An Integrated Theory of Intermediate Representations in Multitasking

In which we present our final theory of how intermediate representations are processed in the mind, and how this results in multitasking interference.
Abstract

In this article we propose an integrated theory of how intermediate representations – e.g., ‘3x = 24’ when solving ‘3x – 6 = 18’ – are processed in human multitasking. The theory, working memory in multitasking (WMM), suggests that working memory limitations are an important cause of multitasking interference. WMM states that (a) at most a single intermediate representation can be stored without decay in the so-called problem state resource, (b) representations that are not currently in the problem state resource are temporarily stored in a declarative memory store that is subject to decay, and (c) the concurrent use of multiple representations for different tasks therefore leads to interference. We will review previously published studies and present three new experiments to support the three major aspects of the theory: a single-sized problem state resource, involvement of a declarative memory store that is subject to decay, and the strategic use of intermediate representations and the environment. In addition, we will present computational models that show that the WMM theory gives a quantitative account of the observed interference effects.
Introduction

Anyone who has observed a car drifting out of its lane because the driver tries to enter a new destination in the navigation device is familiar with the negative effects that multitasking can have on performance. As early as 1931, Telford investigated interference due to human multitasking. He introduced the psychological refractory period (PRP) paradigm, and showed that people are slower to respond to the second of two tasks when these tasks have to be performed concurrently. In addition to concurrent multitasking, theorists have recently started looking at the detrimental effects that sequential multitasking (interleaving tasks) can have (e.g., Altmann & Gray, 2008; González & Mark, 2004; Monk et al., 2008; Monsell, 2003). However, both in concurrent and sequential multitasking, most studies have focused on relatively simple tasks that do not require maintaining information. In real-world tasks, which often involve multitasking, maintaining and using intermediate information is typically an important part of the task. In the current article we will therefore focus on the use of intermediate information in multitasking. We will show that the use of intermediate representations – for example $3x = 14$ when solving $3x - 5 = 9$ – is an important cause of multitasking interference, both in concurrent and sequential multitasking. To account for this kind of interference we will propose a computational theory, Working Memory in Multitasking, which yields quantitative predictions of multitasking interference due to the use, storage, and retrieval of intermediate representations.

Background

Since Telford (1931), many theories have been put forward to explain interference effects in multitasking (see for overviews, Meyer & Kieras, 1997a; Salvucci & Taatgen, 2008). Theories on multitasking can be divided into three general groups: bottleneck theories, resource theories, and cognitive control theories. Bottleneck theories assume fixed bottlenecks in human cognition that can only process one task at a time, causing interference when used by multiple tasks concurrently (e.g., Broadbent, 1958; Keele, 1973; Pashler, 1994; Welford, 1952). Theorists have identified several different bottlenecks, ranging from perceptual bottlenecks (e.g., Broadbent, 1958), to response-selection bottlenecks (e.g., Pashler, 1984; 1994), to motor bottlenecks (e.g., Keele, 1973). To unify these different bottleneck accounts, resource theories were introduced. These theories assume that attention can be flexibly employed, and that multitasking interference occurs when cognitive resources are required by multiple tasks at the same time, but not when tasks require different resources (e.g., Kahneman, 1973; Navon & Gopher, 1979; Wickens, 1984, 2002). A third research tradition focuses on executive processing and cognitive control to explain multitasking interference (e.g., Baddeley, 1986; Cooper & Shallice, 2000; Meyer & Kieras, 1997a, 1997b; Norman & Shallice, 1986). In these theories, multitasking interference arises because of scheduling problems between tasks. That is, while tasks could in principle be carried out concurrently, executive control mechanisms enforce a certain task order, leading to interference. Using a cognitively bounded rational analysis, Howes, Lewis, and Vera (2009) have recently shown that...
any theory of the classical PRP effect (Schumacher et al., 1999; Telford, 1931) should contain cognitive control mechanisms, a motor bottleneck, and a response-selection bottleneck.

The recently proposed threaded cognition theory of multitasking indeed incorporates these elements (Salvucci & Taatgen, 2008, 2011; Salvucci, Taatgen, et al., 2009). Threaded cognition is a general theory of human multitasking that was proposed to integrate all findings to date. It assumes multiple different bottlenecks, and states that while multiple tasks can be performed concurrently, every resource in human cognition can only process one task at a time and therefore acts as a bottleneck when required by multiple tasks concurrently. Depending on the requirements of the tasks at hand, these bottlenecks lead to different patterns of interference. For instance, when two tasks need to retrieve a fact from declarative memory at the same time, threaded cognition predicts that one of the tasks will have to wait for the other task, resulting in multitasking interference. While all resources are singular in nature, the resources themselves act in parallel (cf. Byrne & Anderson, 2001). This implies that no multitasking interference will occur as long as tasks have different resource requirements (i.e. perfect time sharing, Anderson, Taatgen, et al., 2005; Hazeltine, Teague, & Ivry, 2002; Schumacher et al., 2001).

In was shown that threaded cognition can account for interference caused by two peripheral bottlenecks (vision, motor) and two cognitive bottlenecks (procedural and declarative memory; Salvucci & Taatgen, 2008; cf. Howes et al., 2009). In addition, based on its integration in the cognitive architecture ACT-R (e.g., Anderson, 2007), one more source of multitasking interference was predicted: the so-called problem state resource. The problem state resource is used to store intermediate representations that are necessary for performing a task. For example, when calculating ‘2 + 3 ∑ 4’ mentally, one might use the intermediate representation ‘2 + 12’. According to the ACT-R theory, only a single intermediate representation can be maintained at a time, which should therefore lead to interference when multiple representations are required concurrently. Recently, we provided support for this prediction with a series of experiments (Borst, Taatgen, & Van Rijn, 2010). In a dual-task paradigm, subjects either needed zero, one, or two intermediate representations to perform the tasks. We showed that performance decreased considerably when subjects needed two intermediate representations at the same time, as compared to when subjects needed zero or one representations. To account for these results we developed a cognitive computational model. This model showed that both the increase in response times and the decrease in accuracy could be explained by a so-called problem state bottleneck.

Current Article

In the current article we will present an integrated theory of how intermediate representations are used in multitasking: the Working Memory in Multitasking theory (WMM). While we have previously shown that the use of multiple intermediate

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1 The imaginal buffer in ACT-R terminology.
representations at the same time leads to multitasking interference, we did not investigate how the problem state bottleneck interacts with other elements of human cognition. We will now show that the interplay of the problem state resource, a declarative memory store, and the environment can explain a much wider range of human multitasking phenomena. In the remainder of this article we will first explain the WMM theory in detail. We will then provide supporting data for three major aspects of the theory in the following three sections of the paper. Finally, we will discuss the wider implications of the WMM theory.

Working Memory in Multitasking: An Integrated Theory of Intermediate Representations in Multitasking

In this section we will describe the WMM theory, which accounts for the use of intermediate representations in multitasking and the interference that can result from using them. WMM was implemented in the cognitive architecture ACT-R (e.g., Anderson, 2007; Anderson, Bothell, et al., 2004), to enable quantitative predictions of response times, errors, and neuroimaging data (see Cooper, 2007; Meyer & Kieras, 1997a; Newell, 1973; 1990 for discussions on the advantages of cognitive architectures). Using a cognitive architecture also has the advantage that interactions between central cognitive processes and perception automatically result from the modeling effort, which is crucial for modeling interactions between (often complex) tasks in multitasking (e.g., Kieras & Meyer, 1997; Van Maanen et al., 2009). We will now first discuss the main components of the WMM theory, followed by how it accounts for multitasking interference.

Main Components:

The Problem State Resource and Declarative Memory

Figure 6.1 shows the main components of the WMM theory: the problem state resource and declarative memory. These elements are based on the corresponding elements in ACT-R (e.g., Anderson, 2007). The problem state resource is used to maintain intermediate representations in a task and can maintain a single intermediate representation at a time. It is assumed that a representation in the problem state resource can be used instantly, without incurring a time cost. However, it was estimated that it takes about 200 ms to store a representation in the problem state resource (e.g., Anderson, 2005). When a representation is stored in the problem state resource, its previous contents are automatically encoded in declarative memory. Representations in the problem state resource can originate from three sources: a representation can be perceived, it can be retrieved from declarative memory, or it can be the outcome of a cognitive process.

The code of models described in this article can be downloaded from http://www.jelmerborst.nl/models.
The concept of the problem state resource stems from a series of neuroimaging experiments by Anderson and colleagues, who found that activity in the posterior parietal cortex correlates with the number of transformations of mental representations (Anderson, 2005; Anderson, Albert, et al., 2005; Anderson et al., 2003; Sohn et al., 2005). A region in the posterior parietal cortex (Montreal Neurological Institute, MNI, coordinates: -24, -67, 44; roughly indicated in Figure 6.1) is hypothesized to reflect changes to the problem state resource, while a region in the prefrontal cortex (43, 24, 25) is supposed to reflect retrieving information from declarative memory (e.g., Anderson, 2007; Anderson et al., 2008; Borst, Taatgen, Stocco, et al., 2010).

The second major component of the WMM theory is the involvement of a declarative memory store. To this end, we used ACT-R’s declarative memory store, which simulates short and long term storage of facts. In contrast to the problem state resource, it contains multiple memory items. Each item has a certain activation level, representing the strength of the item in memory. Activation of an item reflects its frequency and recency of use, and decays with a power function (Anderson & Schooler, 1991). An item that has been used more frequently in the past will have a higher activation level, as will an item that has been used more recently. The base-level activation $B_i$ of an item at time $t$ is calculated with the following equation:

$$B_i(t) = \ln \left( \sum_{k=1}^{n} (t - t_k)^{-d} \right)$$  \hspace{1cm} (6.1)

in which $t_1, ..., t_n$ indicate moments in time when the item has been (re-)created or used. The ACT-R literature has reached consensus on a value of .5 for $d$, the decay parameter. Thus, for each memory trace $k$ of an item, the activation is calculated (based on how long ago $k$ was and the decay value: $(t - t_k)^{-d}$); those activation values are summed to calculate the final activation value of an item.

Retrieving information from declarative memory is not always successful: it can either fail altogether (because activation is below the predefined retrieval threshold) or a similar but incorrect element can be retrieved (e.g., ‘$15 - 7 = 8$’ when trying to retrieve a fact containing ‘$15 - 8$’). This is implemented in the ACT-R theory as a process of partial matching: items can be retrieved when they do not match a retrieval request completely, in which case their activation receives a mismatch penalty (see for details of partial matching, Anderson et al., 1996; Lebiere, 1999; Taatgen & van Rijn, 2011).

When retrieval of an item from declarative memory is attempted, activation of memory items is calculated with:

$$A_i = B_i - MP_i + \epsilon$$ \hspace{1cm} (6.2)

in which $B_i$ is the base level activation of an item calculated with Equation 1, $MP_i$ the mismatch penalty the item receives, and $\epsilon$ noise drawn from a logistic distribution. Because the item with the highest activation is retrieved, noise will sometimes result in the retrieval of an incorrect (but similar) item. The probability of retrieving an incorrect

\[^3\] ACT-R’s complete activation equation also incorporates spreading activation (see e.g., Anderson, 2007). As spreading activation does not play a role in the current article we simplified the equation.
item depends on the activation difference between items: the closer the activation levels of two items, the higher the chance that an incorrect item will be retrieved.

Retrieving an item from declarative memory takes time. The duration of a retrieval depends on the activation level $A_i$ of the item:

$$RT = Fe^{-A_i}$$

in which $F$ is a latency scale factor (normally set between .1 and 2, Anderson et al., 1998). Thus, the higher the activation level of an item, the faster it will be retrieved from memory.

Summarizing, the main components of the WMM theory are a single-sized problem state resource and the use of a declarative memory store with memory items that are subject to decay.

**Multitasking Interference**

The WMM theory was developed to account for multitasking interference. Figure 6.2 illustrates the origin of multitasking interference in the theory. A dual-task situation is depicted, in which two tasks are alternated (this can be quick or slow alternation, depending on the duration of the ‘General Task Actions’). Panel A shows a situation in which neither Task 1 nor Task 2 needs an intermediate representation, for example drinking coffee while casually listening to music. Only general, non-problem state related
Problem State Resource and Declarative Memory usage in Dual-Task Situations

A) No Representation Situation: Neither task uses the Problem State Resource

B) Single Representation Situation: Only Task 1 uses the Problem State Resource

C) Multiple Representations Situation: Task 1 & 2 both use the Problem State Resource

Figure 6.2 Multitasking interference in the WMM theory.
actions are performed for both tasks. There is thus no intermediate representation related multitasking interference in this situation.

Panel B shows a situation in which only Task 1 needs an intermediate representation. For instance, writing an article and taking a sip of coffee. At the start of Task 1, a representation – say, a reference that has to be included in the current paragraph – is stored in the problem state resource, which takes 200 ms. This representation can then be used by the ‘General Task 1 actions’: writing a paragraph. When the switch to Task 2 occurs, the problem state resource is not overwritten, because Task 2, drinking coffee, does not need an intermediate representation. After the next task switch, Task 1 can therefore still use its representation, and continue writing where it left off. Again, as in Panel A, there is no multitasking interference due to the use of intermediate representations.

Panel C of Figure 6.2 depicts the situation in which multitasking interference occurs: both tasks need an intermediate representation. For example, being interrupted by a phone call while writing an article. Also in this situation a representation for Task 1 is stored in the problem state resource at the start of the dual-task. However, Task 2 now also needs to use the problem state resource, and therefore stores its own intermediate representation – the topic of the call – after the switch from Task 1. By doing so, the representation of Task 1 is automatically encoded in declarative memory, where its activation starts to decay. After Task 2 finished its General Task 2 actions and the call is terminated, Task 1 recommences. However, before it can start, it first has to restore its intermediate representation from declarative memory – the reference that was relevant for the current paragraph.

This process is shown in detail in Figure 6.3. First, Task 1 notices that the problem state resource has the wrong contents, and it starts retrieving its own representation from declarative memory. This retrieval takes a certain amount of time, depending on how long ago the intermediate representation was encoded in declarative memory: the
longer ago it was encoded, the longer it will take to retrieve it (calculated with Equations 6.1–6.3). When the representation is recalled, the command to restore it to the problem state resource is issued, and it is restored. Only then can Task 1 start its normal actions.

Thus, starting Task 1 after Task 2 in situation C takes 2 × 50 ms (procedural memory firing time; e.g., Anderson, 2007) + 200 ms (default value of storing an item in the problem state resource) + the retrieval time of the intermediate representation from declarative memory = at least 300 ms longer, as compared to situations A and B. The exact length of the interference depends on the duration of Task 2: the longer Task 2, the more the representation of Task 1 will have decayed in declarative memory, the longer it will take to retrieve it. This is depicted in Figure 6.4: panel A shows the decay of the intermediate representation in declarative memory while the intervening task is performed (in this case Task 2), while panel B shows the effect on the time cost of recommencing the first task. The basic costs represent the 300 ms of procedural memory usage and restoring the problem state resource. The other costs are influenced by the latency factor \( F \) (Equation 6.2), which was set to .3 for all models in this article.

The duration of the intervening task does not only increase the time cost of restarting the first task, it also increases the probability of not being able to retrieve the intermediate representation of Task 1 at all, because its activation dropped below the retrieval threshold due to decay. This would either lead to errors because of guessing, or, when possible, to reconstructing the representation from the environment, which has its own associated costs. Even if the model retrieves a representation from memory, a less active intermediate representation will also make it more likely that a similar but incorrect representation is retrieved (see the text on partial matching and noise above).

Summarizing, the WMM theory predicts that as long as at most one intermediate representation is required no interference will occur. However, as soon as more than one representation is needed, it predicts interference both in response times and errors due...
to a single-sized problem state resource. Moreover, the interference costs increase with the duration of the intervening task, because representations in declarative memory are subject to decay.

**Strategic use of the Problem State Resource and the Environment**

The WMM theory explains how mentally maintaining intermediate representations can lead to multitasking interference. However, Figure 6.1 shows that an intermediate representation can also originate in perception, opening up the possibility to use the environment as an external memory, and thereby avoiding the limits of the problem state resource. For example, when solving a multicolumn subtraction problem on paper it is not uncommon to indicate whether a carry is in progress, which decreases the problem state resource requirements. Even when one relies on memory, and stores the carry in the problem state resource, there are two possible strategies to continue after losing the representation due to an interruption: recalling whether a carry was in progress from declarative memory, or reconstructing it by recalculating the previous column. While reconstruction is the safer option, it is also likely to take more time than recall from memory.

We assume that these are strategic processes: when reconstructing or perceiving a representation from the environment takes less time than a cognitive ‘in-the-head’ strategy (using the problem state resource as it is, or retrieving it from memory), humans will use the environment, otherwise they will use a cognitive strategy. This is in accordance with the Soft Constraints Hypothesis, which proposes that our strategy choices aim at minimizing temporal costs instead of, for example, mental effort (Gray & Fu, 2004; Gray, Sims, Fu, & Schoelles, 2006). To support this, Gray et al. showed in four experiments that subjects always used the fastest local strategy, instead of minimizing mental effort or total time-on-task. Even when minimizing local time led to suboptimal behavior (using fast but imperfect knowledge in-the-head vs. slower but perfect knowledge in-the-world) or to more memory effort (memorizing multiple facts instead of perceptually revisiting a display), subjects opted for the fastest method (that is, the fastest local method, as this often relied on imperfect knowledge in-the-head it could lead to mistakes and longer total time-on-task). The assumption of the WMM theory is that the Soft Constraints Hypothesis also holds for processing intermediate representations, and therefore that people always choose the fastest way of performing a task, whether that is using the problem state resource, declarative memory, or the environment.

**Overview of the Article**

In the remainder of this article we will provide support for the following three aspects of the WMM theory:

- the single-sized problem state resource, leading to multitasking interference when more than one representation is required for a task;
• the involvement of a declarative memory store with decay, leading to more interference with longer task interruptions;
• the strategic nature of using the problem state resource, declarative memory, and the environment.

We will discuss support for these aspects of the theory in the next three sections of this article.

The Single Element Size of the Problem State Resource

In this section we will review an experiment that supports the assumption that the problem state resource can contain at most one representation at a time. The experiment shows that using the problem state resource for two tasks at the same time leads to interference. In addition to the behavioral data we will also present model fits, to show that the WMM theory can account for the patterns in the behavioral data. The experiment has been published before as Experiment 1 in Borst, Taatgen, and Van Rijn (2010).

To test whether the problem state resource can at most contain a single intermediate representation, a dual-task experiment was designed in which subjects had to alternate between solving multi-column subtraction problems and entering text. Both tasks had two versions: an easy version in which no intermediate representations were required and a hard version in which subjects needed intermediate representations to perform the task. The experiment had a 2 × 2 factorial within-subjects design: Subtraction Difficulty (easy/hard) × Text-Entry Difficulty (easy/hard).

Experimental Design

Figure 6.5 shows a screenshot of the experiment. On the left side of the screen subjects had to solve 10-column subtraction problems in standard right-to-left order. In the easy version of the subtraction task the lower term was always smaller or equal to the upper term in each column, meaning that subjects never had to carry between columns. In the hard version (depicted in Figure 6.5) subjects had to carry in 6 out of 10 columns. The assumption is that subjects used their problem state resource to keep track of whether a carry was in progress.

On the right side of the screen subjects had to enter 10-letter strings using the mouse. In the easy, no problem state version these strings were presented letter by letter (an ‘I’ is presented in Figure 6.5). Subjects had to click on the corresponding button, after which the next letter appeared. In the hard version subjects had to enter 10-letter words without feedback. That is, at the start of a trial a complete 10-letter word was presented, but as soon as they clicked on the first letter, the word disappeared (i.e. subjects could neither see what word they were entering, nor what they had already entered). It was assumed that subjects used their problem state resource to maintain the word and the position in the word (e.g., ‘information, 4th letter’).
The interesting part of the experiment is that subjects had to alternate between the two tasks after every digit and letter. Thus, they had to maintain the intermediate representations – the carries and words – while giving a response on the other task. According to the WMM theory, this should result in interference in the hard subtraction – hard text-entry condition, because then the problem state resource has to be swapped out on each step in a trial as it can only contain a single element (situation C in Figure 6.2). In all other conditions at most one intermediate representation is required to do the tasks, which, according to the theory, does not result in interference (easy – easy: Figure 6.2A, easy – hard and hard – easy: Figure 6.2B). See Borst, Taatgen, and Van Rijn (2010) for further details of the methods.

Results

Figure 6.6 shows the results of the experiment (black bars). The top two panels show the response times, the bottom panels accuracy. As predicted by the WMM theory, both in the text-entry task (left) and in the subtraction task (right) there is a clear increase in response times in the hard-hard condition as compared to all other conditions. In the response times of the subtraction task there is also a clear effect of subtraction difficulty: response times increase when subtraction becomes hard. However, in the hard-hard condition response times are even higher. These results were confirmed by
significant interaction effects between Subtraction Difficulty and Text-Entry Difficulty for both tasks.

In the accuracy data (Figure 6.6, lower panels, black bars) similar effects were observed. Accuracy decreased with task difficulty of the tasks itself, but even more in the hard-hard conditions. For instance, in the subtraction task subjects hardly made any mistakes as long as subtraction was easy. When subtraction was hard the amount of mistakes increased, but it increased even more when text-entry was hard as well. The same effects can be seen in the text-entry data. Statistically, the interaction effect between Subtraction Difficulty and Text-Entry Difficulty was significant for the subtraction task, and it showed a trend towards significance for the text-entry task.

**Model**

To see whether a single-sized problem state resource could have caused the effects in the data, we implemented a computational model of the task. The grey bars in Figure
6.6 show the results. Based on general characteristics of ACT-R, response times and accuracy data in the easy-easy, hard-easy, and easy-hard conditions were estimated (see for details, Borst, Taatgen, & Van Rijn, 2010). The WMM theory adds the interference effects in the hard-hard condition: increased response times and decreased accuracy. The increased response times are accounted for by swapping the contents of the problem state resource on each step of a trial, as explained above (Figure 6.2C). The model produces the decrease in accuracy by sometimes retrieving an older, incorrect representation from memory when swapping the problem state resource.

Discussion

The experiment was performed to test whether the problem state resource can contain a single or multiple intermediate representations. As predicted, the data show that when more than one representation is needed concurrently, performance decreases considerably. The model fit shows that the WMM theory can account both for the effects on response times and on accuracy.

One thing to note is that, instead of using a mental strategy, it is possible to reconstruct the intermediate representation of the subtraction task by reprocessing the previous column (see Figure 6.5). If subjects had used this strategy in all conditions, we would not have found a difference between the hard subtraction – easy text-entry and the hard subtraction – hard text-entry conditions. However, it is conceivable that subjects reconstructed the intermediate representation in the hard-hard condition, but not in the hard-easy condition. This would have resulted in the same effects on response times: response times would have been higher in the hard-hard condition because of the costs of reconstructing the representation. We controlled for this in Experiment 3 in Borst, Taatgen, and Van Rijn (2010) and in several other experiments (e.g., Borst, Taatgen, Stocco, et al., 2010) by masking previous columns. These experiments yielded comparable results as the current experiment. This is in accordance with the prediction of the WMM theory that reconstruction via the environment only takes place when it takes less time than recalling a representation from memory, as the model predicts that reconstruction would take longer than the observed interference effect of 400 ms (see for more on the strategic use of the problem state resource the section ‘The Strategic Nature of using the Problem State Resource and the Environment’ below). Furthermore, reconstruction would not have explained the effects in the accuracy data: there is no reason why accuracy would be lower in the hard-hard condition in that case.

The presence of interference in the hard-hard condition indicates that the difficulty of one task affects both tasks. The simplest explanation for this interference is a resource that is shared by both tasks. As the tasks are never performed concurrently, this is probably a resource that is used while doing the other task. The obvious candidate for that is the resource that maintains intermediate information required by the tasks, the problem state resource in the WMM theory. According to the theory, the interference effects in the data are caused by swapping out a single-sized problem state resource. However, there are at least two alternative explanations to explain the data of this experiment: memory load (e.g., Logan, 1979; Woodman et al., 2001) and a
phonological loop bottleneck. To test these possibilities, Borst, Taatgen, and Van Rijn (2010) conducted two additional experiments. These experiment clearly showed that these alternatives did not hold, and they concluded that a single-sized problem state resource was the most likely explanation of the results.

Summary

In this section we set out to support the assumption of the WMM theory that the problem state resource can only maintain a single representation at a time. The experiment that we reviewed showed that when subjects had to maintain more than one representation at a time, considerable interference occurred. These results are in line with the WMM theory, and imply a single-sized problem state resource.

The WMM model showed a nice fit to the results: it predicted interference effects both in response times and accuracy data, which were indeed observed. Fitting the model to the data showed that it could also account for the size of the effects. This is not surprising, given that there are two parameters that determine the size of the time cost. Figure 6.4 shows that this time cost is determined by the basic costs and the declarative memory latency factor \( F \), which scales the time of retrieving a representation from declarative memory. To fit the model to the data we set the latency factor \( F \) to .3 for both experiments.

In the next section we will look at the assumption of the WMM theory that there are two separate memory stores involved in processing intermediate representations: the problem state resource and a declarative memory store.

Two Memory Stores for Intermediate Representations

In the previous section, we reviewed an experiment that supports a single-sized problem state resource. According to the WMM theory, this single-sized problem state resource is a separate resource from declarative memory. Where declarative memory is assumed to consist of multiple elements that take time to retrieve and are subject to decay, the problem state resource can only contain a single element, which is directly accessible and not susceptible to decay. In this section we will discuss support for this assumption. We will first review fMRI data that shows that problem state activity is best represented in a different brain area than declarative memory activity, supporting the view of two separate memory stores. We will then turn to two new experiments, that show that (1) the WMM theory explains interference effects of interruptions, and (2) a declarative memory resource with decay is needed to account for these effects, in addition to a single-sized problem state resource.

Neuroimaging Evidence for Two Separate Memory Stores

To investigate the neural correlates of the WMM theory we conducted two fMRI experiments. Based on ACT-R’s predefined resource-brain mapping (e.g., Anderson,
Two Memory Stores for Intermediate Representations

2007; Anderson et al., 2008), we first conducted confirmatory region-of-interest analyses. These analyses showed that the WMM theory could make plausible \textit{a priori} fMRI predictions (Borst, Taatgen, Stocco, et al., 2010; Borst, Taatgen, Van Rijn, Stocco, & Fincham, 2009). These predictions were based on the assumption that declarative memory and the problem state resource are separate entities, and that they are reflected by activity in different brain areas (e.g., Anderson et al., 2007). To test this assumption, we subsequently applied a novel exploratory fMRI analysis method to the data (Borst, Taatgen, & Van Rijn, 2011). This method, termed \textit{model-based fMRI}, confirmed that the problem state resource and declarative memory are best represented by two different brain areas (posterior parietal and prefrontal cortex, respectively). We will now discuss this experiment and analysis in more detail.

\textbf{Design}

To investigate the neural correlates of the WMM theory, we conducted the subtraction – text-entry experiment in an fMRI scanner. That is, the interface was adapted to minimize eye- and head-movements, and all responses now had to be given with a mouse, but the basic task remained unchanged. Thus, subjects had to constantly alternate between solving 10-column subtraction problems (of which only one column was shown at a time in this experiment) and entering 10-letter strings. Both tasks again had an easy, no intermediate representation condition, and a hard condition with intermediate representations (see for details, Borst, Taatgen, Stocco, et al., 2010).

\textbf{Analysis}

The behavioral data showed similar effects as the data reviewed above, further corroborating the single-sized problem state resource hypothesis (Borst et al., 2011). To analyze the fMRI data, we applied a novel fMRI analysis technique, which has previously been used to investigate the neural mechanisms of reinforcement learning (e.g., Gläscher & O’Doherty, 2010; O’Doherty et al., 2007). Instead of regressing the conditions of the experiment against the experimental data, as is traditionally done in fMRI research (e.g., Friston et al., 2007), we regressed the activity of the model’s resources directly against the fMRI data.

To that end we first fitted the WMM model to the behavioral data: We performed model simulations of each individual subject, using the same stimuli, in the same order, as the subject received. In addition, we lined up the key-presses of the model to the key-presses in the data, resulting in a perfect model-behavioral data fit. We then convolved the activity of the model’s resources with a hemodynamic response function (describing the sluggish brain response that is measured with an fMRI scanner; e.g., Friston et al., 2007), and entered the resulting signal into General Linear Models (GLM). This results in regressing the model’s resource activity directly against the brain activity in all voxels of the brain, and shows which voxels correlate significantly with the predicted activity of the model’s resources. Thus, it shows where in the brain the resources of a model are most likely represented.
Results

Figure 6.7 shows the model activity and the predicted hemodynamic response for the problem state resource and declarative memory over the course of four trials (note that this is just an example, the exact signal was different for each trial depending on the stimuli in a trial; a trial constitutes solving a complete subtraction problem and entering a 10-letter string). The grey line shows the activity of the resources. The problem state resource is not used in the easy-easy condition, used for one of the tasks in the easy-hard and hard-easy conditions, and used most in the hard-hard condition: not only is it used for both tasks, but its contents are also swapped on each step of a trial. Declarative memory shows a very similar pattern. First, declarative memory is hardly used in the easy-easy condition (as the subtraction task only requires simple, and thus fast, retrievals, e.g., ‘5 – 2 = 3’). Second, we see increased levels in the hard subtraction – easy text-entry condition, because in that condition additional retrievals are necessary for processing the carries (e.g., ‘5 – 8 = -3’, but also ‘15 – 8 = 7’). Third, declarative memory is used for the spelling processes of the words in the text-entry task (Borst, Taatgen, Stocco, et al., 2010; Borst, Taatgen, & Van Rijn, 2010), resulting in increased levels in the easy subtraction – hard text-entry condition. Finally, it is used most in the hard-hard condition, on the one hand for the tasks themselves, and on the other hand for retrieving a representation to reconstruct the contents of the problem state resource on each step of a trial. The black line in Figure 6.7 shows the convolution of the resource activity with the hemodynamic response function, yielding a very detailed prediction of brain activity (such a prediction was made for all subjects over all trials in the experiment). This signal was subsequently regressed against the brain data: showing which areas of the brain correlate significantly with these predicted signals. As the predictions for the problem state resource and declarative memory were very similar, it was relatively unlikely to find different brain areas for these resources.
Two Memory Stores for Intermediate Representations

Figure 6.8 shows the results. The best fitting area for the problem state resource was located in the inferior parietal lobule, around the intraparietal sulcus (Borst et al., 2011). This area has not only been linked to ACT-R’s problem state resource in the past (e.g., Anderson, 2005; Anderson, Albert, et al., 2005; Anderson et al., 2003; Sohn et al., 2005), but has also been found in other studies on working memory (e.g., LaBar et al., 1999; Smith et al., 1998; Wager & Smith, 2003). Declarative memory correlated best with a region in the prefrontal cortex, around the inferior frontal gyrus. This area is known to be involved in retrievals from memory (e.g., Cabeza et al., 2002; Fletcher & Henson, 2001; Wagner et al., 2001). Furthermore, when we lowered the significance threshold, it became apparent that both areas are part of a larger fronto-parietal network, a network that is often implicated in working memory research (e.g., Collette et al., 2006; Collette & Van der Linden, 2002).

Discussion

While the predicted hemodynamic response functions of the problem state resource and declarative memory were quite similar, the current analysis shows that they correlate best with different areas in the brain (see for a detailed discussion of the power of model-based fMRI, Borst et al., 2011). That we found two significant, spatially quite different areas, suggests that the functions of those resources are indeed best represented by two separate memory stores as the WMM theory assumes. In this scheme, the problem state resource is used for maintaining and updating a single intermediate representation for the task at hand, while declarative memory is used for storage of information when it is not directly available.

If it is indeed the case that intermediate representations are swapped in and out of the problem state resource via declarative memory, we should find a typical declarative memory effect on these representations in memory: decay. In the next section we will discuss two experiments that test this prediction.
Interuption Experiments: Decay in Declarative Memory

One major assumption of the WMM theory is that intermediate representations are swapped in and out of the problem state resource via declarative memory. Because the activation of a representation in declarative memory decays while an intervening task is performed (Figure 6.2C), this leads to the prediction that the longer an intervening task lasts, the higher the costs of restoring an intermediate representation will be (see Figure 6.4). To test this prediction, we conducted two ‘interruption experiments’ (e.g., Gillie & Broadbent, 1989).

It is well known that interruptions of a task lead to a decrease in performance (e.g., Gillie & Broadbent, 1989; McFarlane & Latorella, 2002). Two important factors that determine the disruptiveness of interruptions are the duration and the complexity of the interrupting task. The longer the interrupting task, the longer it takes to resume the primary task (Hodgetts & Jones, 2006; Monk et al., 2008), and the more complex the interrupting task, the longer the resumption time (e.g., Gillie & Broadbent, 1989; Hodgetts & Jones, 2006; Monk et al., 2008; Zijlstra, Roe, Leonora, & Krediet, 1999). This maps well onto the WMM theory, if we assume that an important factor in the disruptiveness of interruptions is the loss of intermediate representations of the primary task and subsequent decay of these representations in memory. According to the WMM theory, intermediate representations of the primary task would only be disturbed when the interrupting task is sufficiently complex to need an intermediate representation for itself, at least partly explaining the complexity effect. At the same time, the longer the interrupting task, the further a representation would have decayed in declarative memory, leading to increased resumption times. The latter idea is similar to the memory for goals model (Altmann & Trafton, 2002; Salvucci, Monk, et al., 2009; Trafton et al., 2003).

The hypothesis that intermediate representations are an important factor in the disruptiveness of interruptions leads to an interesting new prediction: the duration of an interruption should only influence the resumption time of the primary task if both tasks need an intermediate representation. If the primary task does not need an intermediate representation, there should be no resumption costs other than costs for re-attending the task, and these costs should not increase with the duration of the interruption. If the secondary task does not need an intermediate representation, the same holds: an intermediate representation of the primary task can now be maintained throughout the interruption, enabling the primary task to be continued directly after the interruption (cf. Figure 6.2B). Only when both tasks need an intermediate representation (Figure 6.2C), there should be an increase of resumption costs with the length of the interruption, in addition to the extra costs of restoring the representation to the problem state resource itself (basic costs in Figure 6.4).

To test this prediction we conducted two interruption experiments. In these experiments we interrupted a primary task with a secondary task. As before, both tasks had two conditions: an easy condition that did not require an intermediate representation, and a hard condition that did require the use of an intermediate representation. In addition, we now varied the length of the interruptions, to test
whether the costs of restoring a representation increase with the duration of an interruption. If that were the case, it would imply that intermediate representations are indeed swapped in and out of the problem state resource via a declarative memory store that is subject to decay.

**Interruption Experiment 1: Text-Entry and N-Back**

In the first interruption experiment, we used the text-entry task from the previous experiments as the primary task, and interrupted it twice every trial with a so-called n-back task. Figure 6.9 shows the setup of the experiment: subjects started with the text-entry task, which was unpredictably interrupted by the n-back task. After doing a varying number of steps in the n-back task, the text-entry task recommenced.

The text-entry task was the same task as described earlier: in the easy condition subjects were presented with a letter, they had to click on the corresponding button, followed by the next letter, etc. In the hard version, subjects had to enter a 10-letter word without feedback.

In the n-back task (Kirchner, 1958), a rapid stream of digits was sequentially presented to the subjects (Figure 6.9). Each number was on the screen for 1100 ms, followed by a mask (a #-mark) for 233 ms. In the easy, no representation condition, subjects had to do a 1-back task: they had to indicate whether the current number was the same or different as the previous number. A response had to be made while the stimulus was

![Figure 6.9 Setup of Interruption Experiment 1, in which the text-entry task is interrupted by an n back task. The figure shows the easy text-entry – easy n-back condition, with a 4 second interruption.](image-url)
shown, within 1100 ms. No response was required to the first number. As the presented
mask was very short, this did not require the use of an intermediate representation:
subjects could simply judge whether the shape was the same or different before and
after the short mask. In the hard version of the task, subjects had to do a 2-back task:
they had to judge whether the current number was the same as two numbers back. In
this condition no response was required on the first two steps in the n-back task. Now
subjects had to use intermediate representations to perform to the task: they constantly
had to keep track of what the number two back was. When subjects made a mistake
on the n-back task, a loud buzzer sounded, reminding the subject to focus on the task.

Each text-entry trial (entering a 10-letter string) was interrupted twice by the n-back
task. The points of interruption were varied between the 2\textsuperscript{nd} letter and the 9\textsuperscript{th} letter,
that is, subjects always started, and also ended, with typing at least two letters in the
text-entry task. There were also at least two letters between the two interruptions. This
gave 15 different trial-types: the points of interruption were therefore unpredictable
to the subjects. The length of the interruptions was 3, 6, or 9 n-back steps, thus 4, 8,
or 12 seconds. There was no relation between the length of the first and the second
interruption in a trial. The experiment had a 2 × 2 × 3 factorial within-subjects design
(Text-Entry Difficulty (easy/hard) × N-Back Difficulty (easy/hard) × Interruption Duration
(4/8/12 sec). Additional methods are reported in Appendix A.

\textbf{Predictions.} Figure 6.10A shows predictions of a WMM model for this task. Resumption
cost is plotted against interruption duration, which is the duration of the n-back
task. Resumption cost is the extra cost after an interruption as compared to normal
responses. We calculated resumption costs by subtracting the average response time of
responses that did not follow an interruption in a condition from the response time of
responses immediately following an interruption.

According to the WMM theory – and assuming that intermediate representations
are the only factor in the disruptiveness of interruptions – as long as the text-entry
task is easy (the dashed lines in Figure 6.10) and does not need an intermediate
representation, there is no effect of the interruptions, independent of the difficulty of
the n-back task. When text-entry is hard and the n-back task is easy, a small resumption
cost is predicted, which does not increase with interruption duration. This cost is
not related to problem state resource updates, but originates from the model already knowing which letter it has to enter next in the hard text-entry condition (in contrast to the easy text-entry condition, in which the next letter has to be perceived from the screen). It can therefore start preparing the next response while still executing the motor action of the current response. However, this is not possible during an interruption, leading to slightly longer response times directly after an interruption. In the hard-hard condition a large cost is predicted that increases with interruption duration. This is due to the single-sized problem state resource: because the n-back task also needs intermediate representations when it is hard, the intermediate representation of the text-entry task has to be restored after the interruption. This cost increases with interruption duration, as the representation will have decayed further in declarative memory the longer the interruption lasts, and it will therefore take more time to retrieve it again (see Figure 6.4).

Results. Accuracy on the n-back task was in all conditions over 90%, indicating that subjects focused on the n-back task. Figure 6.10B shows the resumption costs of the text-entry task. The first thing to note is that as long as text-entry is easy, there are no increasing costs with interruption duration. However, there are resumption costs of about 400 ms in all conditions, which the model did not predict. When text-entry was hard, resumption costs were much higher. Where the model predicted a small cost for hard text-entry – easy n-back, the data show a much larger effect than predicted, which furthermore increases with interruption duration. When both tasks were hard there is an additional increase in resumption costs, which increases slightly steeper with interruption duration than when n-back was easy. The ANOVA largely confirmed these results: besides main effects of Text-Entry Difficulty, N-Back Difficulty, and Interruption Duration, also the two-way interaction effect between Text-Entry Difficulty and N-Back Difficulty was significant. The three-way interaction between Text-Entry Difficulty, N-Back Difficulty, and Interruption Duration showed a trend towards significance. The ANOVA results are reported in full in Table 6.1; detailed analysis procedures are reported in Appendix A.

<table>
<thead>
<tr>
<th>Source</th>
<th>$F(1,15)$</th>
<th>$p$</th>
<th>$\eta^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Text-Entry Difficulty</td>
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<td>&lt; .001</td>
<td>.91</td>
</tr>
<tr>
<td>N-Back Difficulty</td>
<td>18.92</td>
<td>&lt; .001</td>
<td>.56</td>
</tr>
<tr>
<td>Interruption Duration</td>
<td>33.11</td>
<td>&lt; .001</td>
<td>.69</td>
</tr>
<tr>
<td>Text-Entry $\times$ N-Back</td>
<td>16.24</td>
<td>.001</td>
<td>.52</td>
</tr>
<tr>
<td>Text-Entry $\times$ Int Duration</td>
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<td>&lt; .001</td>
<td>.60</td>
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<tr>
<td>N-Back $\times$ Int Duration</td>
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<td>.07</td>
<td>.20</td>
</tr>
<tr>
<td>Text-Entry $\times$ N-Back $\times$ Int</td>
<td>3.18</td>
<td>.09</td>
<td>.17</td>
</tr>
</tbody>
</table>

Table 6.1 ANOVA results for resumption cost in Interruption Experiment 1.
Discussion. Interruption Experiment 1 was conducted to test the assumption of the WMM theory that intermediate representations are processed via a declarative memory store that is subject to decay. The WMM theory predicted that longer interruptions of a task lead to higher resumption costs, but only when both the primary and the interrupting task require an intermediate representation. Indeed, the experiment showed that as long as the primary task did not need an intermediate representation, there were costs due to the interruption, but these costs did not increase with the interruption duration. While this was in accordance with our predictions, it runs counter to one of the standard effects described in the literature: increasing cost with interruption length (e.g., Hodgetts & Jones, 2006; Monk et al., 2008). When the primary task needed an intermediate representation, we found much higher resumption costs, which increased with interruption duration. In addition, when both the primary and the secondary task required an intermediate representation, these costs were even higher. According to the WMM theory, this is due to the single-sized problem state resource, necessitating the restoration of the representation after an interruption in the hard-hard condition. As these costs increase with interruption duration, this argues in favor of the WMM theory’s assumption that intermediate representations are swapped in and out of the problem state resource via a declarative memory store with decay.

However, while the WMM theory predicted a low cost and a flat line in the hard text-entry – easy n-back condition, the data show a high resumption cost with a clear increase with interruption duration. There are at least three possible explanations for this discrepancy between the predictions and the data. One possibility is that the easy n-back task required the use of an intermediate representation, leading to interference in the hard text-entry – easy n-back condition. However, in that case we would not expect a difference between the results of the hard text-entry – easy n-back and the hard text-entry – hard n-back conditions, as they both would be effectively hard-hard. A second possibility is that the problem state resource sometimes loses the stored representation. For instance, Anderson and Qin (2008) proposed that representations were lost on average every 20 seconds. While such a time-scale does not work for the current model, a similar mechanism might explain the data: a representation would sometimes (but not always) be lost during an interruption in the hard text-entry – easy n-back condition, leading to resumption costs that lie between the model’s prediction and the costs in the hard-hard condition. A third possibility is that the text-entry task requires two intermediate representations instead of one: one for the word (‘information’) and one for the position in the word (‘4\textsuperscript{th} letter’). This would mean that one of these representations decays in the hard text-entry – easy n-back condition (as the problem state resource can only be used to maintain one of the representations), leading to increased costs with interruption duration, while both representations decay in the hard-hard condition, leading to even higher costs.

To see whether this last possibility can explain the data we implemented it as a WMM model. When the model is interrupted in the hard text-entry – easy n-back condition it stores the word in the problem state resource, while the position in the word decays in declarative memory. In the hard-hard condition, neither the word nor the position in the word can be stored in the problem state resource, and therefore
they both decay in declarative memory. Figure 6.10C shows the results: the model fits the patterns in the data, making a dual-representation strategy a possible explanation of the data.\(^4\) For this model fit we implemented a dual-representation strategy for the text-entry task and estimated the general costs of interruptions from the data, which were added to the outcome of the model. Thus, we took the average of the resumption costs in the easy text-entry conditions, and added this to the model results. This is not meant to give an explanation of these costs, but only to ensure that we estimated the costs due to intermediate representations correctly.

While a dual-representation strategy seems to be a possible way of explaining the data, we cannot distinguish between this explanation and the other possible explanations discussed above. To test whether it is a more likely explanation than the other explanations, we performed a second interruption experiment, in which we made sure that only a single representation was needed for the primary task.

**Interruption Experiment 2: Subtraction and N-Back.**

In the second interruption experiment we tested whether a dual-representation strategy is a probable explanation for the data of Interruption Experiment 1. Instead of text-entry, we now used the subtraction task described earlier as the primary task, again interrupted with the n-back task. If the dual-representation strategy for the text-entry task explains the data above, then we should find a flat line in the hard subtraction – easy n-back condition (cf. Figure 6.10A), as only a single representation is necessary for the subtraction task. If one of the other explanations is more likely, we should find a pattern similar to the one that was found for the text-entry task.

The only difference between the two experiments is the use of the subtraction task as the primary task instead of text-entry. A complete 10-column subtraction problem was shown on the screen, but solved columns were masked with # marks. Interruption Experiment 2 thus had a 2 × 2 × 3 factorial within-subjects design (Subtraction Difficulty (easy/hard) × N-Back Difficulty (easy/hard) × Interruption Duration (4/8/12 sec). Additional methods are reported in Appendix A.

**Results.** Accuracy on the n-back task was above 85% in all conditions. Figure 6.11A shows the resumption costs in the different conditions; Figure 6.11B the model fit. Again, no effect of interruption duration on the resumption costs was found as long as subtraction was easy. In addition, when subtraction was hard and n-back easy, we also did not observe increasing costs with interruption duration, unlike in the previous experiment. Only when both tasks required an intermediate representation, in the hard-hard condition, we observed increasing costs with interruption duration. The ANOVA (Table 6.2) confirmed main effects of Subtraction Difficulty and N-Back Difficulty. Furthermore, also the interaction effect between Subtraction Difficulty

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\(^4\) If a dual-representation strategy is indeed the correct way of describing behavior in the text-entry task, the question is whether the model fits of Borst, Taatgen, and Van Rijn (2010) and the model-based fMRI results of Borst et al. (2011) still hold. We implemented the dual-representation strategy also for these experiments, which yielded similar results as before. We report these analyses in Appendix B.
and N-Back Difficulty was significant, but the expected three-way interaction between Subtraction Difficulty, Text-Entry Difficulty, and Interruption Duration did not reach significance. However, given that our model made specific *a priori* predictions, the overall ANOVA is overly conservative as it tests for any kind of three-way interaction, instead of the clear directional effects that the model predicted. We therefore subsequently performed simple effects analyses to investigate the model’s prediction that we should only observe increasing costs with interruption duration in the hard-hard condition.

We tested for the separate n-back and subtraction conditions whether there was an effect of Interruption Duration. These analyses confirmed that there was no effect of Interruption Duration as long as either the subtraction task or the n-back task was easy (all $F$s < 1). In the hard-hard condition, on the other hand, we found a significant effect of Interruption Duration ($F(1,32) = 4.17, p = .0495, \eta_p^2 = .12$). Thus, resumption costs only increased with interruption duration in the hard-hard condition, which is in line with the predictions of the WMM theory.

**Discussion.** In the interruption experiments we tested the prediction of the WMM theory that interruptions should only lead to increasing resumption costs with interruption duration when both the primary and the secondary task require an intermediate representation. The two experiments confirm this prediction, and the model fits show that the WMM theory can account for the datasets.

In Interruption Experiment 2 we only observed increasing costs with interruption duration in the hard-hard condition, and no increasing costs in the hard subtraction – easy n-back condition. Thus, this experiment suggests that the increasing costs in Interruption Experiment 1 in the hard text-entry – easy n-back condition were caused by properties of the text-entry task, possibly by a dual-representation strategy. Therefore, the two experiments taken together suggest that interruptions only lead to increasing costs with interruption duration when both tasks require an intermediate representation. This contrasts with earlier findings (e.g., Hodgetts & Jones, 2006; Monk et al., 2008), and with the memory for goals theory that proposes that resumption costs always increase with the duration of an interruption (e.g., Altmann & Trafton, 2002).
The main objective of conducting the interruption experiments was to investigate whether intermediate representations are processed via a declarative memory system with decay, as the WMM theory proposes. The experiments showed that when the primary task required a representation and was interrupted by a task that also needed an intermediate representation, the costs of resumption increased with interruption duration. This argues in favor of a declarative memory system with decay: the longer ago an intermediate representation was stored in declarative memory, the more its activation will have decayed, the longer it takes to retrieve and restore it and to resume the primary task. Furthermore, the WMM model matched the size of the effects (Figure 6.10C and 6.11B), while using the same parameters as in the model fits discussed above.

Summary

In the first major section of this paper, we reviewed experimental evidence that shows that the problem state resource can only maintain a single intermediate representation at a time. In this section, we investigated where intermediate representations are maintained when they are removed from the problem state resource. According to the WMM theory, they are processed via a separate declarative memory store in which items are subject to decay. In the first part of this section, we used a novel model-based fMRI analysis technique to show that activity related to the problem state resource on the one hand, and activity related to declarative memory processes on the other hand, are best represented in two different brain areas, implying two separate memory stores. In the second part of this section, we reported two interruption experiments that show that representations that are not maintained in the problem state resource are subject to decay. Thus, this combination of experiments implies that intermediate representations that cannot be maintained in the problem state resource are processed via a declarative memory store that is subject to decay, while representations in the problem state resource are not subject to decay.

In the next section we will look at the proposed strategic nature of using the problem state resource: according to the WMM theory the problem state resource, in...
combination with declarative memory, will only be used when it is faster than using the environment.

The Strategic Nature of using the Problem State Resource and the Environment

Using intermediate representations is only necessary when information is not available in the environment. For example, when solving a multi-column subtraction problem on paper, one would usually indicate on paper whether a carry is in progress, and thus use the environment as an external representation (e.g., Hollan et al., 2000; Kirsh, 1995; Wickens, 1992). Even when one is interrupted while solving a subtraction problem mentally, it is possible to reconstruct the representation using the previous columns after the interruption, instead of retrieving a representation from memory (as was required in the interruption experiments above). Based on the Soft Constraints Hypothesis (Gray & Fu, 2004; Gray et al., 2006), the WMM theory assumes that people always use the fastest strategy: whether that is using a representation in the problem state resource, retrieving a representation from declarative memory, or using the environment. In this section, we will present an experiment that supports this assumption.

For this experiment we again used the subtraction and text-entry dual-task described above, but added a condition in which on-screen support was provided for the subtraction task (see also Buwalda, Borst, Taatgen, & van Rijn, 2011). Figure 6.12 shows the interface of this condition. The '|' above the subtraction task indicates that currently no carry is in progress, it will turn into a '1' after a column that induced a carry. Thus, no intermediate representation is required in this Support condition for the subtraction task. The experiment had a factorial 2 x 2 x 2 within-subject design (Subtraction Difficulty (easy/hard) x Text-Entry Difficulty (easy/hard) x Support (yes/no)). Additional methods are reported in Appendix C.

Predictions

For this task, the WMM theory predicts the following. In the no-support condition of the subtraction task, intermediate representations cannot be reconstructed from the environment, because only a single column is shown at a time. In the support condition, on the other hand, the intermediate representation is shown on the screen. Thus, the costs of using the environment in the support condition consist of perceiving the support indicator. As long as the subtraction task is easy, no differences are predicted between the support and the no-support condition, as carries are never required. In the hard subtraction – easy text-entry condition, the model also expects the same behavior with and without support: Because a mental strategy is faster than perceiving the support indicator on the screen, the WMM theory predicts that subjects will not use the indicator in the support condition.
The Strategic Nature of using the Problem State Resource and the Environment

Only in the hard subtraction – hard text-entry condition the WMM theory predicts a difference: in the support condition it is faster to use the environment than to use a declarative memory-based reconstruction (as used for all tasks above). However, using the environment in the hard-hard condition is still slower than using a mental representation in the hard subtraction – easy text-entry condition with support (because the support-indicator has to be perceived, which takes time). Therefore, in the support condition, the model expects slightly higher response times in the hard-hard condition than in the hard subtraction – easy text-entry condition. Thus, while an interaction effect between Subtraction Difficulty and Text-Entry Difficulty is expected in the no-support condition, as observed previously, a reduced interaction effect is predicted in the support condition.

While the WMM theory predicts interaction effects for response times both with and without support, for the accuracy data the model predicts that the interaction effect disappears with support. As the model uses the perfect information in the environment in the hard-hard condition with support, there is no reason for it to make more mistakes in this condition than in the hard subtraction – easy text-entry condition.

Results

Figure 6.13 shows the results of the experiment: the top panels show response times, the bottom panels accuracy. The complete ANOVA results are reported in Tables 6.3, 6.4, and 6.5. As the WMM theory predicted, subjects showed significant interaction.
effects between Subtraction Difficulty and Text-Entry Difficulty both with and without support. Moreover, the interaction effect was smaller in the support condition, as shown by a significant three-way interaction effect between Subtraction Difficulty, Text-Entry Difficulty, and Support. This is in line with the predictions described above.

The accuracy data of the subtraction task show a similar pattern, except that the interaction between Subtraction Difficulty and Text-Entry Difficulty completely disappears in the Support condition. This is also in line with the model: while using the environment is slightly slower than using a mental strategy, it should not lead to more errors.

**Model**

As can be seen in Figure 6.13 (grey bars), the WMM model accounted well for the data. Both the effects on response times and accuracy of the subtraction task were captured. The size of the effects was also reflected by the model, which uses the same parameters as before.

**Discussion**

The experiment supports the assumption of the WMM theory that problem state resource usage is strategic: subjects always used the fastest option. As long as a mental
strategy was possible (up to the hard subtraction – easy text-entry condition with support), they seemed to prefer a mental strategy instead of using the environment, even when support was provided. In the hard-hard condition, when they had to use an intermediate representation for both tasks, they switched to environmental support when possible, resulting in faster response times with support than without support.

This is in accordance with the Soft Constraints Hypothesis (Gray & Fu, 2004; Gray et al., 2006), which states that humans adapt their behavior to minimize temporal costs, even if that leads to suboptimal behavior. That is exactly what we observed in the experiment, in which it might make more sense to always use the perfect knowledge in-the-world as opposed to imperfect knowledge in-the-head. While subjects were free to use the indicator in the Support condition – which seems to be the rational option, as it is always correct and requires less effort than remembering whether a carry was in progress – there was a clear difference between the hard subtraction – easy text-entry condition and the hard-hard condition, indicating that they used different strategies in these conditions. According to the WMM theory and the Soft Constraints Hypothesis this is because participants tried to minimize the temporal costs of the task, and therefore prefer the imperfect knowledge in-the-head over the perfect knowledge in-the-world.
General Discussion

In this article we proposed the Working Memory in Multitasking theory, which describes how intermediate representations are processed in human multitasking. The WMM theory states that our cognitive system has a single-sized problem state resource for maintaining intermediate representations. When more than one representation is required for the tasks that make up the ‘multitask’, the representations that are currently not used are temporarily stored in a declarative memory store that is subject to decay. The use of multiple intermediate representations leads therefore to interference, because the representations have to be swapped in and out of the problem state resource via declarative memory. The WMM theory furthermore proposes that intermediate representations are processed mentally as long as that is faster than using the environment, but that otherwise the environment is used.
In the previous three sections we have discussed various data sets that support the WMM theory. First, we reviewed an experiment of Borst, Taatgen, and Van Rijn (2010) that showed that the problem state resource can maintain at most a single representation. We then turned to a novel fMRI analysis technique to support the assumption that discarded representations are stored in a separate memory store. In addition, with two new interruption experiments we showed that representations in this declarative memory store are subject to decay. Finally, we presented an experiment in which external support was given to the subjects, to show that intermediate representations are always processed in the fastest way possible, whether that is using the environment, the problem state resource, or declarative memory.

The main prediction of the WMM theory is that intermediate representations are an important factor in interference in human multitasking. This idea stems from the combination of the threaded cognition theory (Salvucci & Taatgen, 2008, 2011) and the ACT-R theory (e.g., Anderson, 2007). The data sets discussed in this article give therefore also indirect support for these theories. The WMM theory, being based on threaded cognition, is a multiple bottleneck theory (although we focused on the problem state bottleneck in this article). It therefore supports the idea of multiple separate bottlenecks, with interference effects depending on the requirements of the tasks at hand. According to the WMM theory one of those bottlenecks is the problem state resource. As it takes a relatively long time to restore intermediate representations to the problem state resource, this bottleneck causes substantial interference, both in response times and accuracy.

In the remainder of this article we will discuss the relation between the WMM theory and current working memory theories, its consequences for interruption studies, its relation to the Memory for Goals theory and the Soft Constraints Hypothesis, and finally real-world implications of the WMM theory.

**Working Memory**

The function of intermediate representations – temporarily maintaining information – is traditionally part of the concept of short-term or working memory (e.g., Baddeley, 1986; Baddeley & Hitch, 1974; Miller, 1956). However, where theories used to assume a limit of 7±2 items (Miller, 1956) or 4±1 items (Cowan, 2000), the WMM theory assumes a limit of only one directly accessible item. Other items that are traditionally part of working memory are in the WMM/ACT-R framework represented by highly activated items in declarative memory (Anderson, 2005; Daily et al., 2001; Lewis & Vasishth, 2005; Lovett et al., 2000). The combination of a single-sized problem state resource and highly active items in declarative memory gives a more traditional working memory capacity of around four to nine items (Anderson et al., 1998). In this framework, the representation in the problem state resource can be used immediately, while it takes time to retrieve and use the highly activated items in declarative memory.

Recent working memory theories have proposed similar ideas, in which the ‘focus of attention’ represents items in working memory that are directly available (e.g., Cowan, 1995; Garavan, 1998; Jonides et al., 2008; McElree, 2001; Oberauer, 2002, 2009;
Oberauer & Bialkova, 2009). For example, Oberauer (2009) proposed a model in which “declarative working memory” consists of activated items of long term memory, of which only a single item can be in the focus of attention. This idea of one directly available item and other highly active items in declarative memory constituting working memory is very similar to the concept of working memory in the WMM theory, as are other recent working memory theories (e.g., Jonides et al., 2008; McElree, 2001; Oberauer, 2002).

**Interruptions**

We illustrated the WMM theory with two interruption experiments. It is well known that interruptions of a task lead to a decrease in performance when recommencing this task (e.g., Gillie & Broadbent, 1989; McFarlane & Latorella, 2002). Two important factors that determine the severity of an interruption are the complexity and the duration of the interrupting task (e.g., Gillie & Broadbent, 1989; Hodgetts & Jones, 2006; Monk et al., 2008; Zijlstra et al., 1999). According to the WMM theory, these effects are partly caused by intermediate representations. As explained in detail above, whether the tasks need intermediate representations determines whether there is representation-related interference (complexity effect), while decay in declarative memory of intermediate representations causes the duration effect.

Interestingly, this leads to the prediction that the duration effect only plays a role when both tasks need an intermediate representation, as opposed to what is normally assumed (and in contrast to the Memory for Goals theory, e.g., Altmann & Trafton, 2002, see below). The presented experiments confirmed this prediction: as long as the primary task did not need an intermediate representation there was no effect of the duration of the interruption. Moreover, when the primary task required a representation, there was only an effect of interruption duration if the interrupting task also needed an intermediate representation.

While the WMM theory accounts for increasing costs with interruption duration, note that it does not (neither does it mean to) explain the basic interruption costs that we observed in all conditions (Figure 6.10 and 6.11). According to the WMM theory they cannot be ascribed to the processing of intermediate representations, but are caused by a different mechanism.

**Memory for Goals**

The Memory for Goals theory (Altmann & Trafton, 2002; Trafton et al., 2003) has been used to explain resumption costs in interruption tasks such as the ones presented in this article. It assumes that every task has an associated goal in declarative memory, and that when a task is interrupted, this goal starts to decay. When a task is recommenced after an interruption, the associated goal has to be retrieved from memory, which takes more time the longer the interruption was due to decay in memory (cf. Figure 6.4). Thus, Memory for Goals theory explains interruption costs by the time it takes to retrieve a goal from declarative memory.
Salvucci, Monk, et al. (2009) rephrased Memory for Goals in problem state terms: “which they [Altmann & Trafton, 2002] referred to as the goal [...] we call the problem state” (p. 799). Thus, they assume that every task has an associated intermediate representation in the problem state resource (instead of a goal), which has to be retrieved from declarative memory after an interruption. As support they presented a model fit of an interruption experiment by Monk et al. (2008). However, while Salvucci, Monk, et al. assumed that every task has an associated intermediate representation (which was true for the tasks they simulated), the WMM theory proposes that not all tasks need an intermediate representation. According to the WMM theory, only tasks with associated intermediate representations will lead to increasing resumption costs with interruption duration, thereby explaining the flat lines in the easy conditions in the interruption experiments described above.

Strategic Behavior and the Soft Constraints Hypothesis

The WMM theory assumes that humans always use the fastest strategy, whether that is using information in-the-head or using information in-the-world. This assumption is based on the Soft Constraints Hypothesis, which proposes that behavior is adapted to a task by minimizing temporal costs (Gray & Fu, 2004; Gray et al., 2006). The support experiment presented in this article yields additional behavioral evidence for this hypothesis: while it might have been expected that subjects always use external support when it is available, this did not seem to be the case. An open question is how subjects decided which strategy to use: how did they learn that it was faster to use information in-the-head than to use the information presented in the environment?

To discover the best strategy, Gray et al.’s (2006) Ideal Performer Model used reinforcement learning (e.g., Sutton & Barto, 1998). However, they “make no claim that the process followed by the [reinforcement learning] algorithm mimics any process followed by human cognition” (Gray et al., 2006, p. 465). Recently, Janssen and Gray (in press) investigated whether reinforcement learning could also provide a cognitively plausible explanation of the data. They concluded that reinforcement learning could be used to simulate the human data, especially if it used ‘time’ as the reward parameter. This is in line with other efforts to use reinforcement learning to explain human behavior (see, e.g., Daw & Frank, 2009, for a special issue on reinforcement learning and higher-level cognition). As the subjects in our experiment received sufficient practice, it is possible that reinforcement learning can also be used to explain the strategic choices in our dataset.

Real World Implications

In this article we have presented several behavioral experiments that highlight the interference effects of the WMM theory. While these interference effects are relatively large, one could wonder if the processing of intermediate representations also plays a role in everyday life. First evidence that this is the case comes from an experiment in which subjects had to keep a (very basic) simulated car in the middle of the road
while entering addresses into a navigation device (Borst & Taatgen, 2007). Both tasks had two conditions: either they needed an intermediate representation or not. When both tasks required an intermediate representation, performance was slower than in all other conditions.

More recently, Salvucci and Bogunovich (2010) let subjects perform a customer-support task in which the use of intermediate representations was manipulated. Subjects in their experiment had to reply to emails inquiring about the price of a certain product. These prices had to be looked up on a simulated internet. During certain parts of this task, subjects had to maintain an intermediate representation (white bars in Figure 6.14). While replying to the emails and looking up the information on the internet, subjects additionally had to perform a chat task: Sometimes a chat window was highlighted, indicating that a new message had arrived to which the subjects had to respond. Subjects were free to choose when they switched to the chat task. Figure 6.14 shows the results: they switched almost exclusively to the chat task when no intermediate representation had to be maintained (the grey bars). This indicates that the subjects were aware that there is a cost associated with using intermediate representations, and thus that multitasking interference due to the use of intermediate representations has an impact on real-world tasks.

**Conclusion**

In this article we proposed the Working Memory in Multitasking theory. This theory states that intermediate representations are an important factor in multitasking interference. As support for the WMM theory we have reviewed experiments from the literature, and in addition tested predictions of the theory in three new experiments, showing that it accounts for data ranging from concurrent tasks to interruption studies, and from laboratory experiments to more real-world tasks.
Appendix A:

Additional Methods of Interruption Experiment 1 and 2

In this appendix we describe the subjects, stimuli, procedure, and statistical procedure of Interruption Experiments 1 and 2.

Interruption Experiment 1: Text-Entry and N-Back

In this experiment subjects had to perform a text-entry task, which was twice every trial interrupted by an n-back task. The design of the task is discussed in the main text.

Subjects

16 students of the University of Groningen participated in the experiment for course credit (12 female, age range 18–22, mean age 19.2). All subjects had normal or corrected-to-normal visual acuity. Informed consent as approved by the Ethical Committee Psychology of the University of Groningen was obtained before testing.

Stimuli and Apparatus

The 10 letter words for the hard version of the text-entry task were handpicked from a list of high-frequency Dutch words (CELEX database; Baayen et al., 1993) to ensure that similarities between words were kept at a minimum. These stimuli were also used in the easy text-entry task, except that the letters within the words were scrambled (under the constraint that a letter never appeared twice in a row). Thus, subjects were presented pseudo-random sequences of letters that they had to enter one-by-one in the easy condition. By scrambling the words, we controlled for letter-based effects, while preventing the use of strategies to predict the next letter.

The n-back stimuli were generated during the experiment. Subjects had to respond ‘same’ in 50% of the cases (thus, in the easy, 1-back version, the digit was the same as the previous digit, in the 2-back version the same as the digit 2 back), and ‘different’ in the other 50% of the cases. Additionally, no more than three digits in a row could be the same. Subjects had to press ‘x’ or ‘z’ on the keyboard to indicate ‘same’ or ‘different’. Whether ‘x’ or ‘z’ indicated ‘same’ or ‘different’ was counter-balanced over subjects.

Procedure

Each trial in the experiment started with presenting the conditions of the text-entry task and the n-back task on the screen, for example: N-Back: easy, Text-Entry: hard. This was presented for three seconds, after which the text-entry task was shown on the screen. After entering between 2 and 6 letters the first n-back interruption was started. No warning was given, but instead of the next text-entry letter the n-back task was shown (Figure 6.9). The subject had to do 3, 6, or 9 n-back steps (balanced over the text-entry
and n-back conditions). Then the text-entry interface was shown again. After another 2 to 6 letters the second n-back interruption started, after which the subject could finish the text-entry task. When the subject had entered the complete 10-letter word, feedback was presented, indicating the number of correct letters in the text-entry task. The text-entry feedback was presented for 3 seconds, followed by a fixation screen for 4 seconds. Afterwards the next trial started. Feedback was continuously presented for the n-back task; every time an incorrect or no response was given, a buzzer was sounded.

The experiment consisted of a practice block and two experimental blocks. The practice block started with three trials of only the easy text-entry task, followed by three trials of the hard text-entry task, seven 6-step trials of the easy n-back task, and seven 7-step trials of the hard n-back task. Then the real task was practiced in four trials. The seven n-back trials (per condition) increased in speed in four steps: in the first trial the digit was presented for 1700 ms followed by a 733 ms mask, in the second and third trial they were presented for 1500/533 ms, in the fourth and fifth trials for 1300/383 ms, and in the sixth and seventh trials for 1100 ms with a 233 ms mask (as in the real experiment).

The two experimental blocks were the same, each consisted of 36 trials: 2 (easy/hard text-entry) × 2 (easy/hard n-back) × 3 (3/6/9 steps first interruption) × 3 (3/6/9 steps second interruption). The order of these conditions was randomized within a block. The interruption points in each trial were also randomized: the first interruption came after the 2nd up to the 6th letter, the second interruption between the 4th and the 8th letter. The distance between the interruptions was a minimum of 2 letters, resulting in 15 different combinations. The complete experiment consisted of 72 experimental trials, and lasted for about 90 minutes. Between the blocks subjects could take a short break.

**Statistical Procedure**

We only analyzed the data from the experimental phase of the experiment. A response time in the text-entry task was defined as the time between two responses, or, directly after an interruption, as the time between the reappearance of the text-entry task and the response. First responses of each trial were removed. Outliers were removed from the data (RTs < 250 ms or > 10,000 ms), after which we removed data exceeding three standard deviations from the mean per condition per subject (in total 0.92% of the data was removed). All F- and p-values are obtained from repeated measure ANOVAs; all error bars depict standard errors. Analyses on response times are only for correct responses.

**Interruption Experiment 2: Subtraction and N-Back**

In this experiment subjects had to perform a subtraction task, which was twice every trial interrupted by an n-back task. The design is similar to the design of Interruption Experiment 1, except when noted otherwise.
**Subjects**

39 students of the University of Groningen participated in the experiment for course credit. Three subjects had to be excluded because of not being able to do the hard subtraction task (< 65% columns correct or slower than 3,500 ms per response), two subjects for not doing the hard n-back task (< 80% correct), and one subject had to be excluded because of health problems, leaving 33 complete data sets (23 female, age range 18-27, mean age 20.7). All subjects had normal or corrected-to-normal visual acuity. Informed consent as approved by the Ethical Committee Psychology of the University of Groningen was obtained before testing.

**Design**

Instead of text-entry, solving 10-column subtraction problems was the primary task in the second interruption experiment. Responses had to be made using the numeric keypad of the keyboard. The n-back task was again used as the interrupting task, but now with letters instead of digits.

**Stimuli and Apparatus**

The stimuli for the subtraction task were generated anew for each subject. The subtraction problems in the hard version always featured five carries, and resulted in 10-digit answers. The n-back stimuli were again generated on the fly, using the same constraints as in Interruption Experiment 1.

**Statistical Procedure**

We only analyzed the data from the experimental phase of the experiment. A response time in the subtraction task was defined as the time between two responses, or, directly after an interruption, as the time between the reappearance of the subtraction task and the response. First responses of each trial were removed. Outliers were removed from the data (RTs < 250 ms or > 15,000 ms), after which we removed data exceeding three standard deviations from the mean per condition per subject (in total 2.74% of the data was removed). All F- and p-values are obtained from repeated measure ANOVAs; all error bars depict standard errors. Analyses on response times are only for correct responses.
Appendix B:
Effects of a Dual-Representation Strategy on Previous Results

In this appendix we report the effects of a dual-representation strategy for the text-entry task on previously published results. According to the results of Interruption Experiment 1 (see the main text), it is likely that two intermediate representations are used for the text-entry task, instead of one. Thus, when a word has to be entered in the hard text-entry task, one representation is used for storing the word (‘information’) and one for the position in the word (‘6th letter’). Such a model implementation resulted in a good fit for Interruption Experiment 1. However, if a dual-representation strategy is indeed the correct way of explaining the results of the text-entry task, the question is whether previously published model fits still hold. To investigate this we implemented the dual-representation strategy for Experiment 1 of Borst, Taatgen, and Van Rijn (2010) and for the model-based analysis reported in Borst et al. (2011).

Borst, Taatgen, and Van Rijn (2010)

The design of Experiment 1 (Borst, Taatgen, & Van Rijn, 2010) is reported in “Multiple Intermediate Representations cause Multitasking Interference”. Figure 6.6 in the main text shows the original model fit, Figure 6.15 the model fit with a dual-representation strategy. The effect of a dual-representation strategy for the text-entry task is small: the costs in response times and accuracy for the text-entry task are slightly over-estimated. This is caused by the model now having to swap out two intermediate representations for the text-entry task throughout the experiment. In the easy subtraction – hard text-entry condition this leads to slightly higher response times, because the new model has to retrieve an intermediate representation from memory on each step of a trial, even in this condition. However, most of these costs are absorbed in the normal costs of doing the task (i.e., perceptual and motor costs). In the hard-hard condition the model now has to retrieve two intermediate representations from memory at each step of a trial, leading to similar interaction effects as observed before. Taken into account that we did not refit the model parameters, this shows that a dual-representation strategy can account for the data of Experiment 1 of Borst, Taatgen, & Van Rijn.

Model-Based fMRI: Borst, et al. (2011)

In “Neuroimaging Evidence for Two Separate Memory Stores” we discussed a model-based fMRI analysis that showed that the problem state resource and declarative memory are best represented by two different brain areas (Figure 6.8, main text). We now reanalyzed the data with a dual-representation model. Figure 6.16 shows the results. The analysis still found two separate regions for the problem state resource and declarative memory. This indicates that a dual-representation model is also compatible with the brain results we found before, which, in turn, correspond to the standard mapping between ACT-R modules and brain regions (e.g., Anderson, 2007).
Appendix B: Effects of a Dual-Representation Strategy on Previous Results

Figure 6.15 Results of Experiment 1 with a dual-representation model. Error bars represent standard errors. RMSD = root-mean-square deviation; RT = response time.

Figure 6.16 Results of the model-based fMRI analysis with a dual-representation model. The best fitting areas for a) the problem state resource and b) declarative memory. The white squares indicate ACT-R’s predefined regions (e.g., Anderson et al., 2008), xyz-coordinates are of the most significant voxel.
Appendix C:
Additional Methods of the Support Experiment

In this appendix we describe the subjects, design, and statistical procedure of the experiment described in the section ‘The Strategic Nature of using the Problem State Resource and the Environment.’ In this experiment subjects had to alternate between a subtraction task and a text-entry task (as in Borst, Taatgen, & Van Rijn, 2010). Both tasks were presented in two versions: an easy version in which there was no need to maintain an intermediate representation, and a hard version in which participants had to maintain an intermediate representation from one response to the next. In addition, in one condition external support was displayed on the screen for the subtraction task. The general design of the task is discussed in the main text.

Subjects

33 students of the University of Groningen participated in the experiment for course credit or monetary compensation of €10. Four participants were rejected because they scored less than 75% correct where the other participants scored >95% correct. Two subjects were rejected because they did not adhere to task instructions, and three because of recording problems of the eye tracker. This leaves 24 complete datasets (17 female, age range 18–43, mean age 20.5). All subjects had normal or corrected-to-normal visual acuity. Informed consent as approved by the Ethical Committee Psychology of the University of Groningen was obtained before testing.

Stimuli and Apparatus

The stimuli for the subtraction task were generated anew for each subject. The subtraction problems in the hard version always featured six carries, and resulted in 10-digit answers. The 10 letter words for the hard version of the text-entry task were handpicked from a list of high-frequency Dutch words (CELEX database; Baayen et al., 1993) to ensure that similarities between words were kept at a minimum. These stimuli were also used in the easy text-entry task, except that the letters within the words were scrambled (under the constraint that a letter never appeared twice in a row). Thus, participants were presented pseudo-random sequences of letters that they had to enter one-by-one in the easy condition. By scrambling the words, we controlled for letter-based effects, while preventing the use of strategies to predict the next letter.

The experiment was presented full screen on a 20.1” monitor. Participants were sitting at a normal viewing distance, about 70 cm from the screen.

Procedure

Each trial started with the presentation of a fixation cross for 6 seconds. The fixation cross was followed by two horizontally aligned colored circles representing the tasks.
The color of the circles indicated the difficulty levels of the tasks (on the left for the subtraction task, on the right for the text-entry task; green for easy, red for hard). The circles stayed on the screen for 1 second, followed by a fixation cross for 600 ms, after which the subtraction and text-entry tasks appeared. Subjects had to begin with the subtraction task, and then alternate between the two tasks. After completing both tasks, a feedback screen was shown for 2 seconds, indicating how many letters/digits were entered correctly. Before the next trial started, a fixation screen was shown for 2 seconds.

The experiment consisted of a practice block and two experimental blocks. One of the experimental blocks contained the support condition; the order was counter-balanced over participants. The practice block consisted of 12 single task trials (4 subtraction trials with 10 columns visible, 4 subtraction trials with one column visible, and 4 text-entry trials), followed by a block of 4 multitasking trials: all combinations of subtraction and text-entry (easy-easy, hard-easy, easy-hard, and hard-hard). Both experimental blocks consisted of 28 multitasking trials. Before the second block the subtraction task was practiced again, to familiarize the participants with using the carry indicator if they did not use this in the first block, or with performing the task without the indicator in the other case. Subtraction and text-entry conditions were randomized within a block. The complete experiment consisted of 56 experimental trials, and lasted for about 90 minutes. In between blocks participants could take a short break.

Statistical Procedure

We only analyzed the data from the experimental phase of the experiment. A response time in the subtraction task is defined as the time between a response in the text-entry task and a response in the subtraction task; a response time in the text-entry task as the time between a response in the subtraction task and a response in the text-entry task. First responses of each trial were removed. Outliers were removed from the data (RTs < 250 ms or > 10,000 ms), after which we removed data exceeding three standard deviations from the mean per condition per participant (in total 2.2% of the data was removed). All F- and p-values are obtained from repeated measure ANOVAs; all error bars depict standard errors. Accuracy data were transformed using an arcsine transformation before being submitted to the ANOVA.