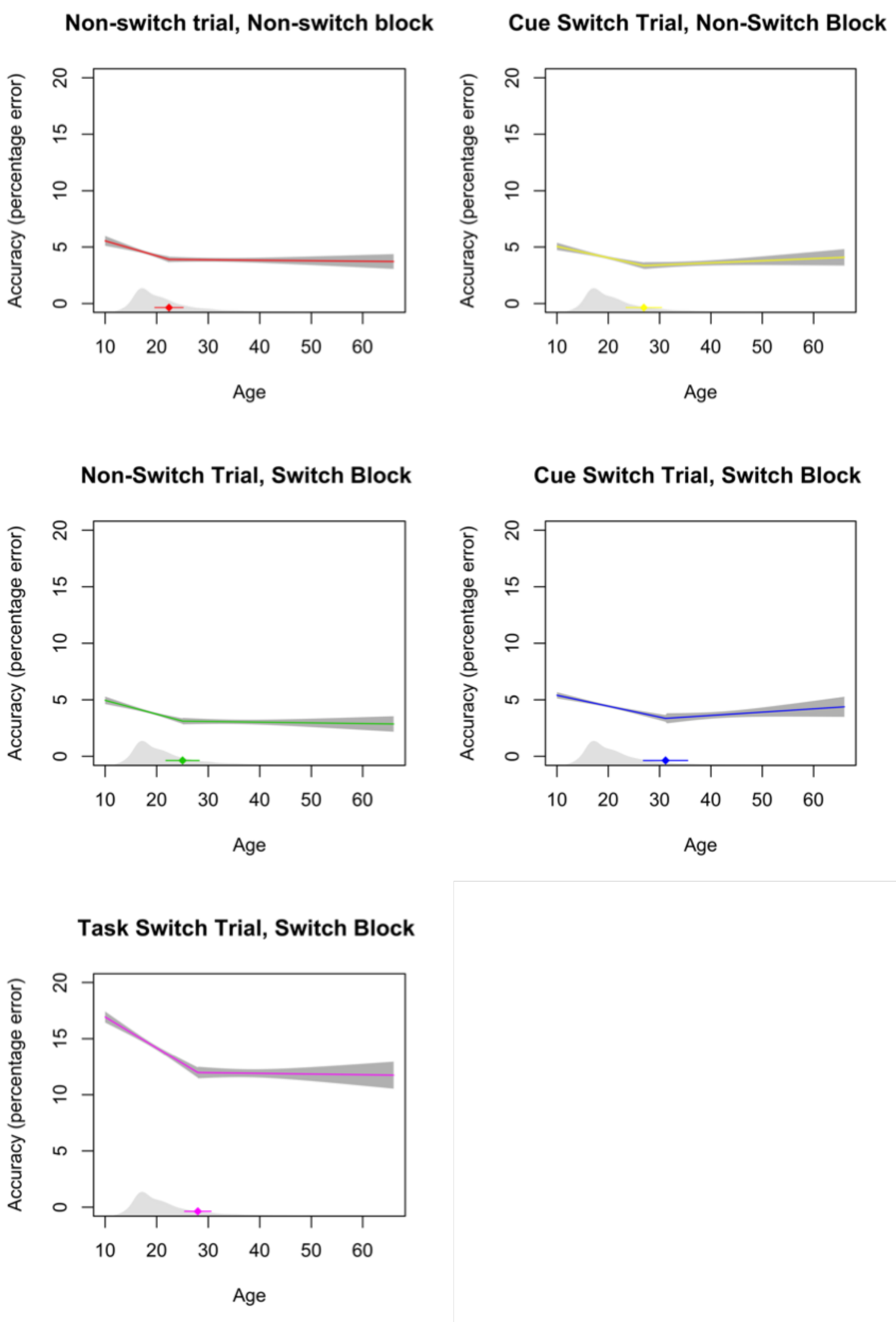

Figure 4.5: **Segmented regression models of mean accuracy**

Segmented linear regression models of mean percent error per condition. Breakpoints [95% CI] and population density curves are shown along the horizontal axis.

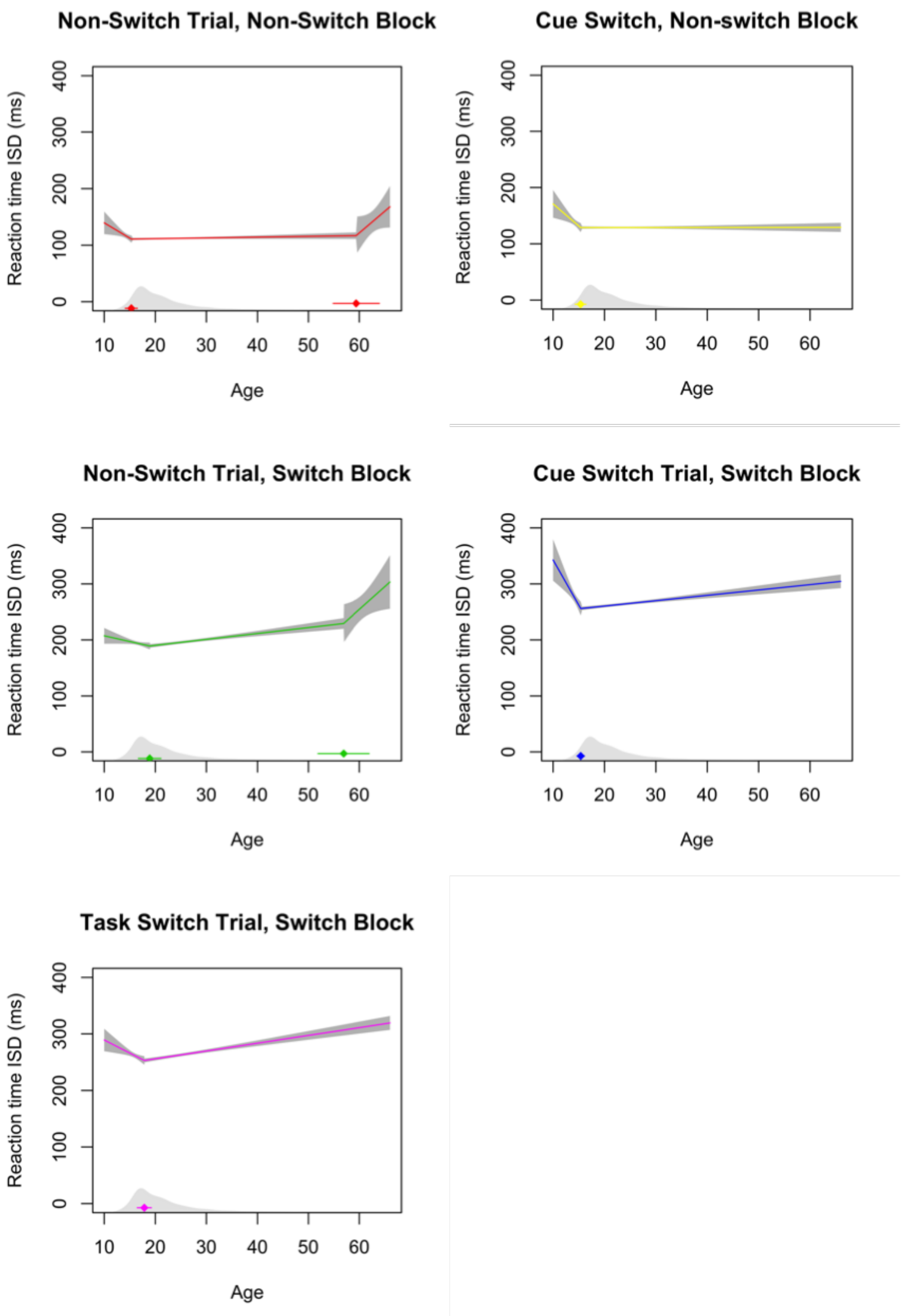

Figure 4.6: Segmented regression models of reaction time standard deviations

Segmented linear regression models of mean intra-individual standard deviation (ISD) in reaction times per condition. Breakpoints [95% CI] and population density curves are shown along the horizontal axis.

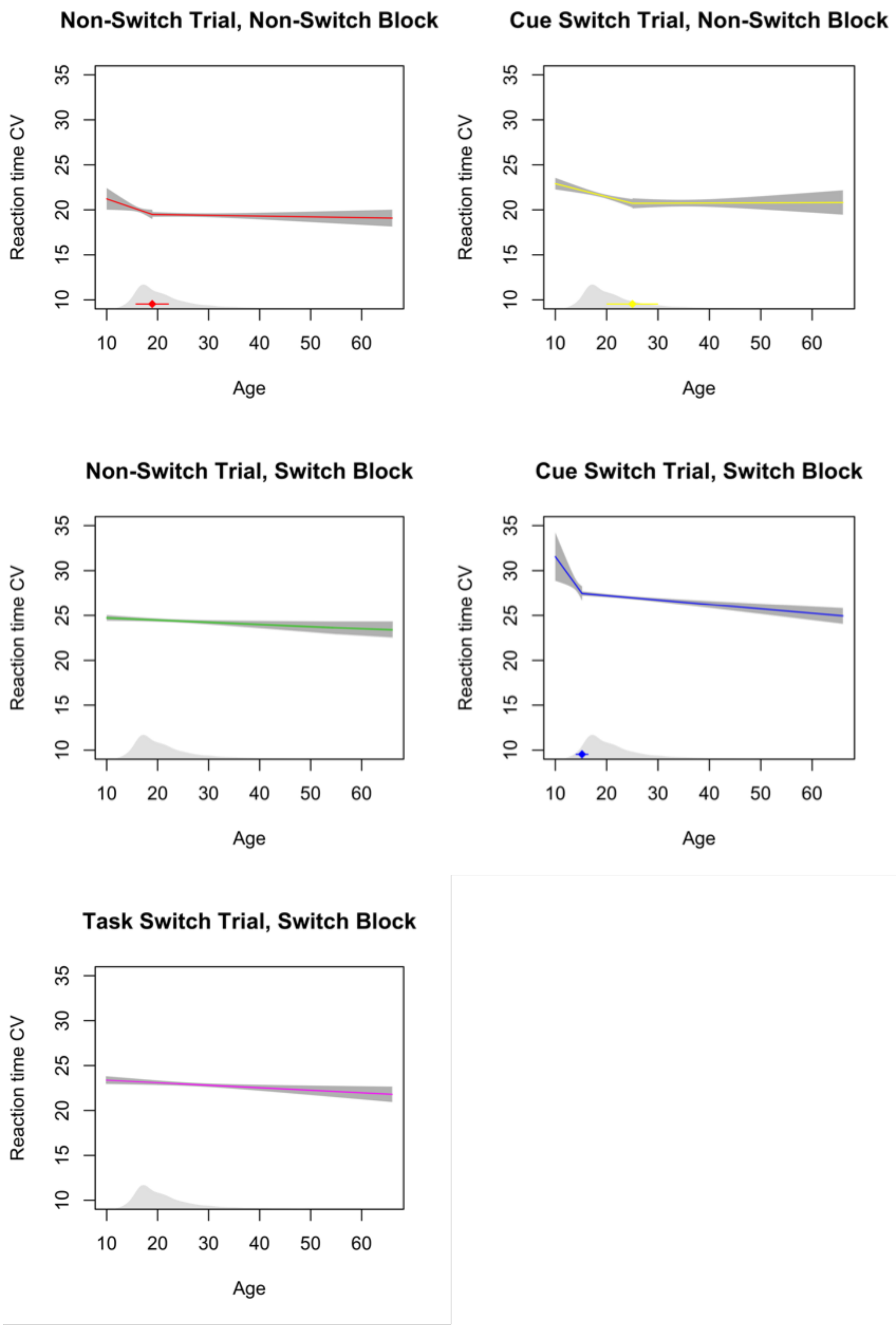

Figure 4.7: Segmented regression models of reaction time coefficient of variability

Segmented linear regression models of mean coefficient of variability (CV) in reaction times per condition. Breakpoints [95% CI] and population density curves are shown along the horizontal axis.

4.4.3 Sample size and truncated dataset

Since the dataset had fewer individuals at both ends of the lifespan, a truncated dataset was created to exclude age groups with sample sizes smaller than *n*=20. The truncated dataset consisted of ages 12 to 56 years (*n*=14,898). Analyses were re-run on the truncated dataset. Results from the truncated analysis, and a comparison to the original and complete replication sample are reported in the supplementary material. The overall pattern of results was similar to the complete dataset, although with a smaller ability to detect change at both ends of the lifespan. Note that the truncated dataset cannot be compared with the original dataset, since we varied two things: 1) time of data collection, and 2) range of ages.

The truncated dataset contains fewer outliers and larger sample sizes per age group. However, it is recommended that data points outside the range of other data not be removed unless they substantially affect model fit (Ryan & Porth, 2006), which was not the case for our study. Further, sample sizes in the complete dataset met published metrics to reliably detect and estimate change points. Detection of the change point does not depend on sample size, but the precision of the estimate does (Schwarz, 2015). Our sample met guidelines for a conservative metric to estimate change points with uneven sample sizes in the regressor, and across error precisions (White et al., 2018). Hence it was decided to report the complete dataset.

4.5 Discussion

The current study measured lifespan change in task switching using a massive lifespan sample to model fine-grained effects of age. To date there have been a larger number of small-sample investigations comparing groups of adolescents or older adults to young adults (*n*=30 to 400 per study) and two investigations comparing age groups over the lifespan (*n*=152 and *n*=5,271). We add to past studies by fractionating task switching into components and modelling ability per year of age. We found differential patterns for each component. Processing speed and maintenance of readiness for a possible shift showed development and decline, while using a cue for task decision making had a developmental effect but no decline. Detecting a cue and alternating a task did not vary with age. Our findings show that the parsing into continuous age effects and task switching components may provide valuable information about age-related shifts in performance.

Our study is the first to measure detailed changes in task and cue processing with age, since past studies were limited to measurements of global and local switch cost. It is also the first to measure variation within a participant's responses (intraindividual variability) in task switching, with past studies limited to between-participant speed (reaction times) or error rates (accuracy) as the primary outcome measure.

4.5.1 Findings and comparison to original study

The overall effects of age were extremely similar to the original study. An asymmetrical lifespan pattern was found for reaction time means in both our studies, with a rapid developmental improvement during adolescence, followed by a gradual decline. Importantly, the timing of shifts in both studies was nearly identical. Effects of development on reaction times ended in mid-adolescence for processing speed and task decision and late adolescence for maintenance of readiness.

In contrast, accuracy in both studies showed a small developmental improvement that continued later, into the twenties, with no decline after. These findings are in line with past studies in which accuracy on task switching improved through development but did not decline after (Verhaeghen & Cerella, 2002; Wasylyshyn et al., 2011). The earlier maturation of reaction times than accuracy confirms past findings (Crone et al., 2006; Huizinga et al., 2006; Davidson et al., 2002).

Reaction time intraindividual variability had a U-curve in both studies, with an improvement till the end of adolescence, followed a gradual decline, and a further decline later in life. These findings confirm past studies in which reaction time intraindividual variability on general cognitive ability showed a U-curve (Dykiert, Der, Starr, & Deary, 2012a, 2012b; Williams, Strauss, Hultsch, & Hunter, 2007).

The biggest age effects were for processing speed and maintenance of readiness. Our findings support past studies that maintaining readiness for a possible shift (i.e., global switch cost) shows larger and more reliable age differences than a task shift itself (i.e., local switch cost; Reimers & Maylor, 2005; Wasylyshyn et al., 2011). We support previous findings on age differences in processing speed, but also show that age differences in task switching go beyond age differences in processing speed (Cepeda et al., 2001; Verhaeghen & Cerella, 2002; Wasylyshyn et al., 2011).

Our results clarify past findings of inconsistent age differences in local switch cost, by accounting for the role of the cue. We found a developmental improvement of using a cue to make a task decision (i.e., the informative cue switch cost component of local switch cost), followed by no decline. We found no developmental improvement for task alternation itself (i.e., the task switch cost component of local switch cost).

Our findings further clarify the circumstances under which a cue has an effect with age. We used a novel component to measure effects of age on cue detection (i.e., the non-informative cue switch cost). We found no effects of age on this component.

We showed the start of aging in adulthood, but the current study did not replicate all our original findings on decline in aging. There was no statistically significant decline on task alternation in mid adulthood, or steeper decline on processing speed and maintenance of readiness in middle age.

Original and replication study differences can be explained by sample characteristics. The replication dataset had sparser sampling of older ages. Our sample size was adequately powered to detect two breakpoints. However, aging at the end of middle adulthood is likely a small effect size, so our relatively small sample of participants at older ages in the replication sample may have been insufficient to detect an effect. In past lifespan studies, a second aging shift was found in the study that measured older adults until age 90 years, but in only one of the studies that measured older adults over 65 years (Cepeda et al., 2001; Reimers & Maylor, 2005; Wiseheart et al., submitted, Study 2A). Performance in older adults is also more variable, so effects may be masked without a large enough sample. Further studies can address this by collecting more individuals at lower and higher ages.

We replicated our overall finding that, while ability peaks in late-adolescence and young adulthood, aging is not merely a reversal of development. Development was considerably faster than decline in both studies: up to 20 times slower in the original study, and seven times in the current study. The difference may be because the original study had more people at the end of middle adulthood.

Middle age might also produce compensatory strategies. With aging, adults respond more slowly, but they maintain accuracy. They have difficulty on global switch cost, either because more tasks must be held in mind or more attention is needed for the probability of a switch (Eppinger et al., 2007; Kramer et al., 1999). They compensate by selecting a new task on all trials, even when there is no task change (Mayr, 2001), or by maintaining readiness even when it is not needed for a potential task change (Mayr & Liebescher, 2001). This could explain the decline in global switch cost (maintenance of readiness) but not local switch cost (task alternation)—responses may be slower across trials in a switch block, without further slowing on task switch trials.

Older adults also may compensate by outsourcing cognitive control to the environment by using cues, even when cues are no longer needed (Amer & Hasher, 2014; Kray et al., 2002; 2004; Schapkin et al., 2014; Spieler et al., 2006). Cues offer an external aid to lower memory demands, orient top-down attention, and aid task selection (Eppinger et al., 2007; Gilchrist, Duarte, & Verhaeghen, 2015; Kramer et al., 1999). Older adults are especially able to use cues that are informative (Gilchrist et al., 2015). This explains the lack of decline in an informative cue switch cost of using a cue to select a task (task decision).

We propose that future research use segmented regression and web-based testing as powerful techniques to precisely model variability in psychological processes over the lifespan. Past investigations have confirmed the reliability of online data collection for cognitive research (de Leeuw & Motz, 2016). Task-switching is particularly suited to online data collection (Reimers & Stewart, 2016). Online testing enabled us to collect a sample large enough to fit mathematical models of continuous change and discontinuous stages. Our findings paint the positive picture that decline in aging occurs slowly, while development happens relatively quickly.

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6 General Discussion

Understanding the nature of a switch cost is a major goal in task switching research. A robust switch cost has been widely established when frequently shifting between goals. The studies in this dissertation quantify the impact of the switch cost—a 34% immediate decrease, and an additional 74% long-term decrease, in productivity. The studies also highlight the value of parsing task switching into multiple processes. Despite the apparent simplicity of a switch cost, it has taken a body of research efforts to disentangle the complex causation of processes that contribute to the switch cost. Finally, the studies highlight that understanding these processes is a requisite before the effects of age on task switching can be interpreted. Study 1 showed that a number of different processes combine to produce a switch cost, and that processes additional to the shift (using a cue to decide on a task, and maintaining readiness for a shift), can produce a larger cost than shifting itself. Studies 2A and 2B showed that these processes vary differently with age. The good news is that compensatory strategies may be employed to maintain performance when switching, and during early cognitive decline.

5.1 Main findings

5.1.1 The cost of switching

The current results provide key insights on the size of task switching effects. Study 1 showed that it took 534 ms on average to perform a single task. It took 219 ms (or 41%) longer when performing a single task while anticipating a possible shift. It took 148 ms (or 28%) longer to use a cue to decide on the task to perform when anticipating a possible shift, although the cue only has a trivial effect of 25 ms (5%) longer when there is no possibility of a shift. Importantly, the effects of maintaining readiness (i.e., a switch block) and using a cue for a task decision (i.e., a cue change) occur even without an actual shift taking place, indicating the long-term impact of the possibility of a switch costs 74%. It took 183 ms (or 34%) longer for an actual shift. The sum of these effects is 576 ms (or 108%) longer.

The substantial increase of 108 percent on top of the time for a single task highlights the sizable cost of switching. This finding is easily translatable: that the total effect of switching a task is longer than the time it takes to do that task in the first place. The task switching literature has consistently confirmed the existence of a switch cost, but less was known on the magnitude of such an effect or the processes that produce it.

5.1.2 Adaptability of task switching processes

A second emerging picture from the dissertation is that the interplay between task switching processes produces flexibility. These findings reveal that there is a cost of switching, but the cost enables adaptable behaviour. Such adaptability is needed when responding to constantly changing environments, which shows that the switch cost can be beneficial.

An example of adaptability was seen when, in Study 1, individuals slowed down to shift a task (*task alternation*), but also slowed down to use a cue that signalled whether or not they needed to shift. This produces two costs: a *task switch cost* when a task changes, and a *cue switch cost* when a cue changes. Part of the cost of changing a task includes using a cue to select a task (*task decision*). Attending to the cue lowers the cost of switching, since the task only needs to be changed when the cue indicates a task change, rather than the more costly strategy of changing a task on every trial. Another example of adaptability was seen in the *global switch cost* of slowing down in case of a task change, but this slowing down may strategically create more attentiveness change (*maintenance of readiness*) and thus faster responding when a switch occurs.

A novel example of adaptability from Study 1 was that the cue switch cost from slowing down to use a cue depended on whether a cue was useful for the context. Individuals did not slow down to perceive a cue when they were instructed that a task would repeat (*cue detection*), but they did slow down to use a cue when instructed that a task may change. It is strategic to pay attention to the cue only when a task may change, as the cue becomes useful to select which task to perform.

Study 1 also showed that at least some observed components fit theoretical explanations for an automatic underlying process, without requiring an intentional control process. For example, the cue may be used to automatically select a task (as proposed by cue priming theories), without necessarily having to employ the more costly strategy of intentionally preparing to shift to a task (as proposed by task preparation theories). The cue may even be used to resolve interference when shifting away from a past task, without needed to include an additional process of decay from task carryover (as proposed by task priming theories). Future studies could test the sufficiency of an automatic explanation for task switching, but this study offers promising evidence that at least some of the processes for task switching occur without having to slow down and make a voluntary decision.

Study 1 demonstrated a case in which an adaptation technique proposed by previous research did not occur. Researchers have suggested that individuals may be slower when changing from a difficult task to an easy task, as the difficult task carries over and impairs performance on the easy task. This school of thought proposes that switch costs arises from *switching away from* a past task, rather than *switching to* a current task. Since it is quicker to respond to an easy task, people are assumed to bias their attention and responding to the difficult task, which creates the ‘stickiness’ that must be overcome when switching away from the difficult task. This striking counterintuitive backward effect of switching away from a difficult task had been observed, but only inconsistently (review by Koch et al., 2005). The current findings add to the lack of observation of an asymmetric effect of task difficulty.

More examples of adaptability were seen in the way that these processes varied with age in Study 2, which was the first to measure the effects of age on the multiple components of task switching. Past studies of age were limited to only the local and global switch cost. Adaptability was seen in how maintenance of readiness developed and declined over the lifespan, but task alternation itself had much less variation. It appeared that slowing down to be more cautious overall may mean that individuals are more able to then implement a change that needs to be made, without needing to slow down much further for the change itself. Another example of adaptability was seen in how using a cue for a task decision had minimal decline over adulthood, even though alternating a task did decline. It appeared that while it may be internally difficult to implement a new task, individuals may strategically rely more on cues in their environment to decide to respond. A strong example of adaptability was also seen in how accuracy did not decline with age. Middle aged adults were slower than young adults but avoided making mistakes.

The findings show that slowing down on some processes may enable quick responding on other processes. Moreover, slowing down on all processes enabled more accurate responding. Effect sizes showed that each process occurred relatively fast. It is striking how such adaptation occurs in the timespan of a few hundred milliseconds, and possibly even without voluntary responding, indicating the remarkable flexibility with which people can respond to changing goals and surroundings.

The aging adaptations observed in the current dissertation were a stark contrast against the backdrop of normal aging effects that were also observed. The current dissertation showed the standard effects of age that have been demonstrated in previous studies. First, individuals show an overall slowing with age. Studies 2A and 2B replicated this finding and highlighted its significance: the overall slowing was much larger than the slowing on any of the specific task-switching processes. Second, individuals become more variable or inconsistent in their responding on cognitive tasks with age. Studies 2A and 2B replicated this finding specifically for task switching, which had not been previously measured. The results highlighted the significance of studying intraindividual variability: decline of mean reaction times and accuracy were not a mirror of development, but the increase in intraindividual variability did mirror development. In the face of typical age-related decline, it is encouraging to note that adaptive strategies may occur. Future studies can further test other compensatory strategies and trade-offs earlier and later in the lifespan (e.g., Amer & Hasher, 2014; Blackwell, Chatham, Wiseheart, & Munakata, 2014; Verhaeghen, Geigerman, Yang, Montoya, & Rahnev, 2019). As ability changes with age, costs in some processes may lead to benefits in others (Blackwell & Munakata, 2014).

5.2 Future Directions for Psychology research

5.2.1 Web-based data

The findings of this dissertation are strengthened by the use of web-based data to collect unprecedently large sample sizes. The massive sample size enabled estimation of the size of the effects for each contributing process in Study 1. This is much more valuable than simply stating that these processes have a statistically significant contribution. The results detailed how large these contributions were, how the contribution of each process compared to the others, and whether the size of the contribution was meaningful. The massive sample size enabled modelling the effects of age in Study 2 in a far more fine-grained way than past research. This technique enabled collection of a sample size that would have been nearly impossible to collect by lab data collection, especially since the sample included different ages.

Web-based data collection is commonplace but continues to receive skepticism from researchers, particularly for reaction time data. Objections include the limitations of software and technologies, the lack of control, and the increased variation in online studies. However, the reliability of online data collection has been extensively confirmed over a variety of cognitive tasks. Online experiments produce results of a similar effect size to the same experiments run under a lab setting (Chetverikov & Upravitelev, 2015; de Leeuw & Motz, 2016; Enochson & Culbertson, 2015; Slote & Strand, 2015). Replication of lab findings was found with direct comparisons after random assignment to online or lab testing (Hilbig, 2015). Counter to misconceptions on online testing, this body of evidence confirms that reaction time effects of a few hundred milliseconds can be detected in web experiments. Rather than being inferior to lab data collection, online data often provide better estimation due to the increased sample size.

The suitability of Adobe Flash, the particular software used in the current project, has been specifically confirmed (Reimers & Stewart, 2007, 2015). The task switching paradigm has been previously successfully used in online research, with the same gender and emotion tasks used in the current project (Reimers & Maylor, 2005). Task switching is particularly robust to any online data collection issues as it involves collection of data from multiple trials and within-subject comparisons of reaction times (Reimers & Stewart, 2016).

A large dataset with a wide age range offers promise to study cognitive development and aging, but also requires a suitable technique to model the data. The analysis technique of segmented regression was selected as it enabled statistical testing of when and how each process shifted. Segmented regression was a powerful statistical tool that yielded detailed results on the periods in which performance changes from one phase of life to another. The results inform the number of phases that are statistically significant, as well as the size of the effect in each phase (refer following section). Locally weighted regression curves were selected to complement the statistical analyses with qualitative insights from visualizing the pattern of change.

Online testing also lends itself well to replication studies. Study 2B showed that data can be easily collected for more years under the exact same conditions as the original experiment (i.e., Study 2A). Studies 2A and 2B converged on several noteworthy results: that task switching continues to develop into the twenties, that gradual early decline begins soon after, and that later decline is also much slower than the rapid change that occurred over the developmental period.

A challenge for replication studies is to keep up with changes in software. The Flash program used in the current project was just a decade old when data collection began but is being phased out in a few years (Lardinois, 2017). To take its place, there is a lot of promise from the increasing number of online tools dedicated specifically to constructing browser-based studies for the social sciences using easy and intuitive interfaces (de Leeuw, 2015; de Leeuw & Motz, 2016; Henninger, Kieslich, & Hilbig, 2015). Online data collection facilitates replication, which is fundamental to tackle the reproducibility crisis that the field of psychology is currently facing (Open Science Collaboration, 2015).

An important direction for future online studies is to collect more data on late adulthood and older adults. The size of the current samples was skewed towards the earlier end of the lifespan. It is especially important to collect larger samples since our sample showed that data from aging individuals contains more outliers and is more variable. However, even the sparser sample sizes collected in late adulthood were considerably larger than those in most lab investigations. Within age spans of three years, there were at least 100 participants throughout the sample. The sample sizes also met published recommendations, although estimates of sample size are limited and it is always better to collect as many participants as possible (Beribisky & Cribbie, in preparation). A more pressing concern is the need to collect data from older ages. The current dissertation ended measurement at age 65 years, so conclusions are limited to the start of aging from early to middle adulthood. Performance in older adulthood is beyond the scope of this project.

5.2.2 Effect sizes

Focus on effect size is consistent with recent recommendations to always discuss effect sizes in publications, more so than statistical significance (Ferguson, 2009; Wilkinson & APA Task Force on Statistical Inference, 1999). The use of effect sizes is particularly relevant to the current study since significant effects are expected in a sample size as large as the current study. A significant effect was found for an effect of a small magnitude in several cases, so the interpretation of effect sizes provided a more accurate picture of the magnitude of the observed significant effects.

In Study 1, effect sizes offered meaningful information on the changes in speed and accuracy, as well as the percentage increase in speed. Effect sizes provided the noteworthy and intuitive finding that 108% of productivity is lost by task switching. The relatively small switch cost of a few tenths of a second adds up when individuals rapidly move between tasks.

In Study 2, the effect sizes afforded applicable insights on how much change occurred per year of age, and the period in which change began and ended. For example, Study 2A showed that processing speed developed at a rate of 42 ms per year of age until age 15, reached a plateau of 1 ms per year of age until age 36, after which it declined at a rate of 3 ms per year of age (Refer Table 3.2). Looking at the effect sizes provided the key insight that although aging starts early in adulthood, it occurs at a much slower rate than development, in this case, 14 times slower. Such findings can be compared to other components, for example, maintenance of readiness had similar rates of development and decline, development occurred at 7 ms per year until 18, decline at 3 ms per year until 43, and then more rapidly at 5 ms per year. Decline was still at a smaller rate than development, but only 1.4 to 2 times smaller.

95% confidence intervals on each of these measurements provided additional information on the ranges of each of these effects. For example, on processing speed, the rate of development ranged from 32 to 52 ms per year, and the rate of decline from 2 to 3 ms per year. The period of development ranged from age 14 to 15, while the period of decline ranged from 28 to 43. The confidence intervals show that there is a large range in the rates at which individuals develop and decline. There is an especially large range during which early aging may begin, across abilities it could be anywhere from the late twenties to the early fifties.

The dissertation reported unstandardized (simple) effect sizes. Published studies strongly recommend unstandardized effect sizes as they are easier to interpret, more robust, and more versatile than standardized effect size (Baguley, 2009). Recommendations propose calculating unstandardized effect sizes using the units of the measurement instrument. At the same time, avoiding standardized effect sizes, and the arbitrary guidelines used for their interpretation, should not be taken as license to overinterpret weak effect sizes. Hence it is generally recommended to report unstandardized effect sizes, and base interpretation of these on a researcher’s understanding of the effect of interest and the context of the research (Cohen, 2013).

There is a lack of published recommendations for interpreting unstandardized effect sizes for reaction times in task switching. However, unstandardized effect sizes were easy to interpret in the current design based on past reports and our own research knowledge of reaction time effects in task switching. One publication has compared task switching effects to the standard cognitive psychology effects, in which an effect of tens of milliseconds is common, and an effect of hundreds of milliseconds is large (Monsell & Driver, 2000). Hence we interpreted effects above 10 ms as small, above 50 ms as medium, above 100 ms as large, and above 200 ms as very large. These interpretations are arbitrary but are based on our understanding of what classifies as a meaningful effect size in task switching.

The percentage increase has been used by previous researchers in task switching (American Psychological Association, 2006; Rubinstein et al., 2001) as a way of measuring the effect size of a switch cost. The numerator measures the increase, which is essentially the difference score between the new and original value. The denominator measures the original value, which is essentially the baseline reaction time without any manipulations. The new value is the reaction time after an experimental manipulation. Difference scores are widely used as the primary measure of a switch cost in cognitive psychology (Kiesel et al., 2010; Meiran, 2010; Monsell, 2003; Vandierendonck et al., 2010). Hence it is meaningful to interpret the magnitude of a difference score.

The reporting of percentage increase is relatively novel; It has only been done by one other study on task switching (Rubinstein et al., 2001). Percentage increase is useful in situating the impact of a switch cost, which can take around a hundred milliseconds (one tenths of a second), but accounts for a notable increase of up to 40% of the time for doing a single task (American Psychological Association, 2006). Percentage increases are especially easier to interpret by researchers who are not in cognitive psychology or unfamiliar with how to interpret absolute millisecond effects. Absolute millisecond effects can appear trivial on their own, but are large when placed relative to the time it takes to complete a task in the first place. For example, the total cost of a shift is around five hundred milliseconds, or half a second, which seems brief. However, this translates to a 108% decrease in productivity, which is substantial.

5.2.3 Connectivity in psychology research

The popular game in Sesame Street “One of these things (Is not like the other things)” encourages children to see the overlap and distinctions between different objects. As children get older, they are also able to see the overlap and distinctions between different abstract ideas. This game is pleasing to children as they delightedly pick out the stark differences between items on the show but detecting differences in everyday life can be a lot harder. The challenge between differentiating between ideas is one that plagues scientific researchers, who propose different theories and terms to explain everyday phenomena, but do not always connect their ideas to existing ideas or research attempts in the field.

The lack of connectivity in psychological research applies to research endeavours on task switching. Operational definitions and measurements of task switching processes vary over the field. Researchers have used different terms to describe the same empirical process, or the same term to describe different processes. For example, ‘readiness’ in task switching is used differently across researchers, and the term ‘task decision’ also refers to different processes (Rubin & Meiran, 2005; Ruthruff et al., 2001; Sohn & Anderson, 2001). Even what constitutes a ‘task’ in task switching is inconsistent over studies (Schneider & Logan, 2014), although the functional usage of the term ‘task’ tends to converge on referring to a goal that specifies an action (Kiesel et al., 2010; Meiran, 2010; Vandierendonck et al., 2010).

The lack of connectivity among task switching researchers highlights a broader issue among defining and measuring constructs in cognitive psychology. Poor definitions lead to redundancy and ambiguity in research terminology. As studies accumulate, it would be ideal if the field could converge on a classification scheme of cognitive abilities, a taxonomy per se, that defines in a testable way what a proposed process is and what it is not. The lack of connectivity hampers replication, and thus cumulative science (Open Science Collaboration, 2015).

The lack of connectivity was a challenge for the current project. To address this, the project tried to clearly state and explain the selected operational definitions of task switching processes. Study 1 connected previously measured components of task switching (Study 1, Table 2.1). Study 2 connected the different ways in which a switch cost has been measured with age (Study 2B, Table 3.1). Both studies looked at how measured components may connect to previously proposed theoretical processes. Study 1 investigated how interactions between empirical effects align with predictions of opposing theories on task switching. Study 2 connected the different theoretical reasons proposed for the effects of age over the lifespan.

The goal was to examine how the results map on to existing theories, to investigate a comprehensive set of constraints to inform theory on task switching. Many specific theories have been proposed that look at a single switching-specific theoretical mechanism, sometimes in a single phase of the lifespan (e.g., Crone et al., 2006). The overarching goal was to examine commonalities in these theories toward parsimonious explanations. Both studies also looked beyond task switching theories to general theories on cognition or cognitive aging, to see whether these could adequately explain the observed results. Results from Study 1 showed that cognitive priming theories may account for some of the processes in task switching. Results from Study 2 showed that general cognitive theories were not sufficient to explain the variability with age in the processes specific to task switching.

The studies also aimed to connect between independent areas of empirical research in task switching. In cognitive research on task switching, substantial evidence from the task switching paradigm shows a distinction between local and global effects of switching. A separate set of evidence, also substantive, uses the double cuing paradigm to show the role of the cue in task switching. Study 1 examined these contributions together, with the novel contribution of testing whether there were interactions between effects that have been separately demonstrated. In developmental research on task switching, substantial evidence from the task switching paradigm shows a distinction between local and global effects of switching in children. A separate set of substantive evidence shows similar effects in older adults. Studies 2A and 2B examined development, adulthood, and early aging using lifespan studies.

The irony of failing to distinguish terminology is seen in that most tasks in task switching are choice reaction time tasks, in which research participants are instructed to perform the appropriate task by distinguish between overlapping features of an object. Distinguishing among overlapping concepts is practically valuable for choice decision making, and theoretically valuable in advancing scientific knowledge. Future research should work towards uniting efforts toward a taxonomy of task switching to classify which terminology are equivocal, describe relations between different terms, and clearly say which of the things is not like the other things.

5.3 Future Directions for task switching research

5.3.1 The cost of stability

The current project focuses on the cost of flexibility when rapidly shifting between tasks. Although a cost implies a negative effect, the cost of speed and accuracy in responding affords flexibility in responding. Future studies could balance studying the switch cost with studying the cost of *not* switching. A few investigations have shown that not responding flexibly also leads to a cost, the cost of stability (Dreisbach & Goschke, 2004; Grange & Houghton, 2014).

The cost of stability shows that while flexibility has a cost, it also has a benefit. To achieve successful goal-oriented action, individuals must balance between two complementary adaptive aims. On one hand, goals must be maintained and defend against distractions. On the other hand, goals must be adapted and shifted whenever an environment changes. Individuals must strike a balance to address this dilemma between stability and flexibility.

The stability/flexibility trade-off faces other executive functions and complex cognitive abilities (Herd et al., 2014). The task switching paradigm is a prime way to measure this balance between flexibility and stability. In fact, the paradigm has been used to show that forcing individuals to shift more often leads to more flexibility. The slogan "Keep flexible, keep switching" offers a promising strategy for training flexibility (Fröber & Dreisbach, 2017).

5.3.2 Conditions for a switch cost

The current dissertation focused on the process underlying a switch cost. When investigating the nature of the processes for task switching, it is also important to consider why a switch cost occurs, and whether there are cases in which it may not be needed. An associative learning perspective offers a far simpler explanation for task switching. Rather than having to apply a task rule to select a response based on the stimulus, and subsequently shift when the rule changes, a much easier strategy would be to simply memorize all the stimulus-response mappings. Such a strategy would avoid the cost of having to select a task when a task changes.

The standard task switching paradigm contains only two tasks, so the number of stimulus-response mappings is within working memory capacity and could easily be memorized. Interestingly, studies of animal learning show that non-human animals are able to avoid a switch cost by memorizing all the stimulus-response associations. For example, monkeys learn all the stimulus-response mappings instead of switching between task rules, and in doing so, do not show a switch cost (Stoet & Snyder, 2003a, 2003b).

In contrast, humans choose the more taxing strategy of applying a rule each time a task changes, which then requires selecting a task. The reason that humans do so is because uncertainty is a fundamental feature of the task switching paradigm. When switching, a decision must be made in an unpredictable situation, and this decision incurs a cost. Making a decision is considered to be an additional process, that may require intentional top-down processing. Acting intentionally or in a top-down manner is a uniquely human trait, since non-human animals can respond solely using automatically learned associations (Boly, Seth, Wilke, Ingmundson, Baars, Laureys, et al., 2013).

Uncertainty occurs since the standard paradigm uses a set of stimuli that could be classified under either task. Each stimulus affords a different response for each task. Since each stimulus has two response mappings, having alternative rules for the same stimulus would produce incorrect and mutually exclusive actions. The overlapping stimulus-response mappings mean that selection of a new task must occur in response to each stimulus[21].

The observation of a switch cost is directly linked to the need for task selection under uncertainty. Addressing uncertainty is necessary with overlapping stimulus-response mappings, but a switch cost occurs even with univalent stimuli that form non-overlapping stimulus-response

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[21] For example, the stimulus of a happy female in the gender-emotion task could signal the response “HAPPY” if the task was emotion, or “FEMALE” if the task was gender. In most cases, bivalent stimuli are used such that each response is mapped to overlapping response keys. For example, with a stimulus set of a happy female and sad male, the right-facing response key could signal “HAPPY” or “MALE”, while the left-facing response key could signal “SAD” or “FEMALE”. Thus, a stimulus of a happy female offered opposite response options depending on the task. The resulting ambiguity cannot be prepared for in advance since a decision must be made on each trial, thus the easier strategy of memorizing all the stimulus-response mappings is not possible.

mappings, suggesting that individuals still incur the cost of selecting a task. A switch cost can be removed, however, with univalent stimuli and when participants are not given the task rules (Dreisbach et al., 2007). When doing so, individuals memorize all the stimulus-response mappings. However, switch costs emerge as soon as rules are given, even when the rules are casually provided and not specified as instructions. The pervasiveness of the switch cost is seen in that even after participants have practice with the easier strategy of memorizing responses, they revert to the more difficult strategy of task selection when rules are given in the middle of the experiment (despite stating in post-experiment interviews that they did not use the rules!).

All task switching theories[22] have the same functional goal of reducing uncertainty. More generally, cognitive control processes, and their underlying brain networks, share the common goal of dealing with conditions of uncertainty (Fan, 2014). Thus, a fruitful future approach to studying information processing in cognitive control could look at shared processes or networks among cognitive abilities that serve the singular goal of reducing uncertainty. The occasional lack of a switch cost in non-human animals, and in human participants who are not given task rules, is also a case for further study. While most researchers have debated the mechanisms for switch costs, future research should also explore the conditions needed for a switch cost to arise.

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[22] To account for the task selection process, task preparation theories suggest that an a top-down configuration process is required to enable the rules for one task at a time, on each trial. Task priming theories propose that a stimulus can trigger interference from a competing or previous task (Allport et al., 1994). Cue priming theories propose that cues are used to automatically select a task and resolve uncertainty. The cue priming account solves the issue of overlapping stimulus-response mappings, since a cue is included in learning of the representations, thus each stimulus has separate mappings associated with each cue. The compound stimulus-cue-response mappings can be used for task selection by applying the principles of associative learning without needing to include a top-down process for task selection.

5.3.3 Measurements and models of a switch cost

The current dissertation extended the standard behavioural methods that are used in task switching research. Typically, switch costs are measured in behavioural research on local switch cost, with some studies including global, cue, or asymmetric switch costs. In Study 1, a more comprehensive fractionation of switch cost was introduced that was based on measuring these effects in a single paradigm. Further research can look into other supported measures of task switching, such as restart costs. When a cue interrupts a run of trials, individuals are slower to respond than on a trial not interrupted by a cue, indexing a *restart cost* when resuming responding. Restart costs have been linked to both global switch cost and cue switch cost (Poljac, Koch, & Bekkering, 2009).

Study 1 proposed a conceptual framework of task switching processes for future studies to build on. Further research could extend this to a framework that formally models individual processes. As research progresses on a framework, computational simulation and mathematical models offer a helpful way to make sense of the many (and interacting) factors that influence switch costs. Seminal attempts have simulated or mathematically modelled task switching and even task cuing (Logan & Bundensen, 2003; Monsell, 2003; Meiran, 2000; Sohn & Anderson, 2000; Yeung & Monsell, 2003).

Typically, switch costs are measured as between-participant mean reaction times, and occasionally accuracy. Study 2 added the measurement of within-participant reaction time variability. The additions of accuracy and intra-individual variability are particularly fascinating for lifespan research. Children and older adults may slow down to avoid making mistakes, and tend to be more inconsistent (i.e., more variable) in responding.

Future studies can also look beyond reaction times and accuracy to directly model distributions of reaction time performance. Drift diffusion models of reaction time data offer one such promising technique. Diffusion models use data from reaction time tasks to measure different parameters of performance, including the trade-off between speed and accuracy, the cautiousness with which an individual responds, and the bias towards one response over another (Ratcliff & McKoon, 2008; Voss, Rothermund, & Voss, 2004). Diffusion models have the advantage of statistically measuring underlying cognitive processes that are missed with standard measures of mean reaction times and accuracy. Early efforts have applied diffusion models to data in the standard task switching and double cuing paradigms (Schmitz & Voss, 2012, 2014).

Another promising avenue is using neural methods to complement behavioural techniques. In particular, measuring event-related potentials (ERPs) offers added value to behavioural research as it could measure how the timing of events in a task switching paradigm is locked to neural responses. For example, ERP investigations have offered unique insights on how updating working memory (measured using the P_{300} amplitude) relates separately to task cuing and task switching (Hsieh & Liu, 2005). Measuring structural processing could also offer added value. For example, pioneering functional magnetic resonance imaging (fMRI) research confirms that different neural regions underlie local and global switch costs, and task cuing (Braver et al., 2003, 2009). Even more novel and more promising is a neural network model of task switching, which builds on all the purported benefits: the fractionation of behavioural task switching processes, a biologically based neural framework, computer simulation, and mathematical modelling (Herd, O'Reilly, Hazy, Chatham, Brant, & Friedman, 2014).

5.3.4 Independence of processes underlying task switching

Study 1 created a framework that broke a switch cost into measurable components for the processes underlying task switching. The goal was to create a single framework that combines previously supported processes and tests their interactions. The study did not test for independence of processes, although the independence of processes has already been extensively confirmed for each of the processes measured (Mayr & Kliegl, 2003; Jost et al., 2013). These effects were reviewed in the introduction section of Study 1, in which past empirical studies used orthogonal experimental conditions to test the underlying mechanisms for each process, and whether these processes were separate from each other.

Future studies can explore how other factors or manipulations influence each process, and whether each process can be separately influenced. Such endeavours could look at whether different processes are caused by similar or independent underlying mechanisms. A process decomposition technique commonly used to test independence is the additive factors method (Sternberg, 2011). The technique identifies independent processes that make up a complex cognitive process. The defining characteristic for each process is that it serves a different role. The aim is to find an experimental manipulation (factor) that influences process A but not process B, and a second manipulation that influences the process B but not process A. A complementary technique is the cognitive neuropsychology method, which looks for a form of brain damage that impairs the operation of brain region (or network) A but not region B, and a second form of brain damage that influences a region B but not A (Coltheart, 2011). The selective influence of factors or neural impairments suggests that the processes underlying the components have different functions[23]. Both techniques share the goal of discovering the independent parts or functional processes of a cognitive system.

Some additional factors that could be created with the current paradigm include a factor of practice over trials, and a factor of carryover from two trials ago (*n*-1, or backward inhibition). In the current project there were not enough trials for each of these factors. More trials could be used in a future study, although this would limit the ability of study to be run online, since completion of online studies is much more likely with short paradigms. Having a study with additional factors would be ideally run in a lab to monitor participants' attentiveness in a longer paradigm, but this would significantly impact the sample size that could be collected.

5.4 Importance of studying a switch cost

The detailed exploration of switch costs offers generalizable insights on goal-directed behaviour. While most cognitive paradigms focus on a single task, the task switching paradigm studies performance on multiple tasks. In cognitive psychology, task switching studies have implications on the study of executive functions and cognitive control of mental resources.

Beyond cognitive control processes, studying how individuals shift tasks has practical relevance. Everyday life involves frequent shifting between goals in response to rapidly changing environments. The act of task switching is referred to as multitasking in common

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[23] Although a useful technique, the additive factors method does not lend itself to the task switching paradigm. A complete factorial to test local switch cost (cue switch, task switch), global switch cost (switch block, non-switch block), and cue switch cost (non-switch, cue switch), would have to be able to measure all levels of each factor and their interactions. However, it is impossible to have a task change without a cue change, or to have a task change in a non-switch block. To do so would require redefining a task change, but this loses the construct validity of measuring task switching. Thus, the task switch cost cannot be orthogonally compared to a global switch cost or cue switch cost within the same design. A solution to circumvent this issue is to use combinations of factors and test their influence on task switch cost and other processes separately. This has already been done in past studies to confirm the independence of local and global switch cost, and of cue and task switch cost. Another limitation is that the additive factors method assumes that processes occur serially in stages, which may not apply to task switching. The benefit of the cognitive neuropsychology technique is that it does not assume seriality. However, this technique is less feasible to conduct and may not always be practically possible.

usage, and the term multitasking has even been used by the American Psychological Association when describing task switching and a switch cost (American Psychological Association, 2006). It should be noted that in cognitive psychology, multitasking is not technically the same ability as task-switching. Multitasking (termed dual-tasking in cognitive psychology), refers to performing two tasks at the same time, while task switching refers to switching between two tasks. Research shows that multitasking is usually an illusion, and multitaskers are actually switching very rapidly between tasks, or performing one task automatically, rather than simultaneously consciously performing two tasks (Koch, Poljac, Müller, & Kiesel, 2018; Loukopoulos, Dismukes, & Barshi, 2016).

Studying task switching offers applications for fields in which shifting quickly and accurately between competing actions is frequent and expensive, such as driving, education and sports. Studying task switching has practical implications for productivity and workload of a person (or a system) in business corporations, where it is frequently referred to under the term ‘context switching’ (Francis, 2017). Although task switching is a ubiquitous aspect of daily life, most people can also recall a time where task switching put them in a difficult situation. The limits of a person’s (or a system’s) ability to go effectively from one task to another, and the ‘red-line’ at which task switching becomes ineffective and dangerous, warrants further investigation (Grier, Wickens, Kaber, Strayer, Boehm-Davis, Trafton, et al., 2008).

Consideration of the sizeable switch cost is especially important for situations that require individuals to monitor multiple goals and switch constantly between different activities under pressure (e.g., operators of human-machine interfaces, such as air traffic controllers). Operating a vehicle is a situation most individuals are faced with daily, and it poses one of the largest societal implications for task switching studies. Driver distraction from secondary activities (such having a handsfree cellphone conversation) significantly impacts performance in costly ways and is a major source of roadway injuries and deaths (Strayer, Turrill, Cooper, Coleman, Medeiros-Ward, & Biondi, 2015). Distracted driving can reduce the reaction times of younger adults to the same as their older counterparts (Strayer & Drews, 2004). The public, despite being largely aware of such dangers, and despite legislation on cellphone use, still frequently engage in distracted driving (Overton, Rives, Hecht, Shafi, & Gandhi, 2015). Such negative effects highlight a growing demand for research on preventative measures against distracted driving, and on relative effects of types of distraction. Not all types of distracted driving are equal. Activities with a low cognitive load (such as listening to music) may be less harmful than activities with a medium cognitive load (such as talking to someone in the car) or a high cognitive load (such as using a speech-to-text interfaced email system).

Studying task switching also offers insight into the development and decline of cognitive processes. A notable application for aging is the use of dual-task studies in which individuals perform motor and cognitive tasks. Older and younger adults perform differently in motor-cognitive dual tasks, and studying these differences has important implications for training balance and posture in aging (Li, Bherer, Mirelman, Maidan, & Hausdorff, 2018).

The current findings offer several implications to help with daily task switching. Environmental cues may be beneficial to lower the cost of switching. The findings showed that the utility of a cue is contingent on whether a cue is useful, with the cue having no effect when it does not signal a potential task change. Cues are relatively unaffected by aging, which maps on to previous findings that as individuals get older, they rely on environmental cues more, to compensate for aging-related decline in monitoring and holding goals in memory. However, this could also be problematic when cues are not helpful towards a goal or are even distracting.

The inevitable cost of switching, or even from anticipating a possible shift, should be taken into consideration. Writers often find value in blocking time to focus solely on a difficult task. In environments where switching is unavoidable, such as driving a vehicle, individuals could benefit from learning to use informative cues in the environment and minimizing distracting cues. Practice is beneficial in reducing a switch cost, as it leads to responding becoming mostly automatic and outside the need for intentional control. Maintaining overall readiness is also beneficial, especially when, as Study 1 showed, readiness is alerted for cues that could be informative.

Online environments are helpful for researchers who want to study human behaviour with large datasets. However, online environment could be detrimental in everyday life, as they offer more opportunities for task switching. As digital environments continue to create more opportunities for frequently jumping between tasks, individuals should be mindful of the price of doing so. Switching between multiple media (media multitasking) has seen a dramatic rise that accompanies the rise in usage of technology. Media multitasking is commonly employed in adults, but also in developing populations. Even infants and toddlers are saturated with digital technologies in their environments, creating a need for policy guidelines on media usage in younger populations (American Academy of Pediatrics, 2016). Concerned about the problematic effects on normal development, and risks about addiction, many technology executives are banning their children from using screens (Bowles, 2018; Condliffe, 2019).

Lab studies have consistently shown the costs of shifting between tasks during task switching and multitasking (Koch et al., 2018; Monsell, 2003). Experimental studies rarely confirm lay insights on the ways that people interact with media, or on the benefits of media multitasking. The drawbacks of media multitasking and a rise in automated technology have been consistently documented on outcomes such as academic success, cognitive performance, social aggression, ability to form relationships with others, anxiety, delay of emotional gratification, sleep deprivation, and overall health (Brasel & Gips, 2011; Kidron, Evans, Afia, Adler, Bowden-Jones, et al., 2018; Pool, Koolstra, & van der Voort, 2003; Wang & Tchernev, 2012).

A few cases suggest that regular practice in multitasking may improve an individual's ability to switch between tasks (Alzahabi & Becker, 2013; Koch et al., 2018). On the other hand, most self-proclaimed frequent multitaskers often perform poorly at doing either task (Brasel & Gips, 2011; Sanbonmatsu, Strayer, Medeiros-Ward, & Watson, 2013). Frequent multitaskers are also more prone to interference from irrelevant environmental stimuli and memory representations (Ophir, Nass, & Wagner, 2009). Such reports need to be confirmed with controlled studies that manipulate media multitasking in a lab setting. As with different types of distracted driving, research efforts should aim for granular insights on the types of media multitasking, such as the different ways in which screens can be used, and on the potential effects on passive viewers situated near the active screen user.

One controlled experiment showed that the effects of media multitasking are so pervasive that they influence in-classroom learning not only for multitasking individuals, but also for peers in view of the multitaskers (Sana, Weston, & Cepeda, 2013). Another controlled experiment that simulated talking on a cellphone showed that a mere 2.5% of the population were 'supertaskers', and could multitask efficiently (Watson & Strayer, 2010). These striking findings demonstrate how online environments pose new research frontiers for studying the benefits and drawbacks of media multitasking.

5.5 Conclusions

Given the central role of adaptive responding in everyday life, research on task switching offers a lot of promise in understanding goal-directed behaviour. The current findings provide clear unequivocal evidence that switching between two tasks results in inferior performance compared to blocked periods of performing each task separately. This dissertation has added to the literature to show that several processes contribute to a switch cost, each of which incurs an expense of time and accuracy when shifting between competing goals. Moreover, each of these processes varies with age, and they can adapt to maintain performance over the lifespan. More generally, the methods used in this dissertation support online data collection, effect size estimation, and segmented regression as effective techniques to study lifespan cognition. Whether it means limiting conversation when driving a car, or blocking off periods of uninterrupted time when writing a dissertation or research paper, the sizable cost of alternating tasks illustrates that performing a single task at a time will lead to the fastest, and the most accurate, performance.

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