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The Dynamic Effects of Task Demands on Resource Availability, Resource Allocation and Metacognitive States

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Abstract

Changes in task demands can trigger a complex and dynamic self-regulatory process which influences a range of metacognitive and physiological states. Individuals continuously monitor task cues, the level of task performance and other internal states in order to form an assessment of current task demands. Cognitive-energetic theories propose that individuals possess a finite amount of available *resources* which can be allocated to meet task demands. Increased task demands will generate an increase in the level of resources allocated in order to maintain task performance, but only up to a point of maximum effort which is determined by the level of available resources. However, while the level of available resources is finite, it is not necessarily fixed. It is generally held that the sustained allocation of resources depletes the level of available resources, so that prior high task demands will reduce the level of available resources and therefore the maximum level of resources allocated to meet current high task demands. Reduced levels of available resources may also cause a compensatory increase in the level of allocated resources at low demand levels in order to protect against possible performance lapses caused by low resource availability.

The current thesis proposes that, instead of a general process by which all resource allocation depletes the level of available resources, the allocation of *attentional control resources* depletes the level of available resources but the allocation of *information processing resources* provides an opposing short-term increase in the level of available resources. This proposal provides a way of accounting for potentially contradictory empirical data and integrating ego depletion theory and malleable resources theory. The thesis develops a resource-based self-regulatory dynamic control model of the human response to task demands in which the level of available and allocated information processing and attentional control resources both influence and are influenced by current and prior task demands. The model also identifies how the level of available and allocated resources contribute to the metacognitive states of perceived difficulty, effort, activation and valence and the physiological state of pupil diameter. Three experiments were conducted to test predictions arising from the model. Experiments 1 and 2 manipulated the level of task demands within a range of relatively simple, short-term, intermittent cognitive and motor control tasks and Experiment 3 manipulated demand level within a sustained, continuous, and complex control task in order to identify the validity of the proposed model under a range of task conditions.

The experiments provided mixed support for the model. The proposal that attentional control demands and information processing demands had opposing effects on the level of available resources was broadly supported by the empirical data which suggests that resource theories need to distinguish the effects of these two types of task demands. However, the level of available resources did not have a simple or consistent effect on the level of allocated resources across the three experiments which highlights the role of active resource management and suggests that it may not be feasible to identify a general form for this relationship. Only mixed support was found for the proposed relationships between available resources, allocated resources and the metacognitive states of difficulty, effort and valence which suggests that the levels of available and allocated resources may have only a weak effect on the metacognitive states which appeared to be more strongly influenced by task characteristics.

Declaration by author

This thesis is composed of my original work, and contains no material previously published or written by another person except where due reference has been made in the text. I have clearly stated the contribution by others to jointly-authored works that I have included in my thesis.

I have clearly stated the contribution of others to my thesis as a whole, including statistical assistance, survey design, data analysis, significant technical procedures, professional editorial advice, and any other original research work used or reported in my thesis. The content of my thesis is the result of work I have carried out since the commencement of my research higher degree candidature and does not include a substantial part of work that has been submitted to qualify for the award of any other degree or diploma in any university or other tertiary institution. I have clearly stated which parts of my thesis, if any, have been submitted to qualify for another award.

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Publications during candidature

No publications.

Publications included in this thesis

No publications included.

Contributions by others to the thesis

Andrew Neal and Gillian Yeo each made substantial contributions to this thesis by helping to identify the aim and scope of project, suggesting possible theoretical prisms through which to view the research questions, introducing me to and mentoring me on the use of multilevel modelling, and providing invaluable feedback throughout the process which allowed me to greatly improve the analysis, interpretation and presentation of the empirical data.

Alistair Walsh made a substantial contribution to the research by writing the PEBL scripts that controlled the stimulus presentation and data collection during Experiment 2 and running the experimental sessions for this experiment. Vic Demczuk and Dianne Pomeroy also contributed to Experiment 2 by suggesting suitable experimental tasks. Greg Denehy made a substantial technical contribution to Experiment 3 by writing the software that supported the scenario design, stimulus presentation and data collection.

Statement of parts of the thesis submitted to qualify for the award of another degree

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Keywords

self-regulation, metacognition, task demands, attention, information processing, affect, effort, workload, dynamics, multi-level models

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LIST OF ABBREVIATIONS

ANOVA	Analysis of Variance
ANS	Autonomic Nervous System
CI	Confidence Interval
CNV	Contingent Negative Variation
EA	Energetic Arousal
EEG	Electroencephalogram
ES	Electronic Signature
ID	Identity
IFF	Identify Friend or Foe
LCD	Liquid Crystal Display
LRP	Lateralised Readiness Potential
MLM	Multilevel Modeling
OLS	Ordinary Least Squares
PASAT	Paced Serial Addition Task
PEBL	Psychology Experiment Building Language
PNS	Parasympathetic Nervous System
PPI	Plan Position Indicator
SD	Standard Deviation
SNS	Sympathetic Nervous System
TA	Tense Arousal
UMACL	University of Wales Institute of Science and Technology Mood Adjective Checklist

CHAPTER 1: OVERVIEW

Problem statement

The human response to task demands is a complex process that involves changes in a range of psychological and physiological states. The assessment of the demands of mental work has received attention in the psychological literature since the early 1960s (Gopher & Donchin, 1986) and considerable progress has been made in terms of both theoretical understanding and measurement techniques. It has become clear that mental workload is a multidimensional construct, but what remains unclear is the dynamics of the relationships between the multiple variables that both influence and are influenced by the human response to task demands (Hockey, 2008).

An improved understanding of these dynamic processes may provide both theoretical and practical benefits. Theoretically it may allow apparently disparate and contradictory empirical findings to be integrated within a coherent model. Practically it may allow impending task overload to be predicted with a greater degree of reliability and allow timely and appropriate mitigation strategies to be implemented. This may be of critical importance in high-reliability environments such as air traffic control or military operations.

Aim and Scope

Conceptualising the human response to task demands as a dynamic process which is influenced by both current and past external and internal states suggests the use of feedback control models as an explanatory framework. Several theorists have used a control theory framework to produce models of task demands which have focussed on the role of information processing (Hendy, Liao, & Milgram, 1997), positive and negative affect (Carver & Scheier, 1998), and effort (Brehm & Self, 1989; Hockey, 1997, 2013). Given that task demands generate cognitive, motivational and affective responses it would be of benefit if all of these processes could be incorporated into a single model.

This thesis aims to integrate cognitive, affective and motivational states into a dynamic control model of the human response to task demands. It will take a resources perspective, which assumes that individuals have a limited amount of available resources which may be allocated to meet task demands (Kahneman, 1973; Muraven & Baumeister, 2000) but allows that the level of available resources may vary within individuals (Young & Stanton, 2002b). It will also use the core affect model which identifies that valence and activation are fundamental orthogonal dimensions of affect that underpin a wide range of mood and emotional states associated with task performance (Russell & Feldman Barrett, 1999; Yik, Russell, & Feldman Barrett, 1999). This conceptualisation of affect can be linked to resource theories by considering that the level of psychological activation can be used as an index of the current level of available resources (Humphreys & Revelle, 1984).

Description of the model

The current research project tests the model shown in Figure 1. The model proposes that while performing a task people continuously monitor *task cues*, the level of *task performance*, the level of *allocated resources*, and the level of *available resources*. These inputs are combined to form an assessment of *task demands*, in a process called *metacognition*. The level of task demands is an input to a process of *self-regulation* which determines and manages the amount of available resources that are allocated to the task. The model makes a distinction between information processing resources and attentional control resources as separate components of self-regulation. Information processing resources are associated with the manipulation of information in order to meet task demands and are closely aligned with working memory operations. Attentional control resources are required to maintain attention on current task goals and task-relevant information, and away from other, potentially more pleasant, activities. The model proposes that the allocation of information processing resources and attentional control resources have opposing effects on the level of available resources, with the allocation of information processing resources providing a short term increase in the level of available resources and the allocation of attentional control resources acting to deplete the level of available resources. For the sake of clarity these components are not shown in Figure 1 but are included in the more detailed description of the model contained in Chapter 2.

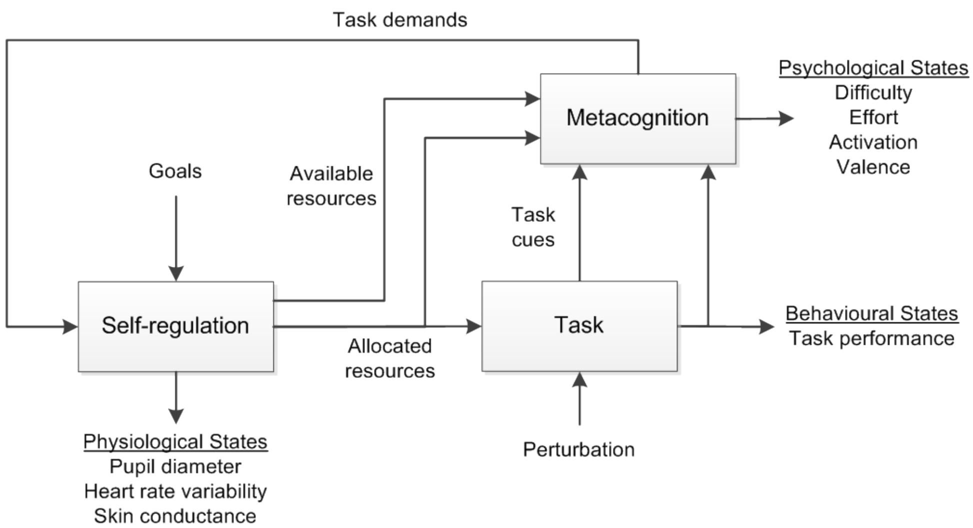

Figure 1. High-level representation of the self-regulatory model tested in the current thesis.

The model represents a process in which an increase in task demands generates an increase in the level of information processing and attentional control resources allocated to the task in order to maintain task performance, but only up to a point where an individual reaches the maximum level of resources that they are able or prepared to allocate. This represents the capacity limit of available resources and further increases in task demands beyond this point will not be accompanied by increased resource allocation. Instead performance levels will begin to degrade due to a mismatch between task demands and allocated resources. Performance failure could be due to an insufficient allocation of information processing resources or attentional control resources.

The metacognition process generates a range of psychological states which are available to self-report, such as *difficulty*, *effort*, *activation* and *valence*. Perceived difficulty is considered to arise from an appraisal of the level of resources required to meet task demands and an assessment of the level of resources available (Kanfer, 2011). An increase in the level of required resources or a decrease in the level of available resources will produce increased perceived difficulty. Effort is considered to be a function of the level of resources currently being allocated to meet task demands (Gendolla & Richter, 2010). An increase in the level of allocated information processing or attentional control resources will produce increased self-report effort. Activation is considered to be a function of the level of currently available resources, which may or may not be allocated to meet task demands (Humphreys & Revelle, 1984). It differs from effort in that activation is only an index of the level of resources available to meet task demands and does not reflect the level of resources actually allocated to meet task demands. Psychological activation is related to, but not the same as, physiological arousal, and increased activation is expected to correspond to an increase in the level of available resources. Valence indexes hedonic tone, or the level of pleasantness or unpleasantness of current experience (Barrett, 2006). Valence is considered to be a function of both the level of task performance and the level of allocated resources (Hockey, 1997; Seo, Barrett, & Bartunek, 2004a). Low performance levels and high levels of allocated resources are expected to produce low valence. Valence is also expected to be influenced by the direction of change in task performance levels, with increasing task performance levels predicting high valence and reduced effort, and decreasing task performance levels predicting low valence and increased effort (Carver & Scheier, 1998).

The self-regulation process produces a range of physiological responses including changes in pupil diameter. Increased task demands produce an increase in pupil diameter which is considered to be an index of the current level of resources allocated to meet task demands (Just, Carpenter, & Miyake, 2003). It is potentially a measure of effort free of the biases that can influence self-report measures. Other potential physiological measures of the self-regulatory response to task demands exist, such as heart-rate variability and skin conductance, but this thesis will only consider pupil diameter as it has the potential to remotely monitor operator state without needing to be physically attached to individuals, which is an important benefit in applied settings.

Hypotheses arising from the model

A number of hypotheses were generated based on the predicted relationships between task demands, the metacognitive states and pupil diameter. These formed three broad categories of predictions which related to 1) the effect of current task demands on perceived difficulty, effort, activation, valence, an pupil diameter; 2) the influence of prior task demands on these states; and 3) the indirect effects of task demands on perceived difficulty and valence.

The level of current task demands was expected to be a positive predictor of perceived difficulty, effort, and pupil diameter but a negative predictor of valence. The effect of current task demands on the level of activation was expected to depend on whether the task imposed information processing demands, which were expected to be a positive predictor of the level of activation, or only attentional control demands which were expected to be a negative predictor of activation.

Prior task demands were expected to deplete the level of activation. They were also expected to influence the level of effort expended to meet current task demands, but not in a completely deterministic fashion as effort was expected to be under volitional control. However, it was predicted that prior task demands may increase the level of effort expended in response to low and moderate task demands but decrease the level of effort allocated in response to high task demands.

The model proposed that changes in task demands have an indirect influence on perceived difficulty and valence through their effect on the level of available resources, allocated resources and task performance. These hypotheses predicted that the effect of task demands on perceived difficulty would be moderated by the level of activation, and that the effect of task demands on valence would be mediated by the level of effort, current task performance levels and the direction of change in task performance levels.

Experimental tests of the model

Three experiments were performed to test specific aspects of the proposed model. Experiments 1 and 2 used traditional cognitive and motor-control tasks which allowed an examination of the responses to short term and sustained task demands under tightly-controlled and well-understood manipulations which could separate information processing and attentional control demands. However these are not conditions present in typical applied settings and Experiment 3 used a ‘microworld’ simulation of the task performed by military air-radar operators to explore whether the predictions arising from the model were supported under conditions which required a series of decisions to be made using a range of information sources in an environment where the state of the decision problem changed over time and as a result of the actions of the decision maker, and where performance feedback was not available.

The chapters

Chapter 2 is the introduction and provides a review of the literature relating to the use of feedback control models to represent the metacognitive and self-regulatory processes involved in the human response to task demands. It introduces each construct and variable included in the proposed model, provides the theoretical and empirical rationale for the proposed structure of the model, and outlines the hypotheses arising from the model that will be tested by the empirical studies.

Chapter 3 provides an overview of multi-level modelling, which is the analytical technique used throughout this thesis. Multi-level models are becoming widely used in organisational and educational psychology but are not yet commonly used in experimental studies that manipulate predictor variables. The aim of the chapter is to provide a basic introduction to multi-level modelling so that the reader can understand the benefits of its use in experimental studies and also outline the analysis strategy used in the experiments.

Chapters 4, 5 and 6 report the three experimental studies conducted. Experiment 1 examined the effect of relatively short term changes in the level of task demands but did not attempt to separate the effects of information processing and attentional control demands or test the effect of sustained task demands. The experiment increased task demands from a low-load baseline using a short working memory task and then reduced task demands again to baseline level. As expected, perceived difficulty, effort, pupil diameter and activation were higher and valence was lower during the working memory task than during the low-load baseline. Increasing demands within the working memory task led to increased perceived difficulty and effort but no change in activation or pupil diameter. Valence decreased by an amount which approached, but did not reach, traditional levels of significance. These results were consistent with the predictions that increased information processing demands lead to increased levels of allocated resources and available resources but reduced valence. Of interest also was the dissociation between self-report effort and pupil diameter during the increasing demands of the working memory task. The level of self-report activation did not differ between the two baseline task demand occasions, which made it difficult to identify the effect of prior task demands on the level of available resources. However, effort and pupil diameter were greater during the second baseline occasion than during the first which was consistent with the prediction that increased effort may be applied in response to low or moderate task demands under conditions of reduced levels of available resources.

Experiment 2 tested whether information processing and attentional regulation demands had different effects on the level of available resources. It also tested whether sustained prior task demands depleted the current level of available resources and produced the predicted effects on the level of allocated resources. The experiment manipulated task demands using two information processing tasks and one motor-control task, which was used to induce primarily attentional control demands, and measured the changes observed during an initial and repeat performance of each task compared to a low-load baseline. As predicted the level of effort increased during the initial performance of all tasks. Also as predicted, the level of activation increased during the initial performance of both information processing tasks but not the motor control task. This supported the prediction that the allocation of information processing resources is required to increase the level of available resources. As predicted, the level of available resources during the repeat performance of all tasks was lower than during initial performance, which supported the hypothesis that sustained attentional control acts to reduce the level of available resources. Reduced activation had no influence on self-report effort, but the pupil diameter results indicated that during the repeat performance of one task participants appeared to reduce the maximum level of effort being applied in response to high demands but that during the repeat performance of another task increased effort was applied in response to high task demands. These results suggest that the level of available resources has a complex effect on the level of applied resources and point to the active management of resources in response to task demands.

Experiment 3 examined the effects of current demand levels, prior demand levels, and the direction of change in demand levels during a sustained multi-tasking information processing activity which lacked clear feedback about the correctness of present or past actions. It aimed to identify whether this type of task generated a similar pattern of responses than was observed during the previous two experiments which used simple, trials-based, tasks that provided clear demand cues and performance feedback. It measured the effects of cyclic task demands during a simulated air-radar task by initially increasing the number of new and existing radar contacts, then decreasing the number of contacts, then again increasing the number of contacts. In addition, participants had substantial flexibility in how they chose to respond to the changes in task demands. The results again suggested that the level of available resources increased with the level of information processing demands but decreased with sustained attentional regulation. They also again suggested a complex relationship between the level of available resources and applied resources, with effort becoming less responsive to changes in task demands as resources were depleted and instead increasing with time on task. As predicted, valence was influenced by the direction of change in task demands and the current level of effort but not the level of task demands.

Chapter 7 is the general discussion. It provides a discussion of the themes explored in the research project and a summary of the implications of the experimental studies for the proposed model. It identifies potential modifications to the model and identifies additional work that could be undertaken to test the proposed changes.

It should be noted that not all of the hypotheses arising from the model were supported by each of the experiments and some hypotheses were not supported by any of the experiments.

However, rather than modifying the hypotheses or ceasing to test them further after the initial absence of empirical support, all but one of the hypotheses were tested in each experiment. This was done to provide converging evidence from multiple methodologies (McGrath, 1981) in order to better understand the degree to which each hypothesis should be accepted, rejected or qualified.

CHAPTER 2: INTRODUCTION

Changes in task demands can trigger a complex set of metacognitive and physiological responses which influence performance. For example, increased task demands can lead to an appraisal of increased difficulty, the application of increased effort to maintain task performance, and changes in affect along with sympathetic and parasympathetic nervous system responses. While task demands may generate some automatic responses, the response to task demands is thought to be predominately under conscious control and people actively self-regulate to maintain acceptable levels of workload and performance (Lord & Levy, 1994).

Self-regulation is a dynamic process that unfolds within individuals over time, which both influences and is influenced by cognitive, affective and motivational states (Lord, Diefendorff, Schmidt, & Hall, 2010). Feedback control models can provide an effective way of defining dynamic systems where states can be an output of one process and an input to another, and this approach has been used in a range of self-regulatory theories in the domains of cognitive, organisational and human factors psychology (Carver & Scheier, 1998; Hendy et al., 1997; Hockey, 1997, 2013; Loft, Neal, Sanderson, & Mooij, 2007; Rouse, 1993; Vancouver, Putka, & Scherbaum, 2005).

However, while the use of feedback control models to describe task-orientated self-regulatory processes has received broad support, there is less agreement on the constructs that need to be included in these models and the nature of the relationships between the constructs. This chapter will review existing theoretical and empirical work that has examined self-regulatory responses to task demands and propose a control model which integrates the predicted effects of the information processing and attentional control requirements of current and prior task demands. The model will adopt a resources-based approach and the concept of resources and their relationship to key self-regulatory and metacognitive states will initially be reviewed.

The allocation and availability of attention and information processing resources

Kahneman (1973) proposed that individuals possess a finite, unitary, amount of attentional resources which are allocated to enable the performance of one or more tasks. The amount of resources allocated is proportional to the demands of each task and the level of allocated resources is sensed as effort. As the level of task demands increase, increased resources will initially be allocated in order to achieve a desired level of task performance. However, as task demands continue to increase, a point will be reached where the level of allocated resources reaches the limit of available resources, and further increases in task demands will not be accompanied by increases in allocated resources. Instead effort may be maintained at the limit of available resources in an attempt to maximise performance levels or be withdrawn if successful task performance is perceived as being unachievable (Brehm & Self, 1989; Hockey, 1997).

Kahneman (1973) used an energy metaphor to suggest that attentional resources ‘activate’ the various cognitive structures that process information inputs. The level of activation influences the amount of information processing that can be performed by a structure and performance failure will occur if the level of resources allocated to a structure is insufficient to allow the structure to adequately process the information input. It may also be possible that structural capacity could limit performance even when enough resources are available but Kahneman (1973) deemphasised the potential influence of cognitive structures on task performance.

The concept of attentional resources was initially used to explain the effect of information processing demands on cognitive task performance, which require the application of executive functions such as working memory operations, inhibition of automatic responses, and task switching (Miyake, Friedman, Emerson, Witzki, & Howerter, 2000). However, successful cognitive task performance also requires self-regulation in order to maintain focus on the current task goals and supress other, potentially more attractive, goals. It has been argued that individuals possess a finite capacity for self-regulation and that performing tasks or activities which require self-regulation depletes the level of available resources which can lead to subsequent failures in task performance due to lapses of self-regulation (Baumeister, Vohs, & Tice, 2007; Muraven & Baumeister, 2000).

It has also been suggested that the resources required for self-regulation are qualitatively different to the executive functions required for information processing (Muraven & Baumeister, 2000). However, executive functions and self-regulation appear to exhibit some parallels. The self-regulatory function of maintaining focus on a particular set of task goals appears conceptually similar to the executive function of controlled attention that is necessary during working memory operations to direct attention towards relevant information and away from irrelevant information (Kane, Bleckley, Conway, & Engle, 2001). The self-regulatory function of inhibiting a shift to other tasks or behaviours can be seen as similar to the executive function of inhibiting automatic responses (Hofmann, Schmeichel, & Baddeley, 2012). These functions broadly relate to the need to direct attention towards certain tasks or information while supressing other tasks or stimuli and may indicate that self-regulation and executive functions are linked by their common demand for attentional control (Kaplan & Berman, 2010).

Resource allocation and decreased available resources

A core tenet of the *ego-depletion* effect proposed by self-regulatory theories is that sustained task performance depletes self-regulatory resources, and evidence for this proposal comes from both the *vigilance* and *dual-task* paradigms. The vigilance paradigm requires that individuals maintain constant attention on a single task which requires perceptual or cognitive processing. Vigilance tasks typically produce a decrement in performance within a period of 20 minutes after the commencement of the task, are accompanied by an increase in self-report effort over time (Warm, Dember, & Hancock, 1996), and result in increased levels of fatigue (Warm, Matthews, & Finomore, 2008). The level of decrement associated with vigilance is also influenced by the nature of the task, with higher stimulus presentation rates, sequential as opposed to simultaneous judgements, and cognitive as opposed to perceptual judgements producing a greater performance decrement and higher effort (See, Howe, Warm, & Dember, 1995). These results have led to the conclusion that, rather than being undemanding, vigilance tasks require that a substantial level of resources be allocated to maintain task performance and that this sustained allocation of resources acts to deplete the level of available resources which leads to performance decrements and fatigue (Warm, Parasuraman, & Matthews, 2008).

A similar pattern of results has been observed in the dual-task paradigm, which requires individuals to perform two, potentially unrelated, consecutive tasks of which the first task either does or does not require self-regulation. An experimental group is assigned to a condition in which the first and second tasks both require self-regulation, while a control group is assigned to a condition in which the only the second task requires self-regulation. A meta-analysis of 193 independent tests of the dual-task paradigm found that the experimental group achieved lower performance but reported higher levels of effort, difficulty, negative affect and fatigue during the second task than the control group (Hagger, Wood, Stiff, & Chatzisarantis, 2010). The analysis found that these effects were significant for a wide range of tasks and, importantly, that tasks which required information processing exhibited an effect that was similar in size to tasks which only required ‘self-control’, such as supressing an emotional response, resisting impulses to eat tempting foods, or controlling thoughts. The meta-analysis also found a marginally significant tendency for complex information processing tasks to have a larger effect size than simple information processing tasks that required rote memory or single arithmetic operations.

Results from the dual-task paradigm therefore appear to closely match the results of vigilance studies and suggest that both information processing tasks and ‘self-control’ tasks which require the suppression of unwanted responses or the maintenance of focussed attention require effortful processes that can lead to a reduction in performance and an increase in fatigue and negative affect. Although other possible interpretations exist (Inzlicht, Schmeichel, & Macrae, 2014; Kurzban, Duckworth, Kable, & Myers, 2013; Matthews & Desmond, 2002), a resources perspective would propose that resources allocated during prior task performance deplete the amount of resources currently available which can lead to performance degradation and the experience of fatigue. However, the results do not necessarily mean that the executive functions required by information processing tasks are responsible for the resource depletion associated with sustained cognitive task performance. As noted above, information processing tasks require the application of both self-regulation in order to persist with the task and executive functions in order to successfully perform the information processing demands. It may still be, as proposed by Muraven and Baumeister (2000), that only the self-regulatory demands and not the information processing demands associated with task performance act to reduce the level of available resources. Indeed it may be the case that some executive functions act to *increase* the level of available resources, and evidence for this proposal will be reviewed next.

Resource allocation and increased available resources

Kahneman (1973) proposed that, while the level of available resources is finite, it may not necessarily be constant and instead may vary with the current level of resource allocation. This idea has received a more recent treatment in malleable attention theory which proposes that the level of available resources will vary with the level of resources currently allocated to a task (Young & Stanton, 2002a, 2002b). This proposal has mostly been evaluated in terms of the effects of underload caused by automation, with increased automation producing decreased efficiency of secondary task performance during simulated driving (Young & Stanton, 2002a, 2002b, 2007) and a reduction in the number of communication tasks performed during naval navigation (Gould et al., 2009).

However, the effects of increased resource allocation have also been tested. Gershon, Ronen, Oron-Gilad, and Shinar (2009) found that the introduction of an interactive cognitive task requiring a response to trivia questions improved driving performance and reduced self-report sleepiness, and Atchley, Chan, and Gregersen (2014) found that a verbal word-association task administered near the end of a 90-minute drive improved driving performance and increased EEG indices of alertness. A set of short cognitive, discrimination and tracking tasks has also been shown to increase task engagement and cerebral blood flow velocity, which may index a state of readiness for resource mobilisation (Matthews et al., 2010). These results support the proposal that changes in the current level of allocated resources may influence the level of available resources.

Reconciling the conflicting effects of resource allocation on the level of available resources

The above discussion suggests that the allocation of resources may either increase or decrease the level of available resources. This thesis proposes that two opposing task-based processes generate this result. The first is that the allocation of information processing resources associated with working memory operations act to increase the level of available resources. The second is that the attentional control processes associated with self-regulation and executive functions act to decrease the level of available resources. Using systems dynamics terms (Coyle, 1996), available resources is a level variable which can accumulate or drain. Attentional control is a rate variable which determines the current rate of decrease in the level of available resources. Increased levels of attentional control increase the rate of decrease in the level of available resources. Information processing is an auxiliary variable which acts as a time-varying constant so that current level of information processing provides a short term increase in the current level of available resources.

Support for the proposal that information processing and attentional control have different and opposing influences on the level of available resources can be found in Matthews et al. (2002) and Matthews et al. (2006) which compared the influence of a reading task, visual and auditory vigilance tasks, a visual working memory task, and an impossible anagrams task on the state dimensions of engagement, distress and worry. The reading task required low effort and caused no change in distress or engagement; the vigilance tasks required high effort but caused increased distress and reduced engagement; the visual working memory task required high effort and caused increased distress, increased engagement in the 2002 study and caused no change in engagement in the 2006 study; and the impossible anagrams task required high effort and caused increased distress but did not change engagement. These findings suggest that, while increased effort is a consistent response to the demands of a range of tasks, different task types produce different affective responses. Both vigilance and working memory tasks appear to increase distress, but vigilance tasks appear to reduce task engagement while working memory tasks appear to maintain or increase task engagement.

The inconsistent effect of a visual working memory task on engagement can be clarified by a closer examination of the results. Matthews et al. (2002; 2006) used the same complex span working memory task but the 2002 study, which found that the working memory task increased engagement levels, applied increasing time pressure across trials whereas the 2006 study, which found that the working memory task did not change engagement levels, maintained a constant time limit in all trials. This suggests that the time-pressure manipulation may have been responsible for the increase in task engagement and makes it difficult to compare this task with the others which did not include a time pressure manipulation. If the time-pressured task is removed from consideration, the studies produce a clearer picture in which non time-pressured working memory tasks increase distress but cause little change in task engagement while vigilance tasks increase distress and reduce task engagement.

Task engagement and distress load onto the dimensions of energetic arousal and tense arousal respectively (Matthews et al., 2002; Matthews, Jones, & Chamberlain, 1990) which are formed by an approximately 45-degree rotation of the dimensions of valence and activation, which are considered to be orthogonal dimensions of core affect (Carroll, Yik, Russell, & Barrett, 1999; Kuppens, Tuerlinckx, Russell, & Barrett, 2013; Yik, Russell, & Steiger, 2011). These relationships are displayed pictorially in Figure 2 and an inspection of this indicates that a combination of increased distress and unchanged engagement corresponds to increased activation and decreased valence. Non time-pressured working memory tasks, which increase distress and maintain engagement, therefore appear to increase activation but decrease valence, Vigilance tasks increase distress and reduce engagement, both of which correspond to a leftward shift on the affect circumplex and therefore reduced valence. The combination of increased distress and reduced engagement associated with vigilance tasks is potentially ambiguous with respect to activation, but as vigilance tasks tend to reduce engagement to a greater extent than they increase distress (Matthews et al., 2002) vigilance tasks appear to reduce activation.

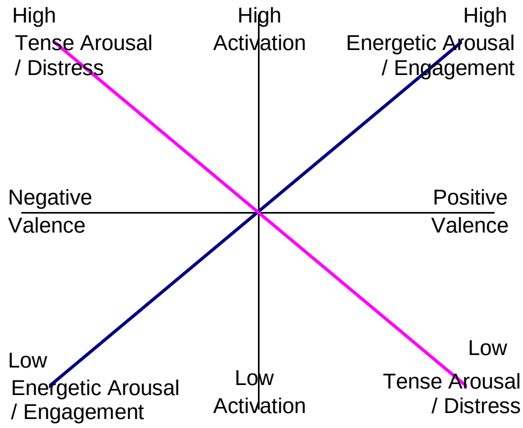

Figure 2. Graphical representation of the relationships between Energetic Arousal, Tense Arousal, Engagement, Distress, Activation and Valence

It has been proposed that the metacognitive experience of activation or arousal is a construct that can be used to index the level of available resources (Humphreys & Revelle, 1984; Young & Stanton, 2002b). In support of this proposal, higher self-report activation has been associated with more efficient processing in demanding attentional tasks (Matthews, Davies, & Lees, 1990) and better performance during vigilance tasks (Helton, Matthews, & Warm, 2009). It may therefore be that the increased self-report activation associated with the working memory tasks described above indicates that information processing contributes to increased levels of available resources whereas tasks that require attentional control but little information processing, such as typical vigilance tasks, do not contribute to increased levels of available resources. This leads to the first of the predictions to be tested:

Hypothesis 1a: Increased information processing demands will increase the level of self-report activation.

Hypothesis 1b: Increased attentional control demands will not increase the level of self-report activation.

Hypothesis 2a: Sustained attentional control demands will decrease the level of self-report activation.

The alphanumeric labelling of the hypotheses acts to organise them according to the three prediction categories identified in the overview: the direct effect of current task demands, the direct effect of prior task demands and the indirect effects of task demands on the metacognitive and physiological states. Hypotheses associated with the effects of current task demands will begin with 1, hypotheses associated with the effects of prior task demands will begin with 2 and the hypotheses associated with the indirect effects of task demands will begin with 3. The letter of each hypothesis label will distinguish hypotheses within each category.

The metacognitive experience of resource allocation and availability

The above discussion identified that self-report activation might be used as an index of the level of available resources and also identified effort, perceived difficulty and valence as key metacognitive states associated with task-based self-regulatory processes. The following section will discuss the proposed relationship of each metacognitive state to the level of allocated and available resources.

Considering difficulty initially, perceived difficulty is thought to reflect an appraisal of task demands and an assessment of the level of resources required for successful task performance (Kanfer & Ackerman, 1989; Yeo & Neal, 2004). Studies that have examined the between-person (Mangos & Steele-Johnson, 2001; Maynard & Hakel, 1997) and within-person (Capa, Audiffren, & Ragot, 2008; Richter, Friedrich, & Gendolla, 2008) response of perceived difficulty to manipulated task demands have found that increased task demands are associated with increased levels of perceived difficulty. Perceived difficulty has also been shown to be influenced by ability beliefs (Wright, Contrada, & Patane, 1986) and the experience of fatigue and resource depletion (Hagger et al., 2010; Wright, Martin, & Bland, 2003; Wright, Patrick, Thomas, & Barreto, 2013). These results suggest that perceived difficulty can be expected to be a function of both the level of resources demanded by the task and the level of resources that are available for task performance. This leads to the following predictions:

Hypothesis 1c: Increased information processing and attentional control demands will increase perceived difficulty.

Hypothesis 3a: The relationship between task demands and perceived difficulty will be moderated by the level of self-report activation.

Considering effort next, some resource-based accounts have considered that the experience of effort corresponds to the level of resources currently allocated to task performance (Gendolla & Richter, 2010; Kahneman, 1973; Kanfer & Ackerman, 1989). Others have considered that it is a signal of the 'cost' of current task performance levels and that sensed effort indicates the proportion, rather than the absolute level, of resources currently allocated (Boksem & Tops, 2008; Hennecke & Freund, 2013). The cost interpretation is consistent with findings that self-report effort increases with sustained task performance (Hagger et al., 2010; Warm et al., 1996) if it is assumed that the level of allocated resources remains constant with time on task while the level of available resources decreases due to the depleting effects of self-regulation. However, the result may also be explained using the concept of compensatory effort, where additional resources can be allocated to protect task performance against environmental stressors or unexpected changes in task demands (Hockey, 1997). This may produce an effect where a reduction in the level of available resources causes additional regulatory resources to be applied in order to protect performance from being disrupted by low resource levels. If so then the interpretation of sensed effort as the absolute level of applied resources would also be consistent with the empirical results that self-report effort increases with sustained task performance.

It is difficult to conclusively resolve these two possibilities empirically without measures that unambiguously index the level of allocated and available resources. This is not currently possible and this thesis will initially take the more parsimonious option and assume that sensed effort indexes the absolute level of applied resources. Given that self-report effort increases with increased task demands and also time on task (Recarte, Perez, Conchillo, & Nunes, 2008) it will also be assumed that both information processing demands and attentional control demands contribute to self-report effort. However, as noted above, it is expected that individuals possess a finite amount of resources which will set an upper limit on effort that will be expended in response to increasing task demands. This relationship is depicted in Figure 3 for high and low levels of available resources and leads to the following prediction:

Hypothesis 1d: Increased information processing and attentional control demands will be accompanied by increased effort, but only up to the point of maximum resource allocation after which effort will remain constant or decrease.

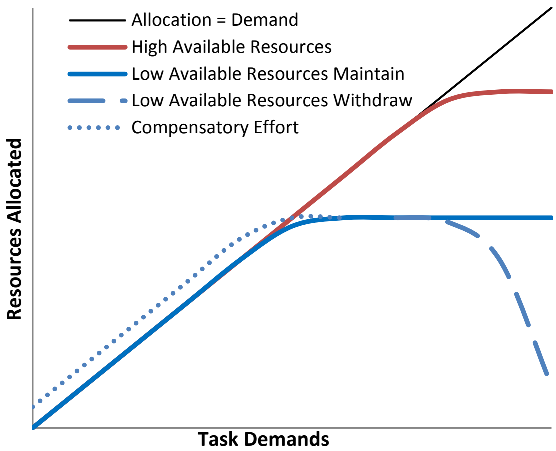

Figure 3. Graphical representation of possible relationships between task demands and resource allocation under conditions of high and low resource availability.

However, the relationship between task demands and the level of allocated resources depicted by the solid and dashed lines in Figure 3 may be an over simplification. As noted above, effort has been found to increase as the level of available resources decrease, which may reflect the application of compensatory effort where additional effort is applied to protect task performance in difficult environments or possibly under conditions of reduced available resources. This effect is consistent with the proposal that the level of resources allocated in response to task demands is not deterministic, but rather is actively managed (Loft et al., 2007) and is depicted by the dotted line in Figure 3. This situation makes it difficult to make a firm prediction about the effect of reduced available resources on effort, but suggests that reduced available resources may lead to increased allocated resources at low and moderate task demand levels but lower allocated resources at high task demand levels.

Hypothesis 2b: Decreased self-report activation will be accompanied by increased effort at low and moderate task demand levels and stable or reduced effort at high task demand levels.

The final metacognitive state that will be considered is valence, which indexes hedonic tone, or the level of the pleasantness or unpleasantness of current experience (Barrett, 2006). High levels of effort are believed to generate an aversive state (Hockey, 1997; Navon, 1989) which should be reflected in low valence. This proposal is supported by the previously-discussed studies of Matthews et al. (2002), Matthews et al. (2006) and Matthews et al. (2010) which found that high effort associated with a range of tasks produced increased distress and either stable or reduced task engagement. As can be seen from Figure 2 an increase in distress with no change in task engagement corresponds to a movement up and left along the Tense Arousal / Distress axis of the affect circumplex, which represents an increase in activation and a decrease in valence. An increase in distress combined with a decrease in engagement corresponds to a movement both up and left along the Tense Arousal / Distress axis and down and left along the Engagement axis. As each of these movements requires a shift left in the affect circumplex the combined effect is to reduce valence. Therefore high levels of effort produce a pattern that is consistent with a reduction in valence. Stewart, Wright, Hull, and Simmons (2009) also found that participants who performed a difficult scanning task had higher negative affect than participants who had performed an easy scanning task and the meta-analysis of Hagger et al. (2010) found that participants who performed a task requiring self-regulation had higher negative affect than participants who performed a task that did not require self-regulation. These results are all consistent with the proposal that high levels of effort are associated with reduced valence, but do not conclusively establish that effort mediates the relationship between task demands and affective valence.

Affective valence may also be a function of task performance levels. In addition to suggesting that effort generates an aversive state, Hockey (1997) proposed that a discrepancy between actual and desired task performance levels will produce negative affect. A similar idea was expressed by Seo, Barrett, and Bartunek (2004b) who proposed that affective valence is a function of an individual's performance level. Carver and Scheier (1998) also identified that task performance may influence affective state but proposed that the rate of change in performance, rather than the instantaneous task performance level, drives the affective response to task demands, with a positive performance trajectory producing positive affect and a negative performance trajectory producing negative affect.

Empirical results provide some support for the proposed influence of task performance on valence. Lawrence, Carver, and Scheier (2002) manipulated performance feedback during an ambiguous task and found that participants who received feedback that their performance improved over the course of the experiment reported a positive mood change and participants who received feedback that their performance worsened over the course of the experiment reported a negative mood change. Chang, Johnson, and Lord (2010) Study 2 also manipulated feedback from an ambiguous task and found that high performance and high improvement velocity independently predicted high task satisfaction but that both low performance and low velocities were required to reduce satisfaction. However, this was a cross-sectional design and therefore its implications for the examination of intra-individual dynamics are unclear. In a longitudinal study, Elicker et al. (2010) measured the performance level and rate of change in performance level at two occasions during an introductory psychology course and found that performance level and the rate of change in performance level independently contributed to perceived satisfaction with goal achievement. These studies offer support for the proposal that both performance level and the rate of change in performance level contribute to the affective response to task demands, but each measured mood or satisfaction, not valence. A more direct measurement was made by Venables and Fairclough (2009) who measured hedonic tone using the University of Wales Institute of Science and Technology Mood Adjective Checklist (UMACL) (Matthews, Jones, et al., 1990) while manipulating performance feedback and found that feedback of improving task performance led to increased hedonic tone and feedback of worsening task performance led to reduced hedonic tone. However, worsening performance feedback was also accompanied by increased effort and no attempt was made to examine the independent influences of perceived performance and effort on affective valence. The current thesis will extend these results by exploring the mediating effects of task performance and effort on the relationship between task demands and valence. The following predictions will be tested:

Hypothesis 1e: Increased information processing and attentional control demands will be accompanied by decreased valence.

Hypothesis 3b: The relationship between task demands and valence will be mediated by the current task performance level, the direction of change in task performance and the current level of effort.

The physiological response to resource allocation

The previous section discussed changes in key metacognitive states associated with the allocation and availability of resources which can be measured through self-report. However, self-report measures are known to be susceptible to a range of problems including inconsistent interpretation of scale descriptors, context effects, and limits to the number of internal states available to consciousness (Annett, 2002). A possible alternative approach is to monitor the physiological responses to task demands which offer the potential to provide an objective, unobtrusive and sensitive measure of resource allocation that can be collected continuously and in real time.

Kahneman (1973) proposed the existence of a link between applied attentional resources and arousal which has also been discussed by more recent researchers (Cacioppo &

Tassinary, 1990). This suggests that physiological measures of arousal generated by sympathetic and parasympathetic activation of the autonomic nervous system (ANS) can potentially be used to index changes in the level of effort, although care must be taken as changes in arousal can also be influenced by other factors such as physical activity and emotional responses to task demands. Heart rate variability has been proposed as a sensitive physiological index of mental effort (Boucsein & Backs, 2000) but this typically requires that a measurement device be attached to individuals which may make it difficult to use in applied settings.

Pupil diameter has also been shown to respond to demand manipulations across a range of cognitive tasks including mental arithmetic, perceptual discrimination, visual search, memory, sustained attention, problem solving and language processing (Ahlstrom & Friedman-Berg, 2006; Beatty, 1982; Beatty & Lucero-Wagoner, 2000; Engelhardt, Ferreira, & Patsenko, 2010; Piquado, Isaacowitz, & Wingfield, 2010; Porter, Troscianko, & Gilchrist, 2007; Van Orden, Limbert, Makeig, & Jung, 2001). The change in pupil diameter in response to task demands is in part driven by parasympathetic inhibition associated with the level of cognitive resources allocated to a task but is also caused by a more general sympathetic activation associated with task performance (Steinhauer, Siegle, Condray, & Pless, 2004). Pupil diameter responds to both the preparation for and processing of task demands (Bitsios, Szabadi, & Bradshaw, 2004) and can be considered to be an instantaneous measure of aggregated neural resources (Just et al., 2003). Recent work has also shown that these effects can be measured using remote video cameras which can collect data on changes in pupil diameter without the need to be attached to individuals (Klingner, Tversky, & Hanrahan, 2011). Given the potential benefits of being able to collect real-time, unobtrusive and objective measures of operator state in applied environments, this thesis will explore the use pupil diameter as a measure of the current level of information processing and attentional resource allocation under visual conditions that can be expected to occur in some applied settings. The following predictions can be made:

Hypothesis 1f: Increased task demands will be accompanied by increased pupil diameter, but only up to the point of maximum resource allocation after which pupil diameter will remain constant or decrease.

Hypothesis 2c: Decreased self-report activation will be accompanied by increased pupil diameter at low and moderate task demand levels and stable or reduced pupil diameter at high task demand levels.

Summary of hypotheses

The eleven hypotheses developed above can be grouped into three broad categories which address 1) the effect of current information processing and attentional control demands on perceived difficulty, effort, activation, valence, and pupil diameter; 2) the influence of prior demands on each state; and 3) the indirect effects of task performance levels on perceived difficulty and valence. The hypotheses are summarised in Table 1.

Table 1 Summary of the hypotheses to be tested

Category		Hypothesis
1	The effect of current information processing and attentional control demand levels	
	1a)	Increased information processing demands will increase the level of self-report activation
	1b)	Increased attentional control demands will not increase the level of self-report activation
	1c)	Increased information processing and attentional control demands will be accompanied by increased perceived difficulty
	1d)	Increased information processing and attentional control demands will be accompanied by increased effort, but only up to a the point of maximum resource allocation after which effort will remain constant or decrease
	1e)	Increased information processing and attentional control demands will be accompanied by increased pupil diameter, but only up to the point of maximum resource allocation after which pupil diameter will remain constant or decrease
	1f)	Increased information processing and attentional control demands will be accompanied by decreased affective valence
2	The effect of prior information processing and attentional control demands	
	2a)	Sustained attentional control demands will decrease the level of self-report activation
	2b)	Decreased self-report activation will be accompanied by increased effort at low and moderate task demand levels and stable or reduced effort at high task demand levels
	2c)	Decreased self-report activation will be accompanied by increased pupil diameter at low and moderate demand levels and stable or reduced pupil diameter at high demand levels
3	The indirect effects of task demands on difficulty and valence	
	3a)	The relationship between task demands and perceived difficulty will be moderated by the level of self-report activation
	3b)	The relationship between task demands and valence will be mediated by the current task performance level, the rate of change in task performance and the current level of effort

The model to be tested

The previous sections identified the expected within-person changes in the level of *allocated resources* and *available resources* arising from short term and sustained information processing and attentional control demands and proposed definitions for the relationships between the level of available and allocated resources and the metacognitive states of perceived difficulty, effort, activation and the physiological state of pupil diameter. While identifying the individual factors that influence the human response to a given set of task demands is an important step, it is also necessary to identify the relationships between these factors in order to develop the ability to describe the underlying dynamic processes (Vancouver, 2005).

The belief that people actively engage in self-regulation of effort in order to maintain task performance levels readily lends itself to the use of feedback control models as a framework to understand the dynamic processes influencing the relationships between task demands, resource levels and the metacognitive and physiological states. The model shown in Figure 4 incorporates the key features of the response to task demands discussed above. Starting in the top-right corner of the figure, the model identifies that *metacognition* produces an assessment of *task demands* which drives a process of *self-regulation* that allocates *attentional control* and *information processing* resources to achieve *task performance*. *Perceived difficulty*, *effort*, *activation* and *valence* are meta-cognitive states which are influenced by the level of *available resources*, *allocated resources* and *task cues*. Perceived difficulty reflects an appraisal of the level of information processing and attentional control required for successful task performance and an assessment of the level of resources that are currently available. Self-report effort reflects the level of information processing attentional and control resources currently allocated. While perceived difficulty should continue to increase with task demands, effort should initially increase in response to both information processing and attentional control demands, but reach a maximum level after which further increases in task demands will result in either maintained or reduced effort. Self-report activation reflects the level of information processing and attentional control resources currently available. Tasks which require information processing will produce a short term increase in the level of information processing resources and therefore self-report activation, but that tasks which do not require information processing will not have this effect. Sustained task demands require attentional control, which will deplete the level of available self-regulatory resources. Valence arises from an assessment of current task performance and the rate of change of task performance as well the current level of effort. The final feature of the model is that the level of available resources will influence the allocation of resources to meet task demands. The existing literature suggests that the allocation of effort is under active control, which means that the response of effort to changes in resource availability was not expected to be deterministic. However, a reduction in the level of available resources was predicted to produce a compensatory increase in effort at low and moderate demand levels to protect task performance but stable or reduced effort at high task demand levels as a result of task disengagement.

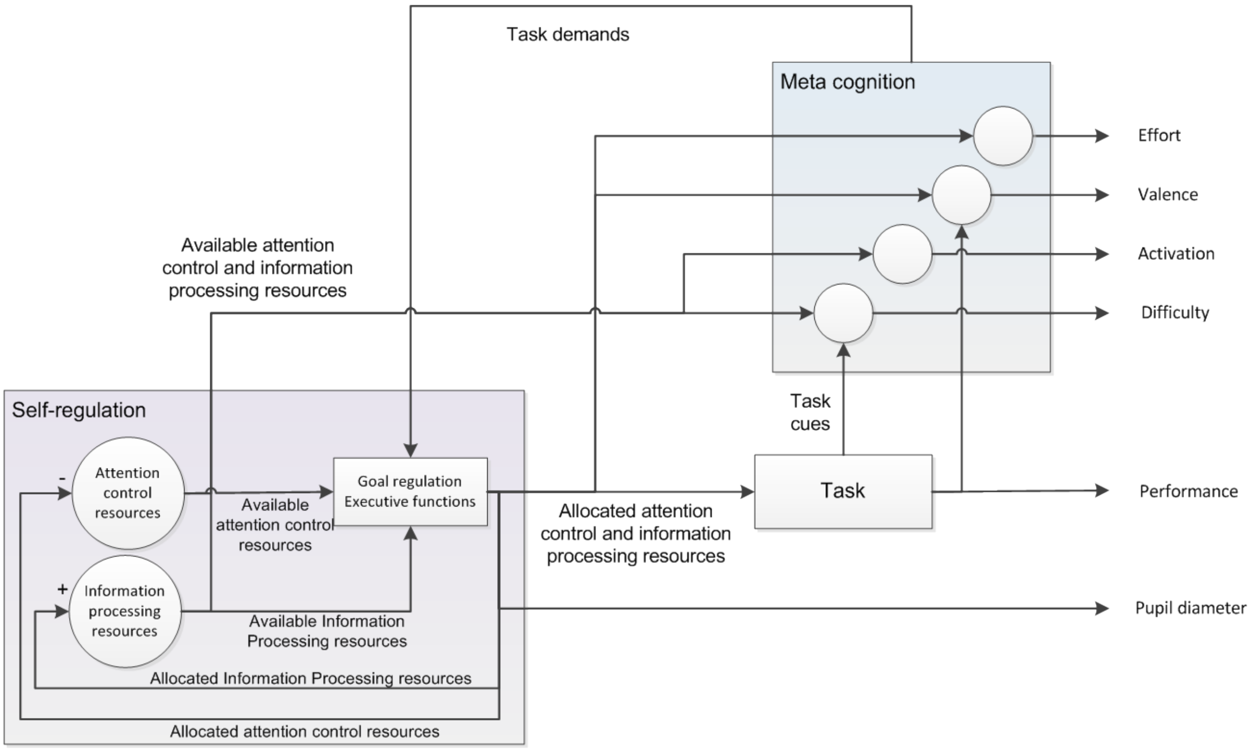

Figure 4. Detailed model of the proposed relationships between available resources, allocated resources, metacognitive states and pupil diameter.

Significance and innovation

While models exist that describe the influence of resource availability or resource allocation on a subset of metacognitive states, to the author's knowledge no models exist that attempt to describe the dynamic within-person relationships between the effect of information processing and attentional control demands on resource levels and all of the metacognitive states discussed. This lack of a comprehensive model is the theoretical gap that the current thesis aims to address.

The current thesis also aims to fill an empirical gap by addressing the limitations of previous studies that have often used between-persons analyses and coarse variations in task demands, which are not suited to testing dynamic within-person states and behaviours that the theoretical model aims to describe. The current study will address this shortfall by collecting performance, self-report and physiological time-series data within individuals which will be analysed using multi-level modelling and enable the potentially complex dynamic interactive effects of multi-task environments to be captured (Hancock & Szalma, 2008).

The proposed study will also make a practical contribution by assessing the ability of remote video cameras to reliably measure task-induced changes in pupil diameter under non-uniform luminance conditions. This will extend previous work (Klingner et al., 2011; Porter et al., 2007) and allow an assessment of whether pupil diameter may be a suitable index of resource allocation levels in some applied environments such as military operations or industrial control rooms.

CHAPTER 3: MULTILEVEL MODELING IN EXPERIMENTAL STUDIES

Introduction

Multilevel Modelling (MLM) is the general term for a statistical technique that can be used with clustered data, which violate the assumption of independence necessary for the more traditional analysis of variance (ANOVA) and ordinary least squares (OLS) regression techniques. Other terms that have been used to describe the technique include Growth Curve Modelling, Hierarchical Linear Modelling, Mixed Effects Modelling and Random Coefficients Modelling. Clustered data can arise in both cross-sectional designs, where individuals might be clustered in some organisational or geographical unit such as classroom or city, and in repeated-measures or longitudinal designs, where a number of observations are nested within individuals. MLM requires that models contain at least two levels, but more may be required to represent the structure of the data. Considering a repeated measures example, if multiple measures were taken during each of several experimental conditions then a three level model may be appropriate to represent that measurement occasion was nested within experimental condition which was nested within individuals. In addition to providing the ability to analyse clustered data, MLM also allows a flexible approach to modelling which can elegantly incorporate unbalanced designs and missing data.

MLM is becoming commonly used in educational and organisational research to identify predictor variables that account for the observed variance in academic achievement and work performance (Raudenbush & Bryk, 2002; Singer & Willett, 2003) but is less frequently used in experimental studies that manipulate independent variables (Hoffman & Rovine, 2007). This chapter will provide an introduction to model specification, model building and the interpretation of model parameters with a focus on the application of MLM to repeated-measures experimental designs, which were extensively used in this thesis. It will cover the inclusion of continuous and discrete independent variables and examine the main effects of variables at each level of a model as well as cross level interactions. This will be done by providing a worked example of the model development process using data from the first experimental study. The chapter will then discuss tests of power and mediation in multilevel models and identify the criteria used to assess statistical significance in this thesis.

Model Specification

Number of levels

The starting point in an MLM analysis is to decide how many levels are needed to model the data and identify what each level represents. The minimum number of levels is two, but more levels may be required in order to accurately represent the structure of the data. For the current purposes of modelling repeated-measures experimental data the highest level of any model will represent individual level variables, and in a two-level model Level 2 would model inter-individual differences and Level 1 would model differences in measurement occasions within individuals. This model structure would be appropriate if each individual performed the same task on a number of different occasions or at several levels of difficulty. However, if several different tasks were each performed on a number of occasions or at various levels of difficulty then there would potentially be three sources of random variation: variation among occasions or difficulty levels within tasks, variation among tasks within individuals and variation among individuals. In this case a three level model would be appropriate in order to represent these different sources of variation.

This chapter will use as an example the data from Experiment 1 of this thesis where individuals each performed a counting task and the Paced Serial Addition Task (PASAT). The counting task was performed on two occasions, with each occasion having the same demand level. The PASAT was performed on three occasions, with each occasion increasing in demand level. All participants initially performed the counting task, followed by the three increasingly difficult levels of the PASAT, followed by the second occasion of the counting task. In order to test a secondary goal of determining whether the size of the pupil diameter response to task demands was moderated by the level of ambient light, half of the participants completed each task under high ambient light and half performed each task under low ambient light. Several dependent variables were measured during the experiment but this example will model pupil diameter as the dependent variable, which will allow an examination of the main effect of the predictors at each level of the model and also whether any cross-level interaction effects existed.

As noted above a 3 level model would be appropriate for this data structure, with Level 1 being the measurement occasion level (and also the demand level for the PASAT), Level 2 being the task level and Level 3 being the individual level. Level 1 would therefore predict the change in pupil diameter across measurement occasions, Level 2 would predict change in pupil diameter between the counting task and the PASAT and Level 3 would predict the change in pupil diameter between the two ambient light levels, which was a between-individual manipulation.

Centering

An important decision to be considered when specifying the Level 1 model is how the independent variables should be centered. Centering can influence the value and interpretation of model coefficients as well as the ability of a model to converge on a solution. If the predictors are scaled in meaningful units such as age, grade, treatment times or the like, centering may not be necessary. In this case the intercept of each predictor can be fixed at a value that is meaningful for the research question of interest, with the proviso that the intercept should lie within or not far beyond the values observed in the data (Singer & Willett, 2003).

However, centering can assist the interpretation of predictors that have no intrinsically meaningful scale or zero point, which is the case for many self-report psychological variables. Two main forms of centering exist which have been termed *grand mean centering* and *group mean centering* or *centering within cluster* (Enders & Tofighi, 2007). Grand mean centering involves translating each data point into its deviation around the mean of all data points. Group mean centering involves translating each data point into its deviation around the mean of data points in the cluster to which each point belongs. In the current example group mean centering would involve centering the measurement occasion data points within the task and ambient light condition to which they belong. It has been recommended that group mean centering be used if the Level 1 association between the independent variable and the dependent variable is of substantive interest and for examining cross-level interactions or interactions between a pair of Level 1 variables (Enders & Tofighi, 2007). This was the case for all analyses conducted in the current thesis and group mean centering was used whenever centering was required.

Given that in the current example the Level 1 predictor of occasion has meaningful values it was not necessary to centre this variable. However, an intercept still needed to be chosen for the predictor, and in this case the first measurement occasion of each task was chosen as the intercept. This meant that the first measurement occasion of each task was coded as 0, the second measurement occasion of each task was coded as 1 and the third measurement occasion of the PASAT task (the counting task had only two measurement occasions) was coded as 2.

The empty model

Once the number of levels has been determined, the ‘empty’ model can be specified, which models the variance in the dependent variable that exists at each level of the model with no predictor variables present. For the dependent variable of pupil diameter (PD), the empty model is shown below:

$PD_{00i} = \pi_{00i} + \varepsilon_{00i}$ (Level 1)

$\pi_{00i} = \beta_{00i} + r_{00i}$ (Level 2)

$\beta_{00i} = \gamma_{00i} + u_{00i}$ (Level 3)

Which can also be expressed as:

$PD_{00i} = \gamma_{00i} + u_{00i} + r_{00i} + \varepsilon_{00i}$

Where

γ_{00i} is the mean pupil diameter across all measurements of individual *i*;

ε_{00i} is the Level 1 residual for individual *i*;

r_{00i} is the Level 2 residual for individual *i;*

u_{00i} is the Level 3 residual for individual *i*.

In the above equations γ_{00i} is the mean pupil diameter across all measurement occasions, which is not of interest. Of more interest, however, are the ε_{00i}, r_{00i}, and u_{00i} terms which represent the variation present in pupil diameter at Level 1, Level 2 and Level 3 of the model respectively. These terms can be used to calculate the proportion of variance present at each level of the model and examine whether significant variance exists at each level, which might be accounted for by the addition of predictor variables.

The Level 1 model

The Level 1 model estimates a regression equation to represent the effect of the Level 1 predictor(s) for each individual. It typically includes an intercept term, which represents the expected value of the dependent variable when the Level 1 predictor is zero and a term to describe the expected change in the dependent variable with a unit change in the predictor variable. The following equation models pupil diameter at measurement occasion zero and the change in pupil diameter in response to an increase in measurement occasion:

$PD_{oti} = \pi_{0ti} + \pi_{1ti}(OCCASION)_{ti} + \varepsilon_{oti}$ (1)

Where:

PD_{oti} is the pupil diameter at OCCASION *o* of task *t* for individual *i*;

π_{0ti} is the intercept of task *t* for individual *i*, where *OCCASION* = 0;

π_{1ti} is the change in pupil diameter for a unit change in OCCASION of task *t* for individual *i*;

$(OCCASION)_{ti}$ is the measurement occasion within each task;

ε_{oti} is the residual at occasion *o* of task *t* for individual *i*.

It is possible to fit higher-order growth models at Level 1 such as quadratic or cubic functions. A quadratic function could be included by adding a $\pi_{2i}(OCCASION^2)_{ti}$ term to Equation (1) and a cubic function could be included by adding a $\pi_{3i}(OCCASION^3)_{ti}$ term. However linear models have the advantage of parsimony and it is difficult to justify a nonlinear trajectory without four or more data points (Singer & Willett, 2003), so a linear model will be used in this example and for all models developed in the current thesis.

The Level 2 model

The Level 2 model estimates a regression equation for each of the parameters of the Level 1 model and allows the introduction of the Level 2 predictor(s). In the current example the Level 2 predictor of task was a categorical variable suitable for dummy coding. Two Level 2 predictor variables were created: COUNT was coded as 1 for the counting task and 0 for the PASAT task, and PASAT was coded as 0 for the counting task and 1 for the PASAT task. The aim of the model was to identify the difference in pupil diameter between the first occasion of the counting task and the first occasion of the PASAT, and also the change in pupil diameter across measurement occasion during the counting task and the PASAT. This could be achieved with the following Level 2 model equations:

$\pi_{0ti} = \beta_{00i} + \beta_{01i}(PASAT) + r_{0ti}$

$\pi_{1ti} = \beta_{11i}(COUNT) + \beta_{12i}(PASAT) + r_{1ti}$ (2a)

Where:

β_{00i} is the mean pupil diameter at the first occasion of the counting task for individual *i*.

β_{01i} is the mean change in pupil diameter between the first occasion of the counting task and the first occasion of the PASAT for individual *i*;

β_{11i} is the mean change in pupil diameter across measurement occasion of the counting task for individual *i*;

β_{11i} is the mean change in pupil diameter across measurement occasion for the PASAT for individual *i*;

r_{0ti} is the residual of the intercept of task *t* for individual *i*;

r_{1ti} is the residual of the change in occasion across task *t* for individual *i*.

A slightly different and more traditional formulation of the Level 2 model equations could have been used where:

$\pi_{0ti} = \beta_{00i} + \beta_{01i}(PASAT) + r_{0ti}$

$\pi_{1ti} = \beta_{10i} + \beta_{11i}(PASAT) + r_{1ti}$ (2b)

In this formulation the interpretation of β_{00i} and β_{01i} would have been the same as above and β_{10i} would be equivalent to β_{11i} and represent the mean change in pupil diameter across measurement occasion of the counting task for individual *i*. However, in this case β_{11i} represents the *difference* in the pupil diameter across measurement occasion between the PASAT and the counting task, not the absolute change in pupil diameter across measurement occasion for the PASAT. As the absolute change in pupil diameter across measurement occasion for each task was of more interest than the difference in the change between tasks, equation (2a) was used as the Level 2 model.

The Level 3 model

The Level 3 model estimates a regression equation for each of the parameters of the Level 2 model and allows the introduction of between-individual predictors. In the current example ambient light was a Level 3 variable which, also being categorical, could be dummy coded and a Level 3 predictor of LIGHT was coded as 0 for the low ambient light condition and 1 for the high ambient light condition. In order to test the main effect of ambient light on pupil diameter and also the moderating effects of ambient light on the pupil diameter response to task and measurement occasion the following Level 3 model equations were used:

$\beta_{00i} = \gamma_{000} + \gamma_{001}(LIGHT) + u_{00i}$

$\beta_{01i} = \gamma_{010} + \gamma_{011}(LIGHT) + u_{01i}$

$\beta_{11i} = \gamma_{110} + \gamma_{111}(LIGHT) + u_{10i}$

$\beta_{12i} = \gamma_{120} + \gamma_{121}(LIGHT) + u_{11i}$ (3)

Where:

γ_{000} is the mean pupil diameter at the first measurement occasion of the counting task for all individuals in the low ambient light condition.

γ_{010} is the difference in mean pupil diameter at the first measurement occasion between the counting task and the PASAT for all individuals in the low ambient light condition.

γ_{110} is the change in mean pupil diameter across measurement occasion of the counting task for all individuals in the low ambient light condition.

γ_{120} is the change in mean pupil diameter across measurement occasion of the PASAT for all individuals in the dark ambient light condition.

γ_{001} is the difference in mean pupil diameter at the first measurement occasion of the counting task between individuals in the low and high ambient light conditions.

γ_{011} is the difference in the change in mean pupil diameter between the first occasion of the counting task and the PASAT between individuals in the low and high ambient light conditions.

γ_{111} is the difference in the change in mean pupil diameter across measurement occasion of the counting task between individuals in the low and high ambient light conditions.

γ_{121} is the difference in the change in mean pupil diameter across measurement occasion of the PASAT between individuals in the low and high ambient light conditions.

u_{00i} is the residual of the initial count occasion for individual *i*;

u_{01i} is the residual of the initial PASAT occasion for individual *i*;

u_{10ti} is the residual of counting task occasion for individual *i*;

u_{011i} is the residual of PASAT occasion for individual *i*;

The above model allows the testing of the main effects of task at the initial measurement occasion, the effect of ambient light at the initial measurement occasion of the counting task, and a range of cross level interaction effects. These are shown in Table 2 where the diagonals of the table represent the main effects and the off-diagonal cells represent the cross-level interactions.

Table 2. The main effects and cross level interactions tested in the model. The main effects are contained on the diagonal of the table and the cross level interactions are contained in the off-diagonal cells.

	Level 1: Occasion	Level 2: Task	Level 3: Ambient Light
Level 1: Occasion	None	Effect of occasion for the counting task and PASAT	Effect of ambient light on the change across measurement occasion for the counting task and PASAT
Level 2: Task		Difference between first occasion of the counting and PASAT under low ambient light	Effect of ambient light on the change between the first occasion of the counting task and PASAT
Level 3: Ambient Light			Effect of ambient light during first occasion of counting task

Fixed and random effects

The π, β, and γ terms in the above equations are called fixed effects and represent the mean value of each coefficient. The ε, r and the u terms are called random effects and represent the variance in each coefficient associated with individual differences. The random effects of each coefficient can be constrained to 0 which has the effect of assuming that there is no systematic difference between individuals associated with that coefficient and assigns the same value for that coefficient to all individuals. It is recommended that a cautious, theory driven, approach be taken to the addition of random effects (Singer & Willett, 2003) as they increase the number of free parameters which can cause difficulties for model convergence.

Example of the Analysis Process and Results

The following section will provide a worked example of the process used to analyse the data collected during Experiment 1 of the current thesis and present the results obtained for the dependent variable of pupil diameter. It is hoped that this will allow the results presented in the subsequent experimental sections of this thesis to be more readily understood.

The standard process for conducting MLM analyses is to initially run an ‘empty’ model and then run one or more models that add predictors test the hypotheses relevant to each level of the analysis (Snijders & Bosker, 1999). MLM software generally provides information about the model fit and HLM 7.01 for Windows (Bryk, Raudenbush, & Congdon, 2013) was used in this thesis which provides a deviance score which can be used to assess the improvements in fit obtained through the addition of predictor variables.

The empty model

The ‘empty’ model allows an examination of the size and the reliability of the variance that exists at each level of the model before any predictor variables are added. The empty model for the current example is shown in Table 3 and indicates that mean pupil diameter across all measurement occasions and participants was 6.26 mm which was significantly greater than zero. It also indicates that 2.1% of the total variance (.020 / (.020 + .209 + .730)) * 100 existed at Level 1 (the measurement occasion level), 21.8% existed at Level 2 (the task level) and 76.1% existed at Level 3 (the individual level). The tests of significance of the variance at each level indicated that reliable differences existed between tasks and individuals which could be accounted for by the addition of predictor variables.

Table 3. Results of the empty model and model incorporating the occasion, task and ambient light predictor variables.

Pupil Diameter		**Empty Model**		**Add Occasion and Task**		**95th % CI**	
Fixed effects		Coefficient	SE	Coefficient	SE	Lower	Upper
L1	Intercept	6.26 ***	0.24	6.52 ***	0.25		
L2	PASAT			0.73 ***	0.09	0.56	0.90
L1xL2	PASAT x Occasion			-0.03	0.06	-0.14	0.08
L1xL2	Count x Occasion			0.15 *	0.07	0.01	0.28
L3	Light			-1.29 **	0.35	-1.98	-0.60
L3xL2	Light x PASAT			-0.03	0.12	-0.27	0.21
L3xL2xL2	Light x PASAT x Occasion			0.01	0.05	-0.08	0.11
L3xL2xL1	Light x Count x Occasion			-0.04	0.10	-0.23	0.15
Random Effects							
L1	Residual, e	0.02		0.02			
L2	Variance, r	0.21 ***		0.01 **			
L3	Variance, u	0.73 ***		0.40 ***			
Model Fit							
	Deviance	44.90		-6.81			
	Parameters	4		11			

† p < .1, * p < .05, ** p < .01, *** p < .001.

Adding predictor variables

The next step in the analysis was to add predictor variables in order to test the experimental hypotheses. One possible approach is to introduce predictor variables one level at a time starting with Level 1 (Bliese & Ployhart, 2002; Kristjansson, Kircher, & Webb, 2007), but if, as is the case in the current example, the variance is greater at higher levels of the model this approach would appear to run the risk of lower level predictors not becoming significant until the higher level variance has been partitioned and possibly being prematurely removed from the model. An alternative approach taken here is to simultaneously add all predictors relevant to the hypotheses to be tested.

Table 3 shows the results of the model when OCCASION was added as a Level 1 predictor, PASAT and COUNT were added as Level 2 predictors, and LIGHT was added as a Level 3 predictor. The intercept of the model reflects the mean pupil diameter across participants when OCCASION, PASAT and LIGHT were all zero which, given how the variables were coded, was the initial occasion of the counting task under low ambient lighting. From the Intercept line of Table 3 it can be seen that the mean pupil diameter across participants in that condition was 6.52 mm and was significantly greater than zero. The PASAT line of Table 3 indicates that under low ambient lighting mean pupil diameter was 0.73 mm greater during the initial occasion of the PASAT than during the initial occasion of the counting task, which was a statistically significant increase. The Count x Occasion line of Table 3 indicates that under low ambient lighting pupil diameter increased by 0.15 mm between the first and second occasion of the counting task, which was a statistically significant increase. The PASAT x Occasion line indicates that under low ambient lighting the change in pupil diameter across PASAT occasion was -0.03 mm, which was not statistically significant. Considering next the Level 3 variable of ambient light, the Light line of Table 3 indicates that the mean pupil diameter during the initial occasion of the counting task when performed under high ambient light was 1.29 mm smaller than when performed under low ambient light. However, the remaining three lines of Table 3 indicate that the level of ambient light had no significant effect on the change in pupil diameter between the initial occasion of the counting task and the PASAT or the change in pupil diameter with measurement occasion for either task. This indicates that ambient light did not moderate the size of the pupil response to task and task occasion.

Model fit and effect sizes

An examination of the Deviance line of Table 3 indicates that the inclusion of the OCCASION, COUNT, PASAT and LIGHT variables reduced model deviance from 44.90 to -6.81. However, this improvement in model fit was accompanied by an increase in the number of free parameters from 4 to 11. A Chi-squared test can be used to identify whether these additional degrees of freedom result in a significant reduction in deviance (Raudenbush & Bryk, 2002), and in the current example the reduction in variance is $-6.81-44.9$ = -51.71

and the increase in parameters is 11 – 4 = 7. As $\chi^2(51.71,7) < .001$, this indicates that the addition of the predictor variables resulted in a significant improvement in model fit.

The effect sizes associated with the addition of predictor variables at each level can also be examined by examining the changes in the variance at each level. An examination of the L2 Variance, *r*, and the L3 Variance, *u*, rows of Table 3 indicates that the inclusion of task as a Level 2 predictor reduced the Level 2 variance from .209 to .011 and accounted for 94.7% (((.209−.011)/.209) * 100) of the Level 2 variance present in the empty model. Similarly, the addition of light as a Level 3 predictor accounted for 44.8% (((.730−.403)/.730) * 100) of the Level 3 variance in the empty model.

Testing Mediation in MLM

As discussed above, moderation hypotheses, where one variable affects the strength of the relationship between an independent and dependent variable, can be tested in MLM by examining cross-level or within-level interactions between the moderator and predictor variables. The current thesis also proposes a mediation hypothesis, which requires a different analysis method. Mediation is proposed when it is thought that a variable intervenes in the process by which an independent variable influences a dependent variable. Mediation can be tested by examining to what extent the proposed mediator variable(s) account for variation in the dependent variable due to the independent variable. Mediation can be represented using a path diagram as shown in Figure 5 where the effect of *X* on *Y* is mediated by *M*.

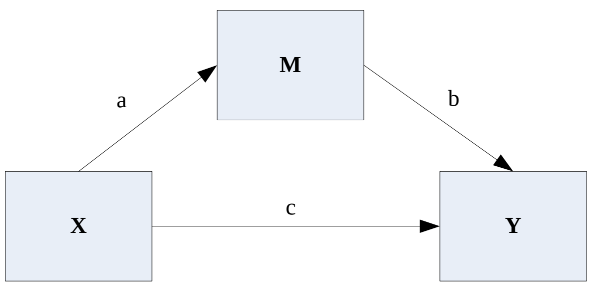

Figure 5 Path diagram of a mediation model where the effect of *X* on *Y* is mediated by *M*.

Baron and Kenny (1986) proposed a three step process to identify mediation where it must be shown that 1) the independent variable is a significant predictor of the proposed mediator variable(s) (path *a* in Figure 5), 2) the independent variable is a significant predictor of the dependent variable (path *c* in Figure 5), and 3) the mediator variable becomes a significant predictor of the dependent variable when included in regression model 2) above (path *b* in Figure 5) and the inclusion of the mediator variable reduces the strength of path *c*.

Complete mediation is established if path c becomes zero with the inclusion of the mediator variable and partial mediation is established if path c remains non zero.

Statistical Power and Criteria for Significance Testing

Few guidelines address the issue of power and sample size in MLM. Some guidance exists to inform sample size decisions for 2-level models (Snijders & Bosker, 1993) but no agreed methods appear to exist for higher level models. One rule of thumb calls for a minimum of 30 units at each level of the analysis (Maas & Hox, 2004, 2005), but these sample sizes are often difficult to achieve and at times clusters may have substantially fewer than 30 units. The main influence on power in MLM is the number of units at the highest level of analysis (Snijders, 2005) and simulation studies indicate that small Level 2 sample sizes may produce unbiased estimates of the fixed effects (Bell, Morgan, Kromrey, & Ferron, 2010). This suggests that, as long as random effects are not tested, small sample sizes may be acceptable in MLM analysis.

The three experiments reported in the current thesis were constrained by the availability of defence personnel and have sample sizes of either $N = 13$ or $N = 14$. While these sample sizes are consistent with many repeated measures experimental designs, they may raise concerns about the ability of the experiments to detect medium or small effects in an MLM analysis. However, an inspection of Table 3 indicates that the 95th percentile confidence intervals for the effects of the PASAT, occasion x PASAT and occasion x counting task on pupil diameter were ± .17 mm, ± .14 mm, and ± .11 mm respectively. These values are substantially less than the expected change in pupil diameter in response to cognitive task demands, which is in the order of .5 mm (Beatty & Lucero-Wagoner, 2000). This indicates that the sample size used in the current example was sufficient to detect the expected changes in pupil diameter in response to task demands. Confidence intervals will be reported throughout the thesis in order to provide an indication of the size of the effects that each analysis could be expected to detect. When absolute measures of effect sizes are not available Cohen's criteria will be applied, where $d = 0.2$ represents a small effect, $d = 0.5$ represents a medium effect size and $d = 0.8$ represents a large effect size (Cohen, 1988). As recommended in Feingold (2009) *d* was calculated by dividing the unstandardised regression coefficient by the raw standard deviation of the sample in the intercept condition.

A traditional significance level of $p < .05$ will be used as the criterion for main effects. However, (Snijders & Bosker, 1999) argue that the power to detect cross-level interactions in multilevel research is frequently low because of reductions in parameter reliability. For this reason, the criterion for cross-level interaction effects was set at the $p < .10$ level (Koy & Yeo, 2008; Smillie, Yeo, Furnham, & Jackson, 2006; Yeo & Neal, 2004). Several hypotheses in the current thesis predicted that some independent variables would have no effect on the dependent variable. This poses problems for traditional null hypothesis significance testing where failure to reject the null hypothesis cannot be directly interpreted as evidence that the null hypothesis should be accepted (Nickerson, 2000). As a possible solution to this problem Frick (1995) proposed that the null hypothesis can be accepted under conditions where $p > .05$, the confidence interval of the effect size is sufficiently small and where a related factor has a significant effect on the dependent variable. A less subjective application of confidence intervals to the acceptance of the null hypothesis was identified by Tryon (2001) and Tryon and Lewis (2008) who proposed that statistical equivalence can be established if the mean effect is not statistically significant and the confidence interval (CI) of the mean lies entirely within an amount that is considered inconsequential. When testing predictions of no effect the current thesis will use the criteria of a non-significant result and that the 95th percentile confidence interval of the effect should not include a small effect size, which was defined as $d = 0.2$.

CHAPTER 4: EXPERIMENT 1

Introduction

The aim of Experiment 1 was to test the predictions arising from the model developed in Chapter 2 about the effect of current and prior task demands on the level of resource allocation, resource availability and the metacognitive states. It manipulated task demands at the within-person level by increasing difficulty from a baseline level to a higher level and then returning to the initial baseline level. It measured perceived difficulty, effort, affect and pupil diameter at each demand level to identify the response to current task demands and compared the change in each variable between the two baseline levels to identify the influence of prior task demands. Experiment 1 used a task that imposed both information processing and attentional control demands and therefore made no attempt to isolate the potentially different effects of information processing and attentional control demands on the level of available resources.

A secondary goal of the experiment was to identify whether remote video cameras were capable of measuring task-induced changes in pupil diameter under conditions where gaze direction shifted across a visual field with non-uniform luminance levels under both low and high ambient light levels. This was not a hypothesis developed in Chapter 2, but was conducted to test whether pupil diameter might be an appropriate measure of resource allocation in some applied conditions such as military control rooms.

Method

Participants

Fourteen employees (four female) of the Defence Science and Technology Organisation, Australia, participated in the study. Their mean age was 39.4 years (*SD* = 7.7 years). No visual or other screening of participants was performed.

Materials and Apparatus

A simulated air-radar display was used as the visual stimulus which is shown in Figure 6. The left half of the display consisted of a map which showed land boundaries, civilian air lanes and a single air track. The right half consisted of track and map information areas which contained text and selection buttons. The visual stimulus was presented on a 22”, 1680 x 1050 pixel LCD monitor controlled by custom software running on an IBM-compatible PC. A computerised version of the Paced Auditory Serial Addition Test (PASAT) was used (Brainmetric, 2010), which was run on a separate IBM-compatible PC.

The luminance of the computer display at each of the three locations shown in Figure 6 and the luminance of the background area surrounding the computer display was measured from a distance of 200 mm using a luminance meter with a 6° measurement field. Under ambient light of 2 lux, Location 1 had a luminance of 0.5 cd/m^2, Location 2 had a luminance of 1.5 cd/m^2, Location 3 had a luminance of 5.5 cd/m^2 and the area behind the computer screen had a luminance of 0.0 cd/m^2. Under ambient light of 290 lux, Location 1 had a luminance of 1.5 cd/m^2, Location 2 had a luminance of 3.0 cd/m^2, Location 3 had a luminance of 7.5 cd/m^2 and the area behind the computer screen had a luminance of 2.5 cd/m^2.

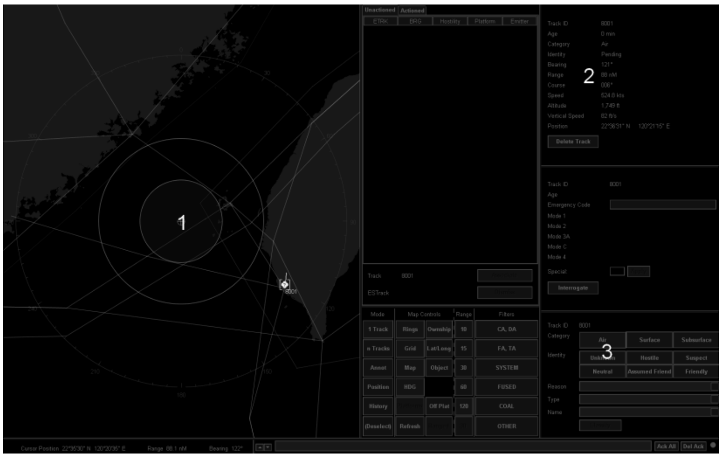

Figure 6 The simulated air-radar display used as the visual stimulus. The numbers represent the location of the three fixation points.

Pupil diameter and gaze direction were recorded using the faceLAB 4.6 eye tracking system (Seeing Machines, Canberra, Australia) which uses remote video cameras and infra-red illumination to track head movement, gaze direction and pupil diameter. The system is capable of resolving pupil diameter to 0.00001 mm (Fairclough, Ewing, & Roberts, 2009). The use of remote cameras allows data to be collected under natural viewing conditions without the need to constrain head movement. The video cameras were mounted just below the LCD monitor, which was viewed from a distance of approximately 70 cm. Head and eye data were collected at a sampling rate of 60 Hz.

Measures

The current study measured self-report task difficulty, effort, tense arousal, energetic arousal, pupil diameter and task performance level. Perceived difficulty and effort were assessed using scales developed by Yeo and Neal (2004, 2008). Perceived difficulty was assessed by asking participants to rate how difficult the task was (0 = extremely easy, 10 = extremely difficult). Cognitive effort was assessed by asking participants to rate how hard they were trying during the task (0 = not at all hard, 10 = extremely hard). Following the recommendation of Russell and Carroll (1999) a bipolar format was used to measure energetic and tense arousal. Anchors were chosen which loaded highly on the energetic arousal and tense arousal dimensions of the UMACL (Matthews, Jones, et al., 1990) and were also rated by Royal Australian Navy Combat System Operators as being frequently experienced during operations. Participants were asked to rate how they felt during the task (Energetic arousal: 0 = extremely tired, 10 = extremely alert; Tense arousal: 0 = extremely calm, 10 = extremely tense). Energetic arousal and tense arousal were transformed into valence and activation by subtracting 5 from each measurement to centre the scales on their midpoint and then using the following standard Cartesian coordinate rotation formulae to rotate the centred scores clockwise by 45 degrees:

$$\text{Valence} = \text{Energetic Arousal} * \cos(45) - \text{Tense Arousal} * \sin(45)$$

$$\text{Activation} = \text{Energetic Arousal} * \sin(45) + \text{Tense Arousal} * \cos(45)$$

Pupil diameter data were cleaned of blink and saccade artefacts by removing points where pupil diameter varied by more than 0.1 mm from the median pupil diameter of the previous or next 167 ms or where gaze direction varied by more than 15 mm from the median gaze direction over the same periods and averaged across each trial. Task performance level was measured as the number of errors made at each demand level.

Manipulations

Task demand was manipulated using two tasks. Counting aloud to 50 at a rate of approximately 1 digit per second served as a low-demand baseline task, and the Paced Auditory Serial Addition Task (PASAT) was used to induce higher levels of cognitive load. The PASAT is a test of attention, working memory and speed of information processing that acoustically presents a sequence of numbers between 1 and 9 at a fixed interval and requires participants to verbally report the sum of the previous two digits presented (Diehr, Heaton, Miller, & Grant, 1998; Gronwall, 1977). Demand is manipulated by varying the rate of number presentation, and the current study tested three levels of task demand by using three 25-digit sets with inter-number intervals of 2.0 seconds (PASAT Set A), 1.6 seconds (PASAT Set B) and 1.2 seconds (PASAT Set C).

Pupil diameter is sensitive to light and the light reflex is typically much larger than task-induced changes in pupil diameter (Loewenfeld, 1999). Most pupillometry studies are therefore conducted under tightly controlled, typically low, luminance conditions and often use auditory stimuli in order to eliminate any influence of the light reflex. They also often use a single fixation point to eliminate any measurement artefacts induced by saccades associated with changes in gaze direction. These conditions potentially place a severe limitation on the use of pupillometry in applied settings, and the current study aims to determine whether the pupil response to task demands can be measured when gaze direction changes regularly across a non-uniform luminance field under low and high ambient lighting. Porter, Troscianko and Gilchrist (2007) demonstrated that this was possible in low ambient light for low-contrast positive polarity (dark stimuli on a lighter background) displays, but many displays used in safety-critical domains such as military operations and air-traffic control still use negative polarity (bright stimuli on a darker background) displays and the current study extends previous work by having gaze direction change regularly over a visual field with a non-uniform background luminance containing visual elements that have higher luminance than the local background. It may also not be possible to tightly control ambient light levels in applied settings, but this may not be a major problem as the level of ambient light is expected to influence baseline pupil diameter but not the size of the task-induced dilation (Beatty & Lucero-Wagoner, 2000). The current study tested whether this prediction held for ambient light levels that ranged from those experienced in darkened military operations room to those present in bright military operations rooms.

A constant visual stimulus was displayed throughout the experiment, and participants were asked to maintain a visual scanning pattern that fixated for approximately one second in turn on the three locations of the display shown in Figure 6. Participants viewed the visual stimulus in a windowless room and were alternately assigned to a low (2.0 lux) or high (290 lux) ambient lighting condition (N = 7 in each condition).

Procedure

On arrival, participants were seated in front of the LCD monitor and informed that the purpose of the experiment was to determine whether the experimental equipment was capable of measuring changes in pupil diameter associated with cognitive load. They were instructed that they would need to count aloud to 50 and also perform the PASAT. The nature of the PASAT was explained and participants were given at least two practice sets of 5 numbers each to ensure they understood the task. The eye-tracking equipment was then calibrated using 9 fixation points. All participants performed the counting task, followed by PASAT Set A, PASAT Set B, PASAT Set C and finally the counting task again. This design allowed a test of how the psychological states of interest responded to increased task demands and also an examination of whether there were any carry-over effects of high task demands. There was a break of approximately 40 seconds between each demand level to allow for the self-report data to be collected. Participants maintained the three-point fixation pattern throughout each task. Each experimental session required about 20 minutes to complete.

Analysis Strategy

As described in Chapter 3 the MLM analysis used a three-level model. Level 1 was the measurement occasion level, which was also the demand level for the PASAT. Level 2 was the task level and Level 3 was the individual level. *OCCASION* was introduced as the Level 1 variable and was coded as 0 for the first occasion of each task, 1 for the second occasion of each task and 2 for the third occasion of the PASAT (the count task was only performed on two occasions). *PASAT* and *COUNT* were introduced as Level 2 variables where *PASAT* was coded as 0 for the counting task and 1 for the PASAT, and *COUNT* was coded as 1 for the counting task and 0 for the PASAT. *LIGHT* was introduced as a Level 3 variable and coded as 0 for the low ambient light condition and 1 for the high ambient light condition.

The equations arising from this coding are shown in Appendix A and the coding meant that the intercept of the model represented the first occasion of the count task under low ambient light, the *PASAT* coefficient modelled the change between the first occasion of the count task and the first occasion of the PASAT, the *PASAT x OCCASION* coefficient modelled the change across PASAT occasion / level, the *COUNT x OCCASION* coefficient modelled change between the first and second occasion of the count task and the *LIGHT* coefficient modelled the change between the low and high ambient light conditions on the model intercept and the effects of task and measurement occasion. The mapping between the hypotheses developed in Chapter 2 and the corresponding statistical tests performed in Experiment 1 is shown Table 4.

Table 4. Mapping of the hypotheses developed in Chapter 2 to the corresponding statistical tests of Experiment 1.

	Hypothesis	Experiment 1 Test
1. The effect of current information processing and attentional control demands		
1a)	Increased information processing demands will increase the level of self-report activation	The PASAT coefficient will be a significant positive predictor of self-report activation The PASAT x OCCASION coefficient will be a significant positive predictor of self-report activation
1b)	Increased attentional control demands will not increase the level of self-report activation	Not tested
1c)	Increased information processing and attentional control demands will be accompanied by increased perceived difficulty	The PASAT coefficient will be a significant positive predictor of perceived difficulty The PASAT x OCCASION coefficient will be a significant positive predictor of perceived difficulty
1d)	Increased information processing and attentional control demands will be accompanied by increased effort, but only up to a the point of maximum resource allocation after which effort will remain constant or decrease	The PASAT coefficient will be a significant positive predictor of effort The PASAT x OCCASION coefficient may be a significant positive predictor of effort
1e)	Increased information processing and attentional control demands will be accompanied by increased pupil diameter, but only up to the point of maximum resource allocation after which pupil diameter will remain constant or decrease	The PASAT coefficient will be a significant positive predictor of pupil diameter The PASAT x OCCASION coefficient may be a significant positive predictor of pupil diameter
1f)	Increased information processing and attentional control demands will be accompanied by decreased affective valence	The PASAT coefficient will be a significant negative predictor of valence The PASAT x OCCASION coefficient will be a significant negative predictor of valence
2. The effect of prior information processing and attentional control demands		
2a)	Sustained attentional control demands will decrease the level of self-report activation	The COUNT x OCCASION coefficient will be a significant negative predictor of self-report activation
2b)	Decreased self-report activation will be accompanied by increased effort at low task demand levels and reduced effort at high task demand levels	The COUNT x OCCASION coefficient will be a significant positive predictor of effort
2c)	Decreased self-report activation will be accompanied by increased pupil diameter at low task demand levels and reduced pupil diameter at high task demand levels	The COUNT x OCCASION coefficient will be a significant positive predictor of pupil diameter

	Hypothesis	Experiment 1 Test
3. The indirect effects of task demands on difficulty and valence		
3a)	The relationship between task demands and perceived difficulty will be moderated by the level of self-report activation	The COUNT x OCCASION x ACTIVATION coefficient will be a significant positive predictor of perceived difficulty
3b)	The relationship between task demands and valence will be mediated by the current task performance level, the rate of change in task performance and the current level of effort	Current task performance level, the change in task performance level and self-report effort will be significant predictors of valence when included in the regression on task demands.

Results

Descriptive Statistics

The mean and 95th percentile confidence intervals of all dependent variables across measurement occasion are shown in Figure 7 and the between-person and within-person correlations are presented in Table 5. All within-person correlations were significant, with correlations between valence and the other variables being negative and all other correlations being positive. Significant positive between-person correlations were observed between self-report difficulty, error, effort and activation. Valence was negatively correlated with errors, difficulty and effort. Pupil diameter was not significantly correlated with any other variable at the between-person level. As expected, no significant effect of ambient light level was observed for any of the self-report variables so this predictor was not included in the analyses when self-report variables were used as outcomes. However, there was a significant effect of ambient light condition on pupil diameter. For this reason, ambient light condition was included in the analyses when pupil diameter was used as an outcome. Referring to Figure 7, valence appeared to be lower during the PASAT than the count task but all other variables appeared to be greater during the PASAT than the count task. These results appear to be consistent with the predictions that difficulty, effort, activation and pupil diameter would increase with task demands but that valence would decrease with task demands. All variables showed less change across PASAT level and count occasion.

Table 5. Correlations among the variables. Between-person correlations (*N* = 14) are shown above the diagonal and within-person correlations (*N* = 70) are shown below the diagonal.

	No. of Errors	Difficulty	Effort	Valence	Activation	Pupil Diameter
No. of Errors	-	.675 **	.689 **	-.580 *	.205	-.367
Difficulty	.823 ***	-	.860 ***	-.548 *	.698 **	-.297
Effort	.546 ***	.781 ***	-	-.590 *	.594 *	-.486
Valence	-.565 ***	-.649 ***	-.412 ***	-	.024	.117
Activation	.656 ***	.751 ***	.808 ***	-.305 *	-	-.139
Pupil Diameter	.760 ***	.826 ***	.698 ***	-.506 ***	.689 ***	-

* *p* < .05. ** p < .01. *** p < .001.

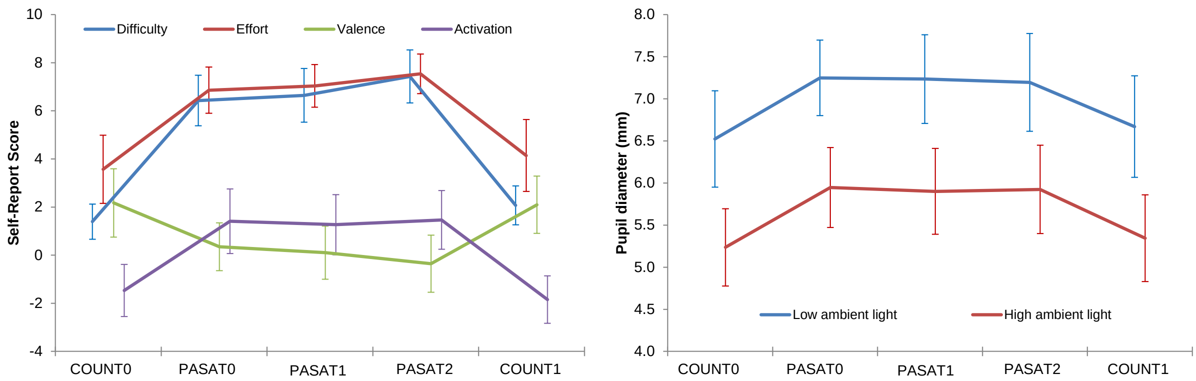

Figure 7 Plots of the self-report variables (left panel) and pupil diameter (right panel) across measurement occasion. Error bars represent the 95th percentile confidence intervals.

Effect of current task demands

Separate MLM models were run for each of the measured variables which are shown in Table 6. Although no specific predictions were made concerning the effect of task demands on performance, it is useful to examine in order to provide context for the effects of task demands on the metacognitive states and pupil diameter. The 'Intercept' line of Table 6 shows that there were no errors made during the initial occasion of the counting task. The 'PASAT' line shows that on average of 5.71 errors were made during the initial, and easiest, occasion of the PASAT which was significantly greater than zero. The 'PASAT x Occasion' line shows that errors increased by an average of 0.57 errors per occasion / demand level of the PASAT, which was a significant increase. This indicates that the task demand manipulations used in the current study appeared to be successful in producing four levels of increasing demands.

Considering next the effects of current task demands on the metacognitive states and pupil diameter, it was predicted that increased current task demands would be accompanied by increased perceived task difficulty, effort, activation, and pupil diameter but reduced valence. The ‘PASAT’ line of Table 6 shows that difficulty, effort, activation and pupil diameter were all higher and valence was lower during the first PASAT occasion than during the first counting task. The ‘PASAT x Occasion’ line of Table 6 shows that perceived difficulty and effort increased with PASAT level but that no significant change was observed for valence, activation or pupil diameter. This pattern of results provides full support for hypotheses 1c and 1d, and partial support for hypotheses 1a, 1e and 1f.

Table 6. Fixed effects models of task and measurement occasion as predictors of current errors, the change in errors, perceived difficulty, effort, valence, activation and pupil diameter.

	Errors			**Change in Errors**		
Fixed effects	Coefficient	SE	*d* 95% CI	Coefficient	SE	*d* 95% CI
Intercept	0.00	0.86		0.00	0.91	
PASAT	5.71 ***	1.21		4.76 **	1.24	
PASAT x Occasion	0.57 *	0.27		-2.43 **	0.65	
Count x Occasion	0.00	0.54		0.00	1.29	
Model Fit						
Deviance	315.65			244.12		
Parameters	7			7		

	Difficulty			**Effort**		
Fixed effects	Coefficient	SE	*d* 95% CI	Coefficient	SE	*d* 95% CI
Intercept	1.39 *	0.47		3.57 ***	0.59	
PASAT	4.94 ***	0.54	[2.8, 4.31]	3.23 ***	0.61	[0.75, 1.64]
PASAT x Occasion	0.50 **	0.14	[0.16, 0.56]	0.34 *	0.15	[0.01, 0.24]
Count x Occasion	0.68 *	0.28	[0.09, 0.89]	0.57 †	0.31	[-0.01, 0.43]
Model Fit						
Deviance	225.98			244.12		
Parameters	7			7		

	Valence			**Activation**		
Fixed effects	Coefficient	SE	*d* 95% CI	Coefficient	SE	*d* 95% CI
Intercept	2.17 **	0.59		-1.46 *	0.57	
PASAT	-1.79 *	0.83	[-1.26, -0.06]	2.82 **	0.61	[0.78, 1.95]
PASAT x Occasion	-0.35 †	0.19	[-0.26, 0.01]	0.03	0.20	[-0.17, 0.2]
Count x Occasion	-0.08	0.37	[-0.3, 0.24]	-0.38	0.39	[-0.55, 0.19]
Model Fit						
Deviance	263.79			261.71		
Parameters	7			7		

	Pupil Diameter		
Fixed effects	Coefficient	SE	*d* 95% CI
Intercept	6.52 ***	0.25	
Light	-1.29 **	0.35	[-2.56, -0.78]
PASAT	0.73 ***	0.09	[0.72, 1.16]
PASAT x Occasion	-0.03	0.03	[-0.12, 0.05]
Count x Occasion	0.15 *	0.07	[0.01, 0.37]
Light x PASAT	-0.03	0.12	[-0.35, 0.28]
Light x PASAT x Occasion	0.01	0.05	[-0.11, 0.14]
Light x Count x Occasion	-0.04	0.10	[-0.3, 0.2]
Model Fit			
Deviance	225.98		
Parameters	7		

† $p < .1$, * $p < .05$, ** $p < .01$, *** $p < .001$.

Effect of prior task demands

It was predicted that prior task demands would lead to decreased levels of self-report activation and have an effect on effort that would depend on the level of current task demands. The effect of prior task demands was tested by measuring the change across the two count occasions, which would be influenced by the intervening demands of the PASAT. The change in self-report activation between the first and second count occasion can be seen in the 'Count x Occasion' row of Table 6 which indicates that there was no significant change in activation across the two count occasion and does not support hypothesis 2c. However, an inspection of the table also reveals that pupil diameter was higher during the second count occasion than during the first and the change in self-report effort approached, but did not reach traditional levels of significance. This is consistent with hypothesis 2b and 2c that reduced activation may be accompanied by increased effort at low levels of task demands as individuals attempt to protect task performance against the potential effects of reduced resource availability.

The indirect effects of available resources, allocated resources and task performance

The final two hypotheses related to the indirect effects of task demands on perceived difficulty and valence. The first predicted that the level of self-report activation would moderate the perceived difficulty of a given level of task demands. This was tested in the current experiment by examining whether the change in difficulty observed across the two counting tasks was moderated by the level of self-report activation. Perceived difficulty was higher in the second counting occasion during the first, which would be expected if resources were depleted during the performance of the PASAT. However, the lack of a significant change in self-report activation across count occasion suggested that the predicted moderating effect may not be statistically significant. As a formal test of the hypothesis a count occasion x activation term was included in the model for self-report difficulty which is shown in the 'Count x Occasion x Activation' line of Table 7. This was not significant and offered no support for hypothesis 3a.

Table 7. Models testing the moderating effects of self-report activation on perceived difficulty across measurement occasion of the PASAT and counting tasks and the mediating effects of effort, the current level of errors and the rate of change in error on the relationship between task demands and valence.

	Difficulty with Moderation			**Valence**			**Valence with Mediators**		
Fixed effects	Coefficient	SE	*d* 95% CI	Coefficient	SE	*d* 95% CI	Coefficient	SE	*d* 95% CI
Intercept	1.39 *	0.48		2.17 **	0.59		2.17 **	0.55	
PASAT	4.95 ***	0.55	[2.78, 4.35]	-1.79 *	0.83	[-1.26, -0.06]	-1.39	1.40	[-1.53, 0.5]
PASAT x Error							-0.22 †	0.12	[-0.17, 0]
PASAT x Effort							0.27	0.26	[-0.09, 0.28]
PASAT x Occasion	0.49 **	0.13	[0.17, 0.54]	-0.35 †	0.19	[-0.26, 0.01]	-0.26	0.20	[-0.24, 0.05]
Count x Occasion	0.70 *	0.27	[0.12, 0.88]	-0.08	0.37	[-0.3, 0.24]	-0.72	0.64	[-0.73, 0.2]
PASAT x Occasion x Activation	0.20 *	0.08	[0.02, 0.26]						
Count x Occasion x Activation	0.05	0.17	[-0.21, 0.28]						
PASAT x Occasion x Error							-0.07	0.14	[-0.13, 0.08]
PASAT x Occasion x Error Change							-0.04	0.12	[-0.1, 0.07]
PASAT x Occasion x Effort							-0.09	0.20	[-0.18, 0.11]
Count x Occasion x Error Change							-0.12	0.08	[-0.1, 0.01]
Count x Occcasion x Effort							-0.35	0.34	[-0.37, 0.11]
Model Fit									
Deviance	221.02			263.79			254.56		
Parameters	9			7			14		

† $p < .1$, * $p < .05$, ** $p < .01$, *** $p < .001$.

The second prediction relating to indirect effects was that the level of effort, current task performance and change in task performance would mediate the effect of task demands on valence. As discussed in Chapter 2 the criteria used to establish mediation require that:

1. The independent variable is a significant predictor of the dependent variable.
2. The independent variable is a significant predictor of the mediator variable(s).
3. The mediator variable(s) becomes a significant predictor when added into regression model 1 above. Complete mediation is established if the inclusion of the mediator variable(s) reduces the effect of the independent variable to non-significance; partial mediation is established if the independent variable remains significant.

As can be seen from Table 6, the PASAT was a significant predictor of valence and the effect of PASAT occasion approached significance, which satisfies criteria 1. The PASAT was also a significant predictor of effort, current errors and the change in errors, and PASAT occasion was a significant predictor of effort, errors and change in errors which satisfies criteria 2. This meant that criteria 3 above could be tested, and the model where effort, current errors and the change in errors were included as predictors of valence is shown in Table 7. The ‘PASAT’ row shows that the inclusion of errors and effort at Level 2 of the model reduced the effect of the first occasion of the PASAT on valence to non-significance. However the ‘PASAT x Error’ and ‘PASAT x Effort’ rows indicate that these mediators did not achieve statistical significance at Level 2. The ‘PASAT x Occasion’ row shows that the inclusion of errors, the change in errors and effort at Level 1 of the model reduced the size effect of PASAT occasion / level on valence but rows 9 to 13 show that none of the mediating variables became significant predictors of valence at Level 1. These results provide only limited support for hypothesis 3b.

Effect of ambient light on pupil diameter

It was predicted that, although ambient light would influence baseline pupil diameter, the size of the pupil diameter response to task demands would be independent of the level of ambient light. Table 6 shows the model where task, task occasion and ambient light predicted pupil diameter. The ‘Light’ row shows that, as expected, pupil diameter was smaller under high ambient light. However, the non-significant coefficients for ‘Light x PASAT’, ‘Light x PASAT x Occasion’, ‘Light x Count x Occasion’ indicate that the level of ambient light did not affect the size of the pupil diameter response to PASAT, PASAT level or count occasion.

Discussion

The current study tested whether current and prior task demands generated the range of responses predicted by the self-regulatory control model developed in Chapter 2. It also aimed to identify whether the pupil-diameter response to changes in task demands could be reliably measured using remote video cameras under conditions where gaze direction moved over a visual field of non-uniform luminance under low and high ambient light.

Effect of current task demands

Considering first the response of the metacognitive states and pupil diameter to current task demands, the predicted relationships that perceived difficulty, effort, activation and pupil diameter would increase with task demands and valence would decrease with task demands were generally observed. These results were most clearly observed in the change between the first count occasion and the first PASAT occasion where all variables responded as predicted. Less consistent changes were observed across the three PASAT occasions, where perceived difficulty and effort increased, but no change was observed in pupil diameter or activation, and valence showed a medium-sized but non-significant reduction.. The lack of a significant response of valence and activation to changes in PASAT level may indicate a lack of sensitivity in these measures of core affect, possibly because they were not measured directly but were instead derived from the measures of energetic and tense arousal. However, the effect of task demands on the measured variables was broadly consistent with the hypotheses and support the argument that cognitive, motivational and affective processes all form part of an integrated response to what may appear to be purely cognitive task demands.

Considering next the pupil diameter response to current task demands, an increase in pupil diameter was observed between the count task and the easiest PASAT level but no increase in pupil diameter was observed across increasing demands within the PASAT. This was not consistent with the pattern of self-report effort which increased across PASAT level. These results represent a pattern where self-report effort continued to increase with task demands but pupil diameter increased with task demands up to a point, after which it remained constant despite further increases in task demands. One possible reason for this result is that the change in pupil diameter in response to PASAT level was too small to be measured under the luminance and gaze-direction conditions used in the current experiment. However, the result that a 0.13 mm change in pupil diameter could reliably be measured across the two count occasions, which nominally had the same level of task demands, argues against this interpretation.

Another possibility is that self-report effort increased without any actual increase in resource allocation. The error results indicate that even the easiest PASAT level was difficult to perform, and it may have been that, despite the increase in self-report effort, participants allocated the maximum level of effort that they were prepared to expend on the task during the initial PASAT occasion and this did not increase over subsequent occasions. It is also possible that this group-level result may have masked individual differences in the allocation of effort in response to the experimental manipulations. A follow-up analysis revealed that participants with high total errors had a larger pupil diameter response to the first PASAT level but a smaller increase in pupil diameter with PASAT level than participants with low total errors. This suggests that participants who had more difficulty with the task may have allocated more resources at the lower demand level and had less capacity to further increase the level of allocated resources as task demands increased. This pattern of individual differences was not observed for self-report effort which suggests that pupil diameter may be a more specific measure of resource allocation than self-report effort, which may also be influenced by other task and experimental cues.

This experiment extends previous work (Porter et al., 2007) by demonstrating that the pupil response to task demands can be measured while fixating multiple locations across a non-uniform visual field containing elements with a higher luminance than the local background. It also confirmed that the absolute size of the task-induced pupil response is constant over a wide range of luminance levels. While future work needs to be done under more naturalistic visual scanning patterns to confirm the robustness of these results, the current experiment suggests that pupilometry could possibly be used to monitor the psychological impact of task demands in settings where screen-based work is performed under reasonably uniform lighting conditions. Examples of possible applications include military command and control centers and industrial control rooms. In such settings pupil diameter may be able to provide a real-time indication of elevated task demand levels and a cue to the implementation of load reduction strategies.

Effect of prior task demands

Considering next the effects of prior task demands, the result that there was no change in self-report activation between the first and second count occasions did not support the prediction that sustained cognitive task performance would be accompanied by a reduction in the level of available resources. However, as discussed above, the indirect measure of available resources used may be somewhat insensitive and it could therefore have been that available resources were lower during the second count occasion although the scales did not reflect this. Alternatively, given the relatively short duration of the working memory task used in Experiment 1, it is also possible that there was not sufficient time for the resource depletion due to the attentional control demands to offset the increase in resource levels in response to the information processing demands. The result that pupil diameter increased across the two count occasions was consistent with the predicted effects of reduced resources at low task demands and suggests that prior task demands did effect the current level of allocated resources although this was not directly measured. It also supports the proposal that the human response to task demands is a dynamic process which is influenced by current and prior task demands and internal psychological states.

The indirect effects of task demands

Considering finally the predicted indirect effects of task demands on perceived difficulty and valence, this experiment offered little support for these predictions. The results suggested that increased activation was associated with increased perceived difficulty across PASAT levels. This was opposite to the prediction that reduced levels of available resources would contribute to a task being perceived as being more difficult. However the result may have been influenced by the increased effort that also accompanied increased PASAT levels which may have contributed to increased activation levels (Young & Stanton, 2002b). The failure to measure any change in activation levels across count occasions also limited the ability of this experiment to test the moderating effects of resource availability on perceived difficulty. The results offered some suggestion that current error levels may have predicted the reduced valence that occurred during the performance of the PASAT, but this was not a highly reliable result and there was no indication that effort or the change in errors mediated the effect of task demands on valence.

In summary, Experiment 1 identified that cognitive, motivational and affective states all need to be considered in order to characterise the human response to tasks which are nominally purely cognitive. It also indicated that in some applied environments it may be feasible to unobtrusively monitor task demands in real time using remote video measurements of pupil diameter. It further indicated that, at least initially, cognitive task demands appeared to generate increased levels of available resources. However, this experiment imposed a relatively short period of task demands and it is not reasonable to consider that this will continue to occur indefinitely as sustained task demands are expected to lead to resource depletion (Hagger et al., 2010). The use of a single task also limited the ability of Experiment 1 to draw conclusions about the energetic implications of the demands imposed by different task types (Matthews et al., 2002). Both of these limitations will be addressed in the second experiment.

CHAPTER 5: EXPERIMENT 2

Introduction

Experiment 1 examined the cognitive, motivational and affective responses to a counting task and a short working memory task and found that the working memory task produced higher perceived difficulty, effort, activation and pupil diameter but lower valence than the counting task. The increased level of self-report activation during the working memory task was consistent with the hypothesis developed in Chapter 2 that information processing increases activation, which is considered to index the level of available resources. However, as Experiment 1 only used a single information processing task it was not able to test the prediction that tasks without a substantial information processing component would not increase the level of available resources. Experiment 1 also failed to measure any depletion in the level of available resources due to prior attentional control demands, possibly due to the short duration of the demands imposed.

Experiment 2 will address these limitations by examining the responses of the metacognitive states and pupil diameter to demand manipulations within three tasks with different information processing requirements. It will also extend the period of task demands to better test the predicted effects of prior task demands on resource depletion. In addition, it will provide a finer-grained analysis of the pupil diameter response to task demands by examining the effect of task type and within-task demand level on pre-trial pupil diameter and the change in pupil diameter within individual trials. The next sections outline the tasks used in this experiment and identify how the demands of each would be expected to influence the metacognitive stages and pupil diameter based on the hypotheses developed in Chapter 2. The demand manipulations and pupil diameter measures used in the current experiment were quite complicated, and in order to simplify the presentation of the predictions the hypotheses relating to the effects of current task demands, prior task demands and the indirect effects of task demands on the metacognitive states will be discussed first, followed by a discussion of the hypothesised effects of task demands on pupil diameter.

The effect of current information processing and attentional control task demands

As identified in Chapter 2, this thesis attempts to reconcile the apparently contradictory predictions arising from malleable resources theory, in which increased mental workload can increase the level of available resources (Young & Stanton, 2002b), and the ego-depletion effect, where cognitive task demands can reduce the level of available resources (Hagger et al., 2010). To achieve this it is proposed that cognitive tasks require two processes which have opposite effects on the level of available resources. The first process is that the information processing required by cognitive tasks acts to increase the level of available resources (Kahneman, 1973). The second process is that sustained attentional control acts to reduce the level of available resources.

One implication of this proposal is that, unlike tasks that require information processing, tasks that require controlled attention but no information processing should not increase the level of available resources. In order to test this proposal, Experiment 2 will compare the changes in self-report activation arising from performing, for the same period of time, two tasks that require both information processing and attentional control and one task that requires only attentional control. If, as proposed, information processing is necessary for task demands to increase the level of available resources then the two information processing tasks would be expected to initially increase the level of self-report activation compared to a low-load baseline while the attentional control task should not initially produce any change in self-report activation compared to a low-load baseline.

Because information processing tasks also require attentional control in order to achieve successful task performance, there is a risk that any increase in activation caused by the application of information processing resources may be masked by a decrease in activation due to resource depletion associated with the simultaneous need for attentional control. In order to mitigate this risk, one information processing task used in the current experiment consisted of a series of discrete trials. This imposed only episodic task demands which potentially permitted any resources that were depleted by attentional control to be replenished between task performance episodes. However, in order to also explore whether the effect of information processing on the level of available resources was evident even when continuous attentional control demands were present, the second information processing task required continuous attentional control. These two tasks are referred to as the episodic information processing task and the continuous information processing task respectively. A column addition task was used as the episodic information processing task and an n-back memory task was used as the continuous information processing task.

Vigilance tasks have traditionally been used to examine the effects of controlled attention with low information processing demands. However, the current experiment used an episodic motor control task as the non-information processing task instead of a vigilance task as it potentially provides a more sensitive test of the hypothesis that tasks without an information processing component would not increase self-report activation. Due to their need for continuous attention, vigilance tasks place heavy demands on attentional control and therefore the level of available resources. In contrast, a non-information processing task that is episodic, rather than continuous, would be expected to require less attentional control and cause less depletion of available resources. Such conditions could be expected to minimise the chance that the depleting effects of attentional control on self-report activation would mask any increase in available resources generated by short-term performance of non-information processing tasks and therefore increase the chance of falsifying the hypothesis.

The following predictions could therefore be expected to apply to each of the tasks used in the current experiment:

Hypothesis 1a1: The episodic information processing task and the continuous information processing task will produce increased activation compared to a low-load baseline.

Hypothesis 1b1: The episodic motor control task will not change activation compared to a low-load baseline.

While working memory and vigilance tasks appear to have opposite effects on activation, both appear to reduce valence (Matthews et al., 2002; Matthews et al., 2006) which suggests that information processing and attentional control may both act to reduce valence. Both information processing tasks would therefore clearly be expected to produce reduced valence due to their demands on information processing and attention regulation resources. The expected effect on valence of a non-information processing task is less clear. While minimal information processing resources are required, episodes of controlled attention are still required for successful performance which may act to reduce valence. However, the size of the effect of the episodic motor-control task may be smaller than the two information processing tasks. The following prediction can therefore be made.

Hypothesis 1f1: Valence will be lower during all tasks than during a low-load baseline.

As discussed earlier, self-report effort is expected to reflect the resources allocated to both information processing and attentional control. Therefore, similarly to valence, it was expected that all three tasks used in Experiment 2 would produce higher self-report effort than a low-load baseline as, even though the episodic motor control task imposed minimal information processing demands, controlled attention was still required for successful performance. Perceived difficulty is thought to reflect an assessment of the resources required to successfully complete a task and, similar to effort, is expected to be insensitive to whether these resources relate to information processing or attentional control demands. This gives rise to the following predictions:

Hypothesis 1c1: The perceived difficulty of each task will be greater than a low-load baseline.

Hypothesis 1d1: Self-report effort during each task will be greater than during a low-load baseline.

Effect of change in within-task demands

The above predictions related to the effects of different tasks, but it was also expected that the effect of changes in demand level within each task would depend on whether these changes influenced information processing or attentional control demands. Just as the performance of any task was predicted to increase the demands on attentional control resources, increased within-task demand level could be expected to increase the level of attentional control required in all three tasks in order to achieve successful performance, a process that has been termed ‘task attentional pull’ (Beal, Weiss, Barros, & MacDermid, 2005). In contrast, information processing demands would only be expected to increase with demand level in the episodic and continuous information processing tasks as the episodic motor control task lacked any information processing component.

As noted above the measures of difficulty and effort were not expected to distinguish between information processing and attentional control demands so it was expected that increases to within-task demand level would produce increases in perceived difficulty for all three tasks. Increased within-task demand may also produce increased effort, but only up to a point of maximum effort after which further increases in within-task demands will not generate additional increases in effort although perceived difficulty should continue to increase.

Also in line with the above arguments, if the information processing component of task demands increases activation then increased within-task demand level would be expected to increase activation for the episodic information processing task. Activation may also increase with demand level during the continuous information processing task but this effect may be smaller due to the need for sustained attentional control which will act to reduce the level of available resources. Increased within-task demand levels would not be expected to increase activation during the episodic motor control task as it requires minimal information processing. However, the increased information processing and attentional control required as demand levels increase would be expected to lead to reduced valence in all tasks. These considerations lead to the following predictions:

Hypothesis 1a2: Increased within-task demands of the episodic information processing task and the continuous information processing task will be accompanied by increased activation.

Hypothesis 1b2: Increased within-task demands of the episodic motor-control tasks will not increase self-report activation.

Hypothesis 1c2: Increased within-task demands will be accompanied by increased perceived difficulty for all tasks.

Hypothesis 1d2: Increased within-task demands will be accompanied by increased effort for all tasks, but only up to a point after which effort will remain constant or decrease.

Hypothesis 1f2: Increased within-task demands will be accompanied by reduced valence in all tasks.

Effect of prior task demands

The previous sections considered the effect of current task demands but, as noted earlier, the sustained performance of both information processing and non-information processing tasks was predicted to deplete the level of available resources. The current experiment examined the effect of prior task demands by requiring participants to perform an initial task phase followed by a repeat task phase. All participants first performed each task during the initial phase and then performed each task again during the repeat phase. The effects of prior task demands were tested by comparing the differences between the initial and repeat performance of each task. The following prediction can be made concerning the effect of prior task demands on self-report activation:

Hypothesis 2a: Activation will be lower during the repeat performance of each task than during initial performance.

As discussed previously, the effect of reduced available resources on effort is not deterministic. Task performance can be maintained by continuing to apply effort, but resource depletion may result in a reduction in the maximum level of effort that individuals apply in response to high task demands (Hockey, 1997). It may also be that increased compensatory effort may be applied at low levels of task demands in order to protect against the potentially deleterious effects of reduced resource availability on performance. This leads to the following prediction about the effect of available resources on the relationship between effort and task demands.

Hypothesis 2b: Effort during the repeat performance phase will be the same or greater than effort during the initial performance phase for low task demands but lower than effort during the initial performance phase for high task demands.

The indirect effects of task demands on difficulty and valence

In addition to the direct effects predicted above, Chapter 2 also proposed two indirect effects of task demands. The first was that the level of available resources should moderate the effect of task demands on perceived difficulty. The second was that the level of effort, current task performance, and change in task performance should mediate the effect of task demands on valence. These effects were not expected to vary by task type and the following predictions can be made:

Hypothesis 3a: Perceived difficulty of all task demand levels will be higher during the repeat performance of each task than during initial performance of each task.

Hypothesis 3b: Self-report effort, current task performance and change in task performance will be significant predictors when included in the regression of task demands predicting valence.

The effect of task demands on pupil diameter

Experiment 1 used the average pupil diameter over the duration of each demand level as a physiological index of effort. This was appropriate as the count and PASAT tasks required continuous information processing and attentional control. However, for trials-based tasks it is possible to examine the pupil-diameter response over each trial which allows the separation of correct and incorrect responses in the analysis and also allows an analysis of both the pre-trial pupil diameter and the change in pupil diameter across each trial. Pre-trial pupil diameter has been shown to be larger before cognitively difficult tasks than simple tasks and also larger before threatening tasks than non-threatening tasks (Bitsios et al., 2004; Steinhauer et al., 2004). This suggests that pre-trial pupil diameter may index the level of information processing and self-regulatory resources mobilised in preparation for task performance The additional resources allocated during the performance of individual trials can be indexed by measuring the increase in pupil diameter from a pre-trial reference (Siegle, Steinhauer, Stenger, Konecky, & Carter, 2003). The following predictions can therefore be made about pre-trial pupil diameter and the increase in pupil diameter within each trial for correct trials of each task:

Hypothesis 1e1: Pre-trial pupil diameter will be larger during each task than during a low-load baseline.

Hypothesis 1e2: Pre-trial pupil diameter will increase with within-task demand level for all tasks, but only up to a point after which pre-trial pupil diameter will remain constant or decrease.

Hypothesis 1e3: The size of the increase in pupil diameter within each trial will increase with within-task demand level, but only up to a point after which the increase in pupil diameter within each trial will remain constant or decrease.

As discussed previously, the influence of reduced available resources on effort, and therefore pupil diameter, is not clear as individuals could adopt a strategy of maintaining effort, withdrawing effort, or possibly augmenting effort at low demand levels. Therefore the following predictions can be made about the effect of available resources on the relationship between pupil diameter and task demands:

Hypothesis 2c1: Pre-trial pupil diameter during the repeat performance phase will be the same or greater than pre-trial pupil diameter during the initial performance phase for low task demands but lower than pre-trial pupil diameter during the initial performance phase for high task demands.

Hypothesis 2c2: The size of the within-trial increase in pupil diameter during the repeat performance phase will be the same or greater than the size of the within-trial increase in pupil diameter during the initial performance phase for low task demands but lower than the size of the increase in pupil diameter within each trial during the initial performance phase for high task demands.

To summarise, Experiment 2 examined the cognitive, motivational, affective and pupil responses to tasks that vary in their information processing and attentional demands. It tested the proposal that information processing increases the level of available resources whereas attentional control reduces the level of available resources. Table 3 summarises how each hypothesis developed in Chapter 2 maps onto the predicted effects on the tasks used in this experiment.

Table 8. Mapping of the hypotheses developed in Chapter 2 to the expected effects on each task used in Experiment 2.

	Hypothesis	Experiment 2 Test
1. The effect of current information processing and attentional control task demands		
1a)	Increased information processing demands will increase the level of self-report activation	1a1: The episodic information processing task and the continuous information processing task will produce increased activation compared to a low-load baseline. 1a2: Increased within-task demands of the episodic information processing task and the continuous information processing task will be accompanied by increased activation.
1b)	Increased attentional control demands will not increase the level of self-report activation	1b1: The episodic motor control task will not change activation compared to a low-load baseline. 1b2: Increased within-task demands of the episodic motor-control tasks will not increase self-report activation.
1c)	Increased information processing and attentional control demands will be accompanied by increased perceived difficulty	1c1: The perceived difficulty of each task will be greater than a low-load baseline. 1c2: Increased within-task demands will be accompanied by increased perceived difficulty for all tasks.
1d)	Increased information processing and attentional control demands will be accompanied by increased effort, but only up to a the point of maximum resource allocation after which effort will remain constant or decrease	1d1: Self-report effort during each task will be greater than during a low-load baseline. 1d2: Increased within-task demands will be accompanied by increased effort for all tasks, but only up to a point after which effort will remain constant or decrease.
1e)	Increased information processing and attentional control demands will be accompanied by increased pupil diameter, but only up to the point of maximum resource allocation after which pupil diameter will remain constant or decrease	1e1: Pre-trial pupil diameter will be larger during each task than during a low-load baseline. 1e2: Pre-trial pupil diameter will increase with within-task demand level for all tasks, but only up to a point after which pre-trial pupil diameter will remain constant or decrease. 1e3: The size of the increase in pupil diameter within each trial will increase with within-task demand level, but only up to a point after which the increase in pupil diameter within each trial will remain constant or decrease.
1f)	Increased information processing and attentional control demands will be accompanied by decreased affective valence	1f1: Valence will be lower during all tasks than a low-load baseline. 1f2: Increased within-task demands will be accompanied by reduced valence in all tasks.

	Hypothesis	Experiment 2 Test
2. The effect of prior information processing and attentional control demands		
2a)	Sustained attentional control demands will decrease the level of self-report activation	2a: Activation will be lower during the repeat performance of each task than during initial performance.
2b)	Decreased self-report activation will be accompanied by increased effort at low task demand levels and reduced effort at high task demand levels	2c: Effort during the repeat performance phase will be the same or greater than effort during the initial performance phase for low task demands but lower than effort during the initial performance phase for high task demands.
2c)	Decreased self-report activation will be accompanied by increased pupil diameter at low task demand levels and reduced pupil diameter at high task demand levels	2c1: Pre-trial pupil diameter during the repeat performance phase will be the same or greater than pre-trial pupil diameter during the initial performance phase for low task demands but lower than pre-trial pupil diameter during the initial performance phase for high task demands.
		2c2: The size of the increase in pupil diameter within each trial during the repeat performance phase will be the same as or greater than the size of the increase during the initial performance phase for low task demands but smaller than the size of the increase during the initial performance phase for high task demands.
3. The indirect effects of task demands on difficulty and valence		
3a)	The relationship between task demands and perceived difficulty will be moderated by the level of self-report activation	3a: Perceived difficulty of all task demand levels will be higher during the repeat performance of each task than during initial performance of each task.
3b)	The relationship between task demands and valence will be mediated by the current task performance level, the rate of change in task performance and the current level of effort	3b: Self-report effort, current task performance and change in task performance will be significant predictors when included in the regression of task demands predicting valence.

Method

Participants

Thirteen people (1 female) took part in the study. The mean age was 22.23 years (*SD* = 2.71). Twelve participants were members of the Australian Defence Force and one was an employee of the Defence Science and Technology Organisation.

Materials and Apparatus

Visual stimuli were presented as black text on a grey background with a luminance of 48 cd/m^2 on a 19 inch 1024 x 768 pixel LCD monitor. Participants viewed the stimuli under ambient lighting of 5 lux. Stimulus presentation and data recording were controlled using the

Psychology Experiment Building Language (PEBL) (Sourceforge, 2012). Pupil diameter and gaze direction were recorded as described in Experiment 1.

Manipulations

Experiment 2 manipulated task demand level within three different tasks: a column addition task was used to generate episodic information processing demands, an n-back memory task was used to generate continuous information processing demands and a Fitts' Law movement task was used to generate episodic motor control demands. The column addition task displayed three numbers vertically on the screen and required participants to mentally calculate their sum. Participants entered the answer via the keyboard and had to enter the digits of the answer from left to right which meant that the final answer needed to be determined before initiating a response. Task demand was manipulated by having each number contain either one, two or three digits which represented low, medium and high demands. Participants had to complete a response within 5 seconds of stimulus presentation for the low demand level, within 10 seconds of stimulus presentation for the medium demand level and within 20 seconds of stimulus presentation for the high demand level. These durations were chosen on the basis of pilot testing to allow sufficient time to complete each calculation at each demand level. Fixed trial periods were chosen to prevent participants increasing the demands of each level through self-induced time pressure. There were 36 trials in the low demand level, 18 trials in the medium demand level and 9 trials in the high demand level so that each demand level lasted for 180 seconds.

The n-back memory task presented a series of 75 nouns on the screen at a rate of one word every 2.4 seconds. After each new word participants pressed '1' on the keypad if it matched the word a particular number of places back in the list or '3' if not. In the low demand level participants had to remember whether the current word matched the word 1-back in the list. In the medium demand level participants had to remember whether the current word matched the word 2-back in the list and in the high demand level participants had to remember whether the current word matched the word 3-back in the list. Each demand level lasted for 180 seconds.

The Fitts' Law movement task displayed a circle at various locations around a radius 170 mm from the centre of the screen and required participants to use a joystick to move the cursor from the centre of the screen into the circle and press the joystick trigger as quickly as possible. The joystick had a self-centring feature which returned the cursor to the centre of the screen after the trigger was pressed. Task demand was manipulated by varying the size of the target circle which had a diameter of 56 mm in the low demand level, 28 mm in the medium demand level and 14 mm in the high demand level. These sizes corresponded to a Fitts' Law difficulty index of 1.6, 2.6 and 3.6 respectively (Fitts, 1954). Each demand level lasted for 180 seconds and the next trial began when the cursor returned to the centre of the screen so in this task the number of trials performed at each level depended on the speed of response.

Measures

Perceived difficulty, effort, activation and valence were measured as described in Experiment 1. Pre-trial pupil diameter was calculated as the mean pupil diameter during the 250 ms prior to the presentation of each stimulus. The within-trial change in pupil diameter was calculated as the difference between the pre-stimulus pupil diameter and the mean pupil diameter during the 250 ms prior to response initiation in each trial. Response time was calculated as the period from stimulus onset to when the first response key was pressed. For the column-addition task the error at each demand level was calculated as the percentage of incorrect or nil responses. For the n-back task error was calculated as the percentage of false alarms and misses. For the Fitts' Law task error was calculated as the percentage of outside-target responses.

Procedure

On arrival participants were briefed on the purpose and nature of the experiment and provided informed consent. They were then seated in front of the monitor while gaze calibration was performed. Participants were asked to relax and stare at a black dot in the centre of the screen for 120 seconds to provide a low-load baseline for the pupil diameter and self-report measurements. The initial performance phase of the experiment was then conducted in which participants completed the low-demand level then the high-demand level of the column addition, n-back and Fitts' Law tasks in that order. The repeat performance phase was then conducted in which participants performed all three demand levels of all three tasks. During the repeat phase demand level was nested within task with the presentation order of task and demand level counterbalanced. After each demand level participants reported perceived task difficulty, effort, tense arousal and energetic arousal.

Analysis strategy

A four-level model was used to analyse the data, with Level 1 being the demand level, Level 2 being the task level, Level 3 being the performance phase level and Level 4 being the person level. *DEMAND* was introduced as a Level 1 variable and coded as -1 for low demand, 0 for medium demand and 1 for high demand. *DEMAND* was coded as 0 for the single demand level of the baseline task, Three dummy-coded Level 2 variables were used: *CADD* was coded as 1 for the column addition task and 0 for the other tasks, *NBACK* was coded as 1 for the n-back memory task and 0 for the other tasks and *FITTS* was coded as 1 for the Fitts' Law movement task and 0 for the other tasks. PHASE was used as the Level 3 variable and coded 0 for the initial performance phase and 1 for the repeat performance phase. No Level 4 variables were used in the analysis. Both performance phases included the low and high demand conditions, which allowed a direct comparison of the hypothesised effects of sustained task demands on each of these levels. A medium demand level was also included in the repeat performance phase to examine whether the effect of task demands was linear. This was achieved by including an additional Level 1 variable of *MID* which was coded as 1 for the medium demand level and 0 for the other demand levels. This provided a test of whether the observed value of effort at the medium demand level of the repeat phase was consistent with a linear response across demand level or whether the rate of increase in error with demand level decreased at high demand levels. The model equations are shown in Appendix B.

Results

The effect of task demands on performance

The current study made no specific hypotheses concerning the performance effects of task type, within-task demand level or task repetition but these are reported here to assist the interpretation of the self-report and pupil diameter results that follow. Plots of the percentage of incorrect trials and correct-trial response time against demand level for the initial and repeat phase of each task are shown in Figure 6. Separate HLM models were developed for percent error and response time, and the results are shown in Table 9. Starting with the Level 1 variable of *DEMAND*, the effect of changing from the low to the high demand level during the initial performance of each task can be seen in the 'Demand Initial Phase' block of Table 9 which indicates that percent error and response time significantly increased across demand level for each task.

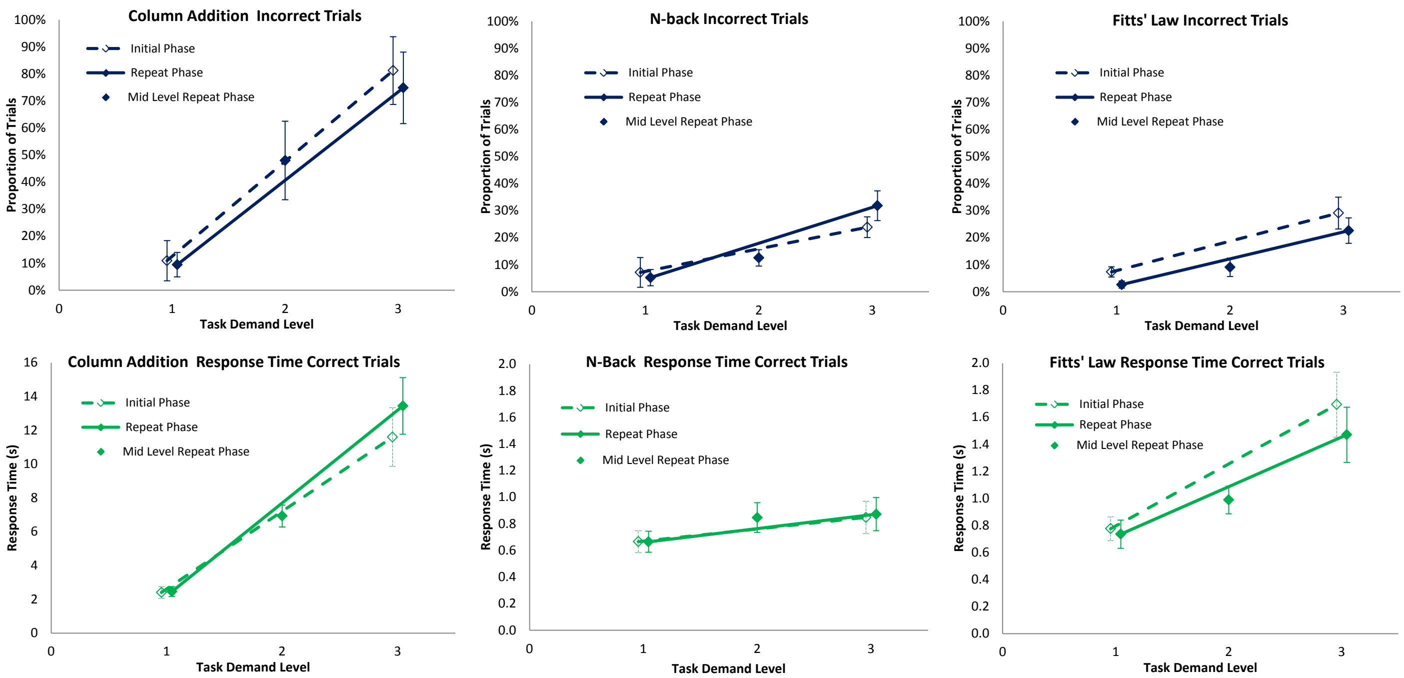

Figure 8 Plots of percentage error and response time against demand level for the initial and repeat phase of each task. Error bars represent 95th percentile confidence intervals.

Table 9. HLM models of the effect of within-task demand, task and task performance phase on errors and correct-trial response time.

	Errors			Response Time		
Fixed effects	Coefficient	SE	*d* 95% CI	Coefficient	SE	*d* 95% CI
Baseline	0.00	0.05		0.00	0.20	
Task Initial Phase						
Column Addition	0.54 ***	0.06		8.03 ***	0.22	
N-back	0.27 ***	0.06		0.77 **	0.22	
Fitts Law	0.18 ***	0.06		1.24 ***	0.22	
Task x Phase						
x Column Addition	-0.03	0.05		0.40 *	0.16	
x N-back	0.03	0.05		0.01	0.16	
x Fitts Law	-0.06	0.05		-0.14	0.16	
Demand Initial Phase						
x Column Addition	0.34 ***	0.02		5.57 ***	0.04	
x N-back	0.16 ***	0.02		0.12 ***	0.01	
x Fitts Law	0.11 ***	0.02		0.46 ***	0.01	
Demand x Phase						
x Column Addition	-0.04	0.03		0.31 ***	0.05	
x N-back	0.03	0.03		0.01	0.02	
x Fitts Law	-0.01	0.03		-0.09 ***	0.02	
Mid-Level Deviation						
Column Addition	0.11 **	0.04		-1.42 ***	0.06	
N-back	0.01	0.04		0.08 **	0.02	
Fitts Law	-0.04	0.04		-0.12 ***	0.02	
Model Fit						
Deviance	-205.17			19843.9		
Parameters	20			20		

† $p < .1$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Considering next the Level 2 variable of TASK, the mean percent error and correct-trial response time during the initial performance of each task can be seen in the 'Task Initial Phase' block of Table 9 which indicates that mean percent error and response time during the initial performance of each task were significantly greater than zero.

Performance phase was the Level 3 variable and the effect of task repetition on the mean percent error and response time during each task can be seen in the 'Task x Phase' block of Table 9 which indicates that there was no significant change in mean error across experimental phase in any task and only the column-addition task showed a significant increase in response time during the repeat phase. The effect of task repetition on the response to within-task demand level can be seen in the 'Demand x Phase' block of Table 9. There was no effect of task repetition on the increase in errors with within-task demand level. Response time showed a significant demand level x phase interaction for the column addition and Fits' Law tasks, but in opposite directions. The increase in response time with demand level was larger during the repeat phase than during the initial phase for the column addition task. In contrast, the increase in response time with level was smaller during the repeat phase than during the initial phase for the Fitts' Law task. The results for the Fitts' Law task appear to reflect skill acquisition as the reduced response time was not accompanied by an increase in errors. The increase in response time for the difficult level of the column addition task may indicate that during the repeat phase participants were more aware that sufficient time was available to complete the calculations and therefore took more time to successfully complete each trial.

The effect of current task demands on the metacognitive states

Considering next the effects of current task demands on the metacognitive states, plots of perceived difficulty, effort, valence and activation against within-task demand level for the initial and repeat phase of each task are shown in Figure 9 and the associated HLM models are shown in Table 10. The results concerning the effects of task on each variable will be discussed first, followed by the results of the effects of within-task demand level for each task.

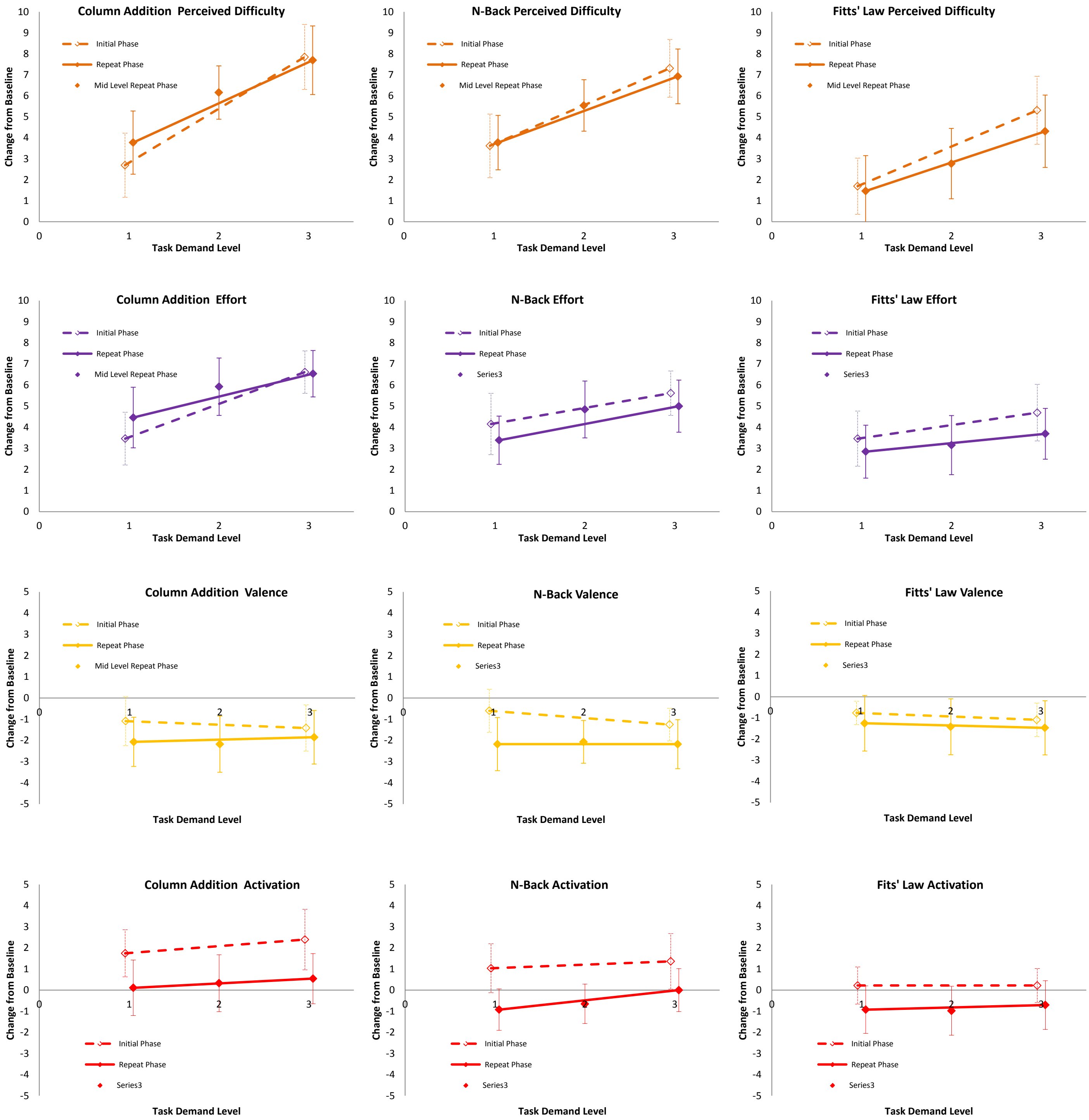

Figure 9 Plots of perceived difficulty, effort, valence and activation against within-task demand level for each task. Error bars represent 95th percentile confidence intervals

Table 10. HLM models of the effect of task, task repeat, and within-task demand on perceived difficulty, effort, valence and activation and the 95th percentile confidence intervals of the Cohen's *d* effect size.

	Difficulty			Effort			Valence			Activation		
Fixed effects	Coefficient	SE	*d* 95% CI	Coefficient	SE	*d* 95% CI	Coefficient	SE	*d* 95% CI	Coefficient	SE	*d* 95% CI
Baseline	0.85	0.57		2.23 **	0.59		2.67 **	0.71		-1.25 *	0.46	
Task Initial Phase												
Column Addition	5.27 ***	0.64	[2.06, 3.34]	5.04 ***	0.52	[1.85, 2.8]	-1.25 *	0.52	[-0.76, -0.08]	2.07 ***	0.47	[0.54, 1.39]
N-back	5.46 ***	0.64	[2.16, 3.44]	4.88 ***	0.52	[1.78, 2.73]	-0.92 †	0.52	[-0.65, 0.03]	1.20 *	0.47	[0.13, 0.99]
Fitts Law	3.50 ***	0.64	[1.15, 2.44]	4.08 ***	0.52	[1.41, 2.35]	-0.92 †	0.52	[-0.65, 0.03]	0.22	0.47	[-0.33, 0.53]
Task x Repeat												
Column Addition	0.46	0.56	[-0.32, 0.79]	0.46	0.46	[-0.21, 0.63]	-0.71	0.51	[-0.57, 0.1]	-1.74 ***	0.44	[-1.21, -0.41]
N-back	-0.12	0.56	[-0.62, 0.5]	-0.69	0.46	[-0.74, 0.1]	-1.25 *	0.51	[-0.75, -0.09]	-1.66 **	0.44	[-1.18, -0.37]
Fitts Law	-0.62	0.56	[-0.87, 0.24]	-0.81 †	0.46	[-0.79, 0.05]	-0.44	0.51	[-0.48, 0.19]	-1.03 *	0.44	[-0.88, -0.08]
Demand Initial Phase												
Column Addition	2.58 ***	0.32	[1, 1.64]	1.58 ***	0.24	[0.51, 0.95]	-0.16	0.13	[-0.14, 0.03]	0.33 *	0.16	[0.01, 0.3]
N-back	1.85 ***	0.32	[0.63, 1.26]	0.73 **	0.24	[0.12, 0.56]	-0.33 *	0.13	[-0.2, -0.02]	0.16	0.16	[-0.07, 0.22]
Fitts Law	1.81 ***	0.32	[0.61, 1.25]	0.62 *	0.24	[0.07, 0.5]	-0.16	0.13	[-0.14, 0.03]	0.00	0.16	[-0.14, 0.14]
Demand x Repeat												
Column Addition	-0.62	0.45	[-0.77, 0.14]	-0.54	0.34	[-0.56, 0.06]	0.27	0.19	[-0.03, 0.21]	-0.11	0.22	[-0.25, 0.15]
N-back	-0.27	0.45	[-0.59, 0.31]	0.08	0.34	[-0.27, 0.34]	0.33 †	0.19	[-0.01, 0.23]	0.30	0.22	[-0.06, 0.34]
Fitts Law	-0.38	0.45	[-0.65, 0.25]	-0.19	0.34	[-0.4, 0.22]	0.05	0.19	[-0.1, 0.14]	0.11	0.22	[-0.15, 0.25]
Repeat Mid-Level Deviation												
Column Addition	0.42	0.55	[-0.34, 0.77]	0.42	0.42	[-0.18, 0.57]	-0.22	0.23	[-0.22, 0.08]	0.00	0.27	[-0.25, 0.25]
N-back	0.19	0.55	[-0.45, 0.65]	0.65	0.42	[-0.08, 0.68]	0.11	0.23	[-0.11, 0.19]	-0.19	0.27	[-0.34, 0.16]
Fitts Law	-0.12	0.55	[-0.61, 0.49]	-0.12	0.42	[-0.43, 0.32]	-0.05	0.23	[-0.17, 0.13]	-0.16	0.27	[-0.32, 0.17]
Model Fit												
Deviance	852.66			770.58			626.98			649.64		
Parameters	20			20			20			20		

† $p < .1$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Effect of task type

It was predicted that activation would be greater after an episodic information processing task and a continuous information processing task than after a low-load baseline task. The results relating to this hypothesis can be seen in the 'Task Initial Phase' block of Table 10. Mean activation after the column addition task and n-back task were both significantly greater than after the low-load baseline task which supports the hypothesis.

It was predicted that activation after an episodic non-information processing task would not differ from activation after a low-load baseline task and, as predicted, mean activation after the Fitts' Law task did not significantly differ from activation after the low-load baseline task. However, the 95th percentile confidence interval for Cohen's *d* ranged from -0.33 to 0.53. This range exceeded $d = 0.2$, which, according to the criterion adopted in Chapter 2, was the largest effect size that could be interpreted as being consistent with a null effect. Therefore the current results do not fully support the hypothesis that there was no difference in activation between the low-load baseline and the Fitts' Law task. However, the change in mean activation was non-significant and the mean effect size was only $d = 0.10$ which is half of Cohen's criteria for a small effect (Cohen, 1988). This indicates that there was very little difference in activation between the low-load baseline and the Fitts' Law task and offers qualified support for the hypothesis. In addition, the increase in activation following the Fitts' Law task was significantly less than the increase in activation following each of the information-processing tasks. This result provides support for a less strict form of the hypothesis that the increase in activation following an attention control task will be less than the increase in activation following an information processing task.

It was predicted that valence would be lower after all tasks than after the low-load baseline task and the results relating to this hypothesis can also be seen in the 'Task Initial Phase' block of Table 10. Inspection of the table indicates that the hypothesis was supported for the column addition task only. The decrease in valence observed in the n-back and Fitts' Law tasks approached, but did not reach, traditional levels of significance. It was predicted that the reduction in valence associated with the continuous non-information processing task may be smaller than the reduction associated with the other two tasks but no evidence for this was found.

The final predictions relating to each task were that mean difficulty and effort respectively would be greater for each task than for the low-load baseline task. These results for difficulty and effort can be seen in the 'Task Initial Phase' block of Table 10 and support the hypotheses.

Effect of within task demand level

Considering next the effect of current within-task demand level on difficulty, effort, activation and valence, the 'Demand Initial Phase' block of Table 10 shows the effect of increasing within-task demand levels during the initial performance of each task for each of these variables. As predicted, perceived difficulty increased with demand level for all tasks. Effort also increased with demand level for all tasks, suggesting that more resources were allocated to the high demand level of each task than were allocated to the low demand level.

It was predicted that activation would increase with demand level for the column addition task, may increase with demand level for the n-back task, but would not increase with demand level for the Fitts' Law task. Activation was observed to significantly increase with demand level during the column addition task which supports the hypothesis. The increase in activation with demand level during the n-back task did not reach significance but the 95th percentile confidence interval of the effect size indicates that there may have been a small increase in activation with demand level. This result that the increase in activation with demand level after a continuous information processing task was smaller than the increase in activation after an episodic information processing task is consistent with predictions that the effect of information processing on the level of available resources may be masked by the effect of attentional control demands. The increase in activation with demand level during the Fitts' Law task had an effect size of $d = 0.0$ and the 95th percentile confidence interval of d did not include $d = 0.2$, which meets the criterion for a null effect. This is consistent with the prediction that no relationship would exist between task demands and activation for tasks with no information processing component and supports the hypothesis.

It was also predicted that valence would decrease with demand level for all tasks, but a significant decrease in valence with demand level was only observed during the n-back task, providing only partial support for this hypothesis.

Effect of prior task demands on the metacognitive states

Turning now to the predicted effects of prior task demands, it was predicted that, if resource depletion had occurred, activation would be lower during the repeat performance of each task than during the initial performance. Results relating to this prediction can be seen in the 'Task x Repeat' block of Table 10. This indicates that the predicted result was observed for all tasks, supporting the hypothesis.

It was also predicted that during repeat task performance effort may be the same or higher at low task demands but lower at high task demands than during initial task performance. However, an inspection of the 'Task x Repeat' and 'Demand x Repeat' blocks of Table 10 indicates that task performance phase had no significant main effect on effort or caused any significant effort by demand level interaction for any task. Effort at the medium demand level during the repeat performance phase did not significantly differ from a linear trend, which suggests a constant increase effort with demand level.

The effect of current and prior task demands on pupil diameter

Plots of the mean change in pre-trial pupil diameter from baseline and the mean within-trial change in pupil diameter against demand level for correct trials in each task during initial and repeat task performance are shown in Figure 10. The associated HLM models are shown in Table 11.

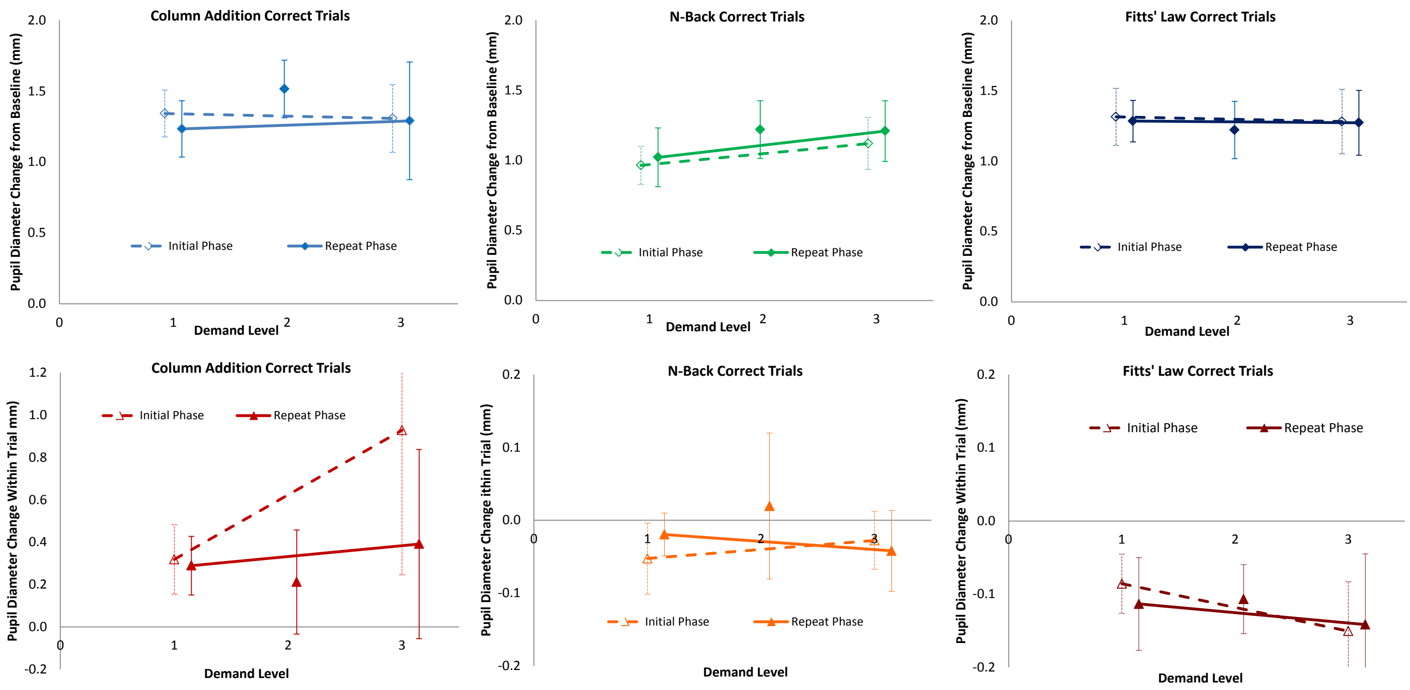

Figure 10 Change in pre-trial pupil diameter from baseline (top row) and within-trial chance pupil diameter (bottom row) across demand level during the initial and repeat task performance phase for each task.

It was predicted that pre-trial pupil diameter would be larger during each task than during the low-load baseline. Inspection of the ‘Task Initial Phase – Correct Trials’ block of Table 11 reveals that pre-stimulus pupil diameter was significantly larger than during the low-load baseline for the initial performance of each task, and that the mean size of this increase ranged from 1.03 mm for the n-back task to 1.37 mm for the column addition task. Therefore this prediction was supported.

It was also predicted that pre-trial pupil diameter and the within-trial change in pupil diameter would increase with within-task demand level for all tasks, but only up to a point after which each would remain constant or decrease. The design of Experiment 2 allowed a test of whether pupil diameter was larger during the high demand level than during the low demand level for the initial and repeat performance of each task, and also allowed a test of whether pupil diameter during the medium demand level for the repeat performance of each task was larger or smaller than would be expected if there was a linear trend between the low and high demand levels. From these tests conclusions can be drawn about the relative effort exerted in the low and high demand levels of each task and whether effort levelled off or was withdrawn during high demand levels.

Table 11. Models of the effect of task, within-task demand level, and task repetition on pre-stimulus pupil diameter and the within-trial change in pupil diameter.

	Pre-Stimulus Pupil Diameter			Within-Trial Change		
Fixed effects	Coefficient	SE	d 95% CI	Coefficient	SE	*d* 95% CI
Baseline	3.04 ***	0.14		0.00	0.07	
Task Initial Phase - Correct Trials						
Column Addition	1.37 ***	0.12	[2.76, 3.86]	0.47 ***	0.09	[0.69, 1.56]
N-back	1.03 ***	0.11	[1.96, 3]	-0.04	0.08	[-0.47, 0.29]
Fitts Law	1.29 ***	0.11	[2.61, 3.65]	-0.12	0.08	[-0.68, 0.09]
Task x Phase - Correct Trials						
x Column Addition	-0.13	0.10	[-0.76, 0.15]	-0.19 *	0.08	[-0.85, -0.09]
x N-back	0.03	0.08	[-0.27, 0.44]	0.00	0.05	[-0.23, 0.25]
x Fitts Law	-0.01	0.07	[-0.37, 0.34]	0.00	0.05	[-0.24, 0.23]
Demand Level Initial Phase - Correct Trials						
x Column Addition	0.03	0.04	[-0.11, 0.28]	0.17 ***	0.04	[0.21, 0.62]
x N-back	0.08 ***	0.01	[0.15, 0.23]	0.01	0.01	[-0.01, 0.06]
x Fitts Law	-0.02 *	0.01	[-0.08, -0.01]	-0.04 ***	0.01	[-0.12, -0.06]
Demand Level x Phase - Correct Trials						
x Column Addition	-0.01	0.06	[-0.3, 0.24]	-0.17 **	0.06	[-0.7, -0.12]
x N-back	0.05 ***	0.01	[0.06, 0.18]	-0.03 *	0.01	[-0.12, -0.01]
x Fitts Law	0.01	0.01	[-0.03, 0.07]	0.02 †	0.01	[0, 0.08]
Medium Repeat Deviation - Correct Trials						
Column Addition	0.24 ***	0.05	[0.34, 0.81]	-0.02	0.06	[-0.32, 0.2]
N-back	0.17 ***	0.02	[0.32, 0.48]	0.00	0.01	[-0.08, 0.06]
Fitts Law	-0.06 ***	0.01	[-0.2, -0.09]	0.02	0.01	[0, 0.09]
Error Initial Phase						
Column Addition	0.13 *	0.06	[0.06, 0.59]	-0.06	0.06	[-0.41, 0.13]
N-back	0.12 ***	0.03	[0.17, 0.43]	0.02	0.02	[-0.06, 0.14]
Fitts Law	0.08 ***	0.02	[0.12, 0.29]	0.04 **	0.01	[0.03, 0.17]
Error Task x Phase						
x Column Addition	0.10	0.08	[-0.15, 0.64]	0.13	0.08	[-0.06, 0.71]
x N-back	-0.03	0.04	[-0.29, 0.13]	-0.04	0.03	[-0.27, 0.06]
x Fitts Law	-0.05	0.04	[-0.29, 0.06]	0.03	0.03	[-0.08, 0.2]
Error Demand Level Initial Phase						
x Column Addition	-0.15 **	0.06	[-0.63, -0.09]	-0.16 **	0.06	[-0.66, -0.12]
x N-back	-0.14 ***	0.03	[-0.48, -0.22]	-0.04 †	0.02	[-0.19, 0.01]
x Fitts Law	-0.04 *	0.02	[-0.18, 0]	0.04 **	0.01	[0.03, 0.17]
Error Demand Level x Phase						
x Column Addition	0.10	0.08	[-0.16, 0.63]	0.25 **	0.08	[0.23, 1]
x N-back	-0.01	0.04	[-0.23, 0.19]	0.10 **	0.03	[0.07, 0.4]
x Fitts Law	0.01	0.04	[-0.16, 0.19]	-0.06 *	0.03	[-0.28, 0]
Medium Repeat Deviation - Error trials						
Column Addition				-0.16 *	0.08	[-0.76, -0.01]
N-back	-0.11 *	0.05	[-0.52, -0.02]	0.06	0.04	[-0.07, 0.34]
Fitts Law	0.01	0.04	[-0.19, 0.22]	-0.04	0.03	[-0.27, 0.06]
No Response Initial Phase						
Column Addition	0.23 **	0.06	[0.26, 0.87]	-0.28 ***	0.06	[-0.95, -0.4]
N-back	0.09 **	0.03	[0.07, 0.36]	-0.03	0.02	[-0.18, 0.05]
No Resposne Task x Phase						
x Column Addition	0.00	0.09	[-0.45, 0.43]	0.11	0.08	[-0.13, 0.65]
x N-back	-0.14 **	0.04	[-0.55, -0.13]	-0.01	0.04	[-0.19, 0.16]
No Response Demand Level Initial Phase						
x Column Addition	-0.14 *	0.06	[-0.63, -0.05]	-0.25 ***	0.05	[-0.86, -0.37]
x N-back	-0.09 **	0.03	[-0.35, -0.09]	-0.03	0.02	[-0.17, 0.04]
No Response Demand Level x Phase						
x Column Addition	-0.02	0.09	[-0.47, 0.37]	0.16 *	0.07	[0.03, 0.73]
x N-back	0.01	0.04	[-0.17, 0.22]	0.08	0.04	[0.03, 0.37]
Medium Repeat Deviation - No Response Trials						
Column Addition				0.03	0.07	[-0.26, 0.43]
N-back	-0.08 †	0.05	[-0.41, 0.02]	-0.01	0.04	[-0.19, 0.15]
Model Fit						
Deviance	3766.09			-606.15		
Parameters	43			45		

† *p* < .1. * *p* < .05. ** *p* < .01. *** *p* < .001.

Considering first the pre-stimulus pupil diameter results, an inspection of the ‘Demand Level Initial Phase – Correct Trials’ block of Table 11 indicates that there was no significant change in pre-stimulus pupil diameter between the low and the high demand level during the initial performance of the column addition task, but that pre-stimulus pupil diameter increased for the n-back task and decreased for the Fitts’ Law task between the low and high demand levels. An inspection of the ‘Demand Level x Phase – Correct Trials’ block of Table 11 indicates that there was no change in this pattern of results during the repeat performance phase for the column addition or Fitts’ Law tasks, but that the increase in pre-stimulus pupil diameter between the easy and difficult level for the n-back task was larger during the repeat performance phase than during the initial performance phase for this task. These results indicate that level of pre-stimulus resources increased between the low and high demand level for the n-back task, did not change for the column addition task and possibly decreased for the Fitts’ Law task. They also indicate that the increase in pre-stimulus resources with demand level in the n-back task was larger for the repeat phase than for the initial phase.

The pre-stimulus pupil diameter did not appear to change between the low and high demand levels of the column addition task, but this may have been due to a withdrawal of effort as the task became too difficult. This can be tested by examining whether the pre-stimulus pupil diameter during the medium demand level of the repeat phase differed from that during the low and high demand levels. An examination of the ‘Medium Repeat Deviation – Correct Trials’ block of Table 11 indicates that the pre-stimulus pupil diameter for the medium demand level during the repeat performance of the column addition task was significantly larger than would be expected if a linear trend existed between the low and high demand levels. This suggests that more pre-stimulus resources were allocated to the medium demand level of the column addition task than were allocated during either the low or high demand levels and suggests that allocated preparatory resources increased between the low and medium demand levels but then decreased between the medium and high demand levels. It can also be noted that pre-stimulus pupil diameter during the medium demand level of the repeat performance of the n-back task was also higher than would be expected if there was a linear trend in preparatory resource allocation between the low and high demand levels. This may also indicate that a ceiling of resource allocation was reached during the medium demand level but that this level was maintained during the high demand level rather than being reduced as appeared to be the case in the column addition task. The decrease in pre-stimulus pupil diameter across all levels of the Fitts’ Law task was an unexpected result that may indicate that pupil diameter responds differently to information processing and non-information processing tasks.

Considering next the within-trial change in pupil diameter with within-task demand level, an inspection of the ‘Demand Level Initial Phase – Correct Trials’ block of Table 11 indicates that during the initial performance of the column addition task the within-trial increase in pupil diameter was larger during the high demand level than during the low demand level. There was no significant difference in the within-trial pupil diameter change between the low and high demand levels for the initial performance of the n-back task but pupil diameter decreased within-trials of the Fitts’ Law task and the size of this decrease was larger during the high demand level than during the low demand level. These results indicate that, although there was no difference in the amount of pre-stimulus resources applied between the low and high demand levels of the column addition task, greater within-trial resources were applied at the high demand level than at the low demand level during initial task performance. A different pattern of response was observed for the n-back task, where the allocated pre-stimulus resources were greater during the high demand level than during the low demand level but further increases in resource allocation were not observed to occur within trials at either demand level. Yet another pattern of response was observed for the Fitts’ Law task, where the allocated pre-stimulus resources appeared to be less during the high demand level than during the low demand level and greater decreases in resource allocation were observed within trials at the high demand level than at the low demand level.

An interesting result was observed in the repeat performance of the column addition and n-back tasks. An inspection of the ‘Demand Level x Phase – Correct Trials’ block of column 2 of Table 11 indicates that, for both tasks, the increase in within-trial pupil diameter between the low and high demand levels was less in the repeat performance phase than during the initial performance phase. Neither of these tasks exhibited any increase in errors during repeat performance but the column addition task exhibited a longer response time during the high demand level in the repeat performance. These results are suggestive of an active resource management process, where effort was minimised during trials while still maintaining performance, which was achieved in the column addition task by taking additional time during repeat task performance to perform the required calculations.

Indirect effects of task demands

It was predicted that the relationship between task demands and perceived difficulty would be moderated by the level of self-report activation. This would imply that, if resource depletion occurred across task performance phase, the same demand level would be perceived as being more difficult during repeat task performance than during initial task performance. Results relating to this prediction can be seen in the ‘Task x Repeat’ and ‘Demand x Repeat’ blocks of Table 10. These indicate that despite self-report activation being significantly lower during the repeat phase than during the initial phase no differences in the perceived difficulty of each demand level were observed between the initial and repeat task performance of any task. This does not support the moderation hypothesis.

The second predicted indirect effect was that the effect of task demands on valence would be mediated by current effort, current performance level and the change in performance level. Again applying the Baron and Kenny (1986) criteria to establish mediation, an inspection of Table 10 indicates that valence was lower than baseline during the initial performance of each task but only the n-back task exhibited a change in valence across within-task demand level. This partially satisfies the first criterion that the independent variable need to be a significant predictor of the dependent variable and means that mediation could be tested at the task level (Level 2) for all tasks but could only be tested at the within-task demand level (Level 1) for the n-back task. Also as shown in Table 9 and Table 10, both task and within-task level were significant predictors of effort and error, which satisfied the second criterion for mediation that the independent variable needs to be a significant predictor of the mediator variables. In order to test the third criterion for mediation, effort and error were added as Level 1 and Level 2 predictors into the model of task and within-task demand level predicting valence. The change in error was added as a Level 1 predictor as it seemed reasonable to consider the effect of the change in error between demand levels within tasks. However, it was not added as a Level 2 predictor as the change in error between tasks was not thought to be psychologically salient as each task differed substantially from the others. The effect of change in error could also only be considered in the repeat task performance phase as all participants experienced the same order of demand level in the initial task performance phase which created collinearity between error and the change in error during the initial task performance phase.

The effect of adding these variables to the model of task demands predicting valence can be seen in Table 12. Considering first the effect of including effort and error at Level 2, the ‘Task Initial Phase’ block of Table 12 indicates that the addition of these two variables reduced the effect of task on valence to non-significance for all tasks, but the ‘Task Mediation’ block indicates that neither effort nor error became a significant predictor of valence. Therefore the mediation hypothesis was not formally supported at the task level.

Considering next the effect of the mediating variables at Level 1, the ‘Demand Initial Phase’ block of Table 12 indicates that adding the mediating variables reduced the effect of within-task demand level on valence to non-significance, but the ‘Task Level Mediation: N-back’ block and the ‘Demand x Repeat Mediation: N-back’ blocks indicate that none of the variables became significant predictors of valence for this task. Therefore the mediation hypothesis was also not supported at the within-task demand level.

Table 12. HLM models showing the effect of including task, task repeat, and within-task demand on into the regression of valence on task demands.

	Valence			Add Effort and Performance		
Fixed effects	Coefficient	SE	*d* 95% CI	Coefficient	SE	*d* 95% CI
Baseline	2.67 **	0.71		2.67 **	0.70	
Task Initial Phase						
Column Addition	-1.25 *	0.52	[-0.76, -0.08]	0.48	0.95	[-0.47, 0.79]
N-back	-0.92 †	0.52	[-0.65, 0.03]	0.47	0.80	[-0.36, 0.68]
Fitts Law	-0.92 †	0.52	[-0.65, 0.03]	0.19	0.71	[-0.4, 0.53]
Task Mediation						
L2 Effort				-0.22 †	0.12	[-0.16, 0.01]
L2 Errors				-1.12	1.32	[-1.24, 0.49]
Task x Repeat						
x Column Addition	-0.71	0.51	[-0.57, 0.1]	-1.87	1.18	[-1.4, 0.15]
x N-back	-1.25 *	0.51	[-0.75, -0.09]	-2.36 *	0.91	[-1.39, -0.19]
x Fitts Law	-0.44	0.51	[-0.48, 0.19]	-1.49 †	0.75	[-0.99, 0]
Task x Repeat Mediation						
L2 Effort				0.25 †	0.16	[-0.02, 0.19]
L2 Errors				-0.23	1.61	[-1.14, 0.98]
Demand Initial Phase						
x Column Addition	-0.16	0.13	[-0.14, 0.03]	-0.16	0.13	[-0.14, 0.03]
x N-back	-0.33 *	0.13	[-0.2, -0.02]	0.09	0.23	[-0.12, 0.18]
x Fitts Law	-0.16	0.13	[-0.14, 0.03]	-0.16	0.13	[-0.14, 0.03]
Demand Mediation: N-back						
Effort Initial Phase				-0.18	0.14	[-0.15, 0.03]
Errors Initial Phase				-1.80	1.23	[-1.41, 0.21]
Demand x Repeat						
x Column Addition	0.27	0.19	[-0.03, 0.21]	0.27	0.18	[-0.03, 0.21]
x N-back	0.33 †	0.19	[-0.01, 0.23]	-0.40	0.32	[-0.35, 0.08]
x Fitts Law	0.05	0.19	[-0.1, 0.14]	0.05	0.18	[-0.1, 0.14]
Demand x Repeat Mediation: N-back						
x Effort Repeat Phase				0.33 †	0.18	[0, 0.23]
x Error Repeat Phase				2.86	1.71	[-0.16, 2.08]
x Change in Error Repeat Phase				-0.07	0.74	[-0.51, 0.46]
Repeat Mid-Level Deviation						
Column Addition	-0.22	0.23	[-0.22, 0.08]	-0.22	0.22	[-0.22, 0.07]
N-back	0.11	0.23	[-0.11, 0.19]	0.01	0.24	[-0.15, 0.16]
Fitts Law	-0.05	0.23	[-0.17, 0.13]	-0.05	0.22	[-0.16, 0.13]
Model Fit						
Deviance	626.98			612.01		
Parameters	20			29		

† $p < .1$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Discussion

Experiment 2 examined how tasks that differed in their information processing and attentional control demands affected self-report difficulty, effort, activation and pupil diameter in order to explore the potentially separate contributions of information processing and attentional regulation to changes in resource availability, resource allocation, and metacognition. It also sought to more clearly identify the effects of prior task demands. The predictions concerning the different influences of current information processing and attention control demands on the metacognitive states and pupil diameter will be discussed first, followed by a discussion of the effects of prior task demands and the indirect effects of task demands.

Influence of current information processing and attentional regulation demands

Considering first the effects of current task demands on the level of available resources, Experiment 2 found that self-report activation was significantly higher than baseline during the initial performance of the two tasks that required information processing but not during the initial performance of the non-information processing task. This occurred even though the non-information processing task only required episodic, rather than continual, attentional control which was expected to produce minimal resource depletion. However, a non-significant effect was only one of the criteria required to support the prediction that an attentional control task would not increase activation. The other criterion was that the confidence interval associated with the mean effect should not exceed that of a small effect size. This criterion was not met which meant that the current experiment did not conclusively demonstrate that information processing is required to increase activation levels. However, evidence for the contribution of information processing to the level of available resources can be found in the result that the size of the increase in activation during the attentional control task was smaller than the increase during the information processing tasks. It is also possible that a small level of information processing was required in the Fitts' Law task due to the uncertainty associated with the required direction of cursor movement in each trial, which may have contributed to this result. Additional evidence for the proposed link between information processing and the level of available resources was found in the response to increased within-task demand levels where increased activation was observed during the episodic information processing task but a non-significant and null effect was observed for the episodic non-information processing task. The increase in activation with demand level for the continuous information processing task had an effect size of d = 0.3 which was not significant, but if the need for sustained attentional control depletes resources (Beal et al., 2005; Muraven & Baumeister, 2000; Muraven, Tice, & Baumeister, 1998; Schmeichel, Vohs, & Baumeister, 2003) then this positive but non-significant result may have been driven by the opposing influences of information processing and attentional control on activation.

The result that short-term information processing task demands appear to increase activation is consistent with the predictions of malleable resources theory (Young & Stanton, 2002b) that workload associated with task performance increases the level of available resources, and is consistent with previous findings that verbal tasks which impose some working memory load can increase activation and driving performance (Atchley et al., 2014; Gershon et al., 2009). The current experiment also potentially clarifies the mechanisms by which these effects are produced. It was possible that in the above two studies the verbal aspect of the tasks, rather than the working memory demands, caused the increased activation observed. However, the current result that non-verbal tasks with minimal motor demands produced increased activation levels suggests that it was the working memory load rather than the need to vocalise that led to the observed increase in activation while driving. The current experiment also potentially helps bound malleable resources theory by identifying that information processing is required to increase the level of available resources and that attentional control does not appear to contribute to increased resource availability.

The current study also tested the predictions that both information processing and attention regulation demands would increase perceived difficulty, effort and pupil diameter but reduce affective valence. The predictions relating to perceived difficulty and self-report effort were clearly supported, with the requirements of the episodic and continuous information processing tasks and the episodic motor control tasks all producing reliable increases in difficulty and effort. These results suggest that these self-report measures index a combination of the information processing and attention control aspects of task demands.

However, the pupil diameter results appear to tell a more complicated story. Considering first the episodic information processing performance task, pre-stimulus pupil diameter did not differ between the low and high demand levels and, while the within-trial increase in pupil diameter was larger for the high demand level than for the low demand level during initial task performance, this effect disappeared during repeat task performance. This suggests that higher levels of effort were initially being applied as demand level increased during initial task performance. However, during the repeat phase similar levels of effort were being applied for the low and high demand level which suggests that participants expended less peak effort during repeat performance than during initial performance. Considering that response time, but not errors, increased more with demand level during repeat task performance than during initial task performance this suggests that participants may have been making a strategic decision to reduce the maximum amount of effort expended, but to expend less effort for a longer period in order to complete the difficult level during repeat task performance. Self-report effort did not capture this pattern of results, and it may be that self-report effort more closely indexes the cumulative effort expended during task performance rather than the peak effort expended which can be captured in the pupil diameter time series.

A somewhat different pattern of pupil diameter results was observed during the continuous information processing task. Pre-stimulus pupil diameter increased between the low and high demand levels during initial task performance but no change in the within-trial pupil diameter was observed across the two demand levels. The size of the increase in pre-stimulus pupil diameter between the low and high demand levels was larger during repeat task performance than during initial task performance, but the size of the increase in within-trial pupil diameter was smaller during repeat task performance. For this task the pre-stimulus pupil diameter indexed the length of the word-list held in working memory and it appears that participants increased their effort response to this manipulation during repeat task performance, perhaps indicating the application of compensatory effort to maintain performance under conditions of reduced resources when little scope exists for the active management of effort.

Considering finally the episodic motor control task, a very different pattern of results was obtained for this task than for the other two tasks. While pre-stimulus pupil diameter was larger during this task than during the low-load baseline, both pre-stimulus pupil diameter and the within-trial change in pupil diameter decreased with increasing task demands during both the initial and repeat task performance phase. This decrease in pupil diameter with increased task demands was an unexpected result, which may indicate that participants allocated fewer resources to the task as its demands increased. However, this interpretation conflicts with the results obtained from self-report effort and the response to increased demands observed during the other two tasks.

It may instead be that cognitive and motor control tasks produce different pupil diameter responses. Relatively few studies have examined the pupil diameter response to motor control tasks, but Hupé, Lamirel, and Lorenceau (2009) found that pupil dilation occurred prior to and after a manual response, and Jainta, Vernet, Yang, and Kapoula (2011) found that pupil dilation occurred prior to saccade initiation, which can be considered to be a special case of motor control. These results indicate that increased pupil diameter accompanies the preparation and execution of motor processes and that the size of the dilation reflects the complexity of the motor response (Richer & Beatty, 1985; Richer, Silverman, & Beatty, 1983). The current finding that pre-stimulus pupil diameter was larger for the motor control task than for the low-load baseline is consistent with the association of increased pupil diameter with motor processes, but the decrease in pupil diameter with increased task demands does not appear to be.

However, it may be that while increased demands of the Fitts' Law task require greater precision of movement, they do not impose greater complexity. A study which examined EEG correlates of the Fitts' Law task found that increased levels of task demands were associated with increased amplitudes of the N2 and P3b components, which were interpreted as indicating an evaluation of increased task difficulty, but found no corresponding increase in activation in the CNV and LRP components which would be expected if increased motor activation occurred (Kourtis, Sebanz, & Knoblich, 2012). This suggests that increased demand levels of the Fitts' Law may not generate higher levels of motor planning, which would be consistent with the lack of increase in pupil diameter found in the current experiment. This does not fully explain the reduction in pupil diameter associated with increased task demands, but this could possibly have been caused by individuals adopting a more 'automatic' and less 'controlled' motor process as task demands increased which would account for the observed effect.

Somewhat mixed results were found for the effects of task and within-task demand level on valence. Valence was reliably lower than baseline during the initial performance of the episodic information processing task but this effect did not reach significance for the continuous information processing task or the episodic non-information processing task. However the confidence intervals for each of these effects were relatively large, making it difficult to draw strong conclusions from this result. Only the continuous episodic task showed a significant decline in valence in response to an increase in within-task demand level, but the other two tasks also had negative coefficients. These results tentatively support the prediction that the attentional regulation aspects of task demands contribute to reduced valence, which is consistent with earlier work that self-control and vigilance tasks can produce negative affect (Hagger et al., 2010; Matthews et al., 2002; Matthews et al., 2006). However the current results do not clearly support the proposal that information processing demands produce an additional reduction in valence. While the episodic information processing task produced lower valence than the episodic motor control task, the size of the difference was not substantial and there was no difference in valence between the continuous information processing task and the episodic motor control task. These results suggest that the level of information processing demands may not strongly predict either positive or negative changes in valence associated with task performance.

Effect of prior task demands

Experiment 2 also sought to examine the effect of prior task demands on available resources, allocated resources, difficulty and valence. Self-report activation was lower during the repeat performance of each task than during the initial performance, which indicates that task repetition appeared to create the expected effect of reducing the level of available resources.

However, Experiment 2 found no difference in the response of self-report effort to high demands between initial and repeat task performance which suggested that, on average, participants did not change the level of effort applied during repeat task performance despite experiencing lower activation. However, the pupil diameter results suggested a more complicated response pattern which will be discussed below.

The indirect effect of task demands

Considering next the indirect effects of task demands on difficulty and valence, the current results provided no support for the proposal that the level of activation would moderate perceived difficulty as there was no difference in the perceived difficulty of the same level of task demands between the initial and repeat task performance phases despite a large reduction in the level of activation. This result did not support the hypothesis and suggests that the level of available resources did not substantially influence the metacognitive assessment of task difficulty. Instead perceived difficulty may have been dominated by the task demand cues, which were strongly salient in the tasks used in the current experiment. This is also a limitation that will be addressed in the next experiment which will use a more complex task than those used in the current experiment.

The current results also did not support predictions that effort, current task performance and the change in task performance accounted for the reduction in valence arising from task performance. The inclusion of the proposed mediating variables reduced the effect of task demands to non-significance but none became significant predictors of valence. However, effort had a moderate-sized effect on valence during initial task performance, which may indicate the presence of an effect that was not reliably established in the current experiment. The design of the current experiment may also not have provided a strong test of the effect of changes in performance levels on valence due to its inability to separate performance level from the change in performance level in the initial test phase. This is a limitation that will be addressed in the next experiment.

Limitations of the current study

One limitation of Experiment 2 is the absence of task counterbalancing during initial task performance which occurred due to the calibration requirements of other physiological measures not reported here. This opens the possibility that the episodic non-information processing task may have generated increased activation but this was masked by resource depletion associated with performance of the previous two tasks. However, the inclusion of task order as a predictor in the regression did not change the result and the result that activation in the episodic non-information processing task was lower than activation in the episodic information processing task during the repeat task performance, where counterbalancing was present, mitigates against this interpretation, as does the result that activation was not observed to change with increased demand level during the episodic motor control task whereas it did during the episodic information processing task.

Another limitation of Experiment 2, which was noted earlier in the discussion, was the use of simple, laboratory-style tasks which each had a single objective, clear demand cues and provided immediate feedback. These task characteristics may have dominated the influence of internally sensed states during the metacognitive process and produced some of the unexpected self-report results that were observed. This limitation will also be addressed in the next experiment which used a complex dynamic decision task in order to more accurately represent the task conditions in many applied environments.

Summary

The current experiment explored the potentially opposing effects of information processing and attention control on the level of available resources, and identified the effect of prior information processing and attentional control demands on the metacognitive states and pupil diameter. It tested 11 hypotheses, of which 8 were fully or partially supported. General support was found for the predictions relating to the effects of current task demands on perceived difficulty, effort, activation, valence and pupil diameter, as well as for the prediction that information processing contributed to an increase in the level of available resources while attentional control contributed to a depletion in the level of available resources. Less support was found for the prediction that the level of available resources would influence perceived difficulty and that effort and performance influenced valence. However, it was identified that the clear demand cues provided by the tasks and manipulations used in in the current experiment may have affected the self-report data and contributed to these results and the next experiment will use a more naturalistic, ecologically valid task in order to reduce this possible effect.

CHAPTER 6: EXPERIMENT 3

Introduction

The previous two experiments examined the dynamics of the cognitive, affective and motivation responses to changes in demands associated with the performance of four traditional laboratory-based tasks, each of which had a single aim, a trial-based structure, clear demand cues and immediate explicit or implicit feedback. However, these are not the conditions present in many applied tasks which can be comparatively unstructured, dynamic, require switching between various sub-goals based on relative priorities, and lack clear feedback about the correctness of present or past actions. These different characteristics may produce a different pattern of responses than were observed previously, and Experiment 3 will extend the first two experiments by testing whether the proposed cognitive, affective and motivational responses to changes in task demands also occurred in a task environment with a higher degree of ecological validity than previously tested.

Self-regulatory responses in complex dynamic control tasks

As noted above, many applied tasks such as military command and control and air traffic control require that a series of real-time, cumulative decisions be made using a range of information sources in an environment where the state of the decision problem changes autonomously over time or as a result of the actions of the decision maker, a situation that been termed dynamic decision making (Brehmer, 1992; Gonzalez, Vanyukov, & Martin, 2005) or, more recently, complex dynamic control (Osman, 2010). While theory acknowledges that complex dynamic control task demands may generate different responses than simple, non-dynamic tasks (Dörner & Güss, 2013; Hockey, 1997), little empirical work appears to exist that clearly identifies how the demands of complex dynamic control tasks influence cognitive, motivation and affective states. Hockey, Wastell, and Sauer (1998) examined the effect of sleep deprivation on the operation of a simulated life support system and found that while sleep deprivation had a significant effect on fatigue, it did not affect anxiety, and time on task did not affect either fatigue or anxiety. Sauer, Wastell, Hockey, and Earle (2003) examined the impact of occasional night work on simulated process control but found no clear change in affective state between day and night shifts. Hockey and Earle (2006) found that high workload during a simulated office task increased fatigue and anxiety, but the demands of this task were largely clerical and did not call for decision making under uncertainty.

These largely null results provide insufficient evidence to identify the effects of complex dynamic control task demands but, noting that complex dynamic control tasks can be expected to require both information processing and attentional control, it was predicted that the hypotheses developed in Chapter 2 will apply.

The experimental task

Experiment 3 measured the effects of cyclic task demands during a simulated dynamic decision task. Such simulated tasks, also termed ‘microworlds’ (Brehmer & Dörner, 1993), allow controlled modelling of the dynamics, complexity and opaqueness characteristic of dynamic decision making tasks (Gonzalez et al., 2005) while engendering high levels of immersion and engagement in participants (Gray, 2002). The current study simulated an air-radar task which required that new and existing aircraft contacts be assigned the correct threat identity based on their behaviour using a set of decision criteria. Task demands were manipulated by systematically varying the number and behaviour of aircraft contacts over the duration of the task. This had the effect of changing the number of outstanding tasks that needed to be performed in order to achieve an accurate ‘air picture’ and, as the goal of the task was to have no outstanding tasks, the level of task demands also served as an indication of task performance. The level of task demands was initially increased over time to create a situation where the number of outstanding tasks became progressively greater, which created a negative performance trajectory. This was followed by a period where the level of task demands was decreased, which reduced the number of outstanding tasks and created a positive performance trajectory. This manipulation allowed the effects of the current level of task performance and the direction of change in performance level to be disambiguated. This was followed by a second cycle of increasing then decreasing demands which allowed a test of whether the responses to changes in task demands varied after sustained prior task performance. The specific predictions relating to these task demand characteristics that arise from the hypotheses developed in Chapter 2 are described in Table 3.

Table 13. Mapping of each hypothesis to the predicted effects in the current experiment.

	Hypothesis	Experiment 3 Prediction
1. The effect of current information processing and attentional control task demands		
1a)	Increased information processing demands will increase the level of self-report activation	Increased task demands will predict increased activation
1b)	Increased attentional control demands will not increase the level of self-report activation	Not tested
1c)	Increased information processing and attentional control demands will be accompanied by increased perceived difficulty	Increased task demands will predict increased difficulty
1d)	Increased information processing and attentional control demands will be accompanied by increased effort, but only up to a the point of maximum resource allocation after which effort will remain constant or decrease	Increased task demands will initially predict increased effort, but this relationship may level out or decrease at high task demand levels
1e)	Increased information processing and attentional control demands will be accompanied by increased pupil diameter, but only up to the point of maximum resource allocation after which pupil diameter will remain constant or decrease	Increased task demands will initially predict increased pupil diameter, but this relationship may level out or decrease at high task demand levels
1f)	Increased information processing and attentional control demands will be accompanied by decreased affective valence	Increased task demands will predict reduced valence
2. The effect of prior information processing and attentional control demand levels		
2a)	Sustained attentional control demands will decrease the level of self-report activation	The level of self-report activation will decrease with time on task
2b)	Decreased self-report activation will be accompanied by increased effort at low task demand levels and reduced effort at high task demand levels	The slope of the relationship between task demands and effort will reduce with time on task
2c)	Decreased self-report activation will be accompanied by increased pupil diameter at low task demand levels and reduced pupil diameter at high task demand levels	The slope of the relationship between task demands and pupil diameter will reduce with time on task
3. The indirect effects of task demands on difficulty and valence		
3a)	The relationship between task demands and perceived difficulty will be moderated by the level of self-report activation	The task demand x activation interaction will be a significant predictor of perceived difficulty
3b)	The relationship between task demands and valence will be mediated by the current task performance level, the rate of change in task performance and the current level of effort	Current effort, current task demands, and task demand trajectory will be significant predictors of valence

Method

Participants

Thirteen employees (four female) of the Defence Science and Technology Organisation participated in the experiment. The mean age was 40.0 years (*SD* = 9.4). Two participants had previous experience with military radar systems. Participants were screened for colour blindness using Ishihara colour plates (Ishihara, 1993).

Materials and Apparatus

The structure of the visual display was identical to the visual stimulus used in Experiment 1. Given that Experiment 1 was able to detect changes in pupil diameter arising from changes in task demands, the use of the same display structure provided some assurance that the current experiment may also be able to detect any demand-related changes in pupil diameter. However, it must be noted that differences existed between the tasks used in each experiment which influenced the visual conditions and therefore pupil diameter. Unlike Experiment 1, which used a constant visual stimulus, the number of visual elements present on the display increased with task demands during the current experiment. This was expected to reduce the size of the effect of task demands on pupil diameter in the current experiment compared to Experiment 1.

The display simulated an air-radar system and is shown in Figure 11. Air tracks were displayed as symbols on a plan position indicator (PPI) located in the left half of the display. A PPI is a birds-eye view of the earth with the position of the radar at the centre and north towards the top. The range and bearing of each track is represented by its distance away from the centre and its angle from north. The course and speed of each track are indicated by the direction and length of a leader line originating from the track symbol. New tracks that had not yet been identified were displayed as a ‘pending’ symbol. Tracks could be allocated an identity of friend, assumed friend, suspect, hostile or unknown, and each identity had its own unique symbol. Tracks could become stale because radar contact had been lost, which was indicated by a light grey ‘X’ placed over the symbol.

Figure 11. The visual display used during the experiment.

The identification process required that track attributes such as position, course, speed, height and identification friend or foe (IFF) status be used to categorise tracks into one of the five identities (friend, assumed friend, suspect, hostile, unknown) based on a set of decision criteria shown in Appendix C. Estimates of position, course and speed could be obtained through visual inspection of the PPI but exact information for these attributes plus altitude and track age (time since last radar contact) could be obtained by clicking on a track to select it which would display the attribute information in the top-right panel of the display. IFF information was obtained by selecting a track and then clicking on the ‘Interrogate’ button located in the centre-right panel of the visual display. The typical track identification process was to search the PPI for the next track to action, select the track, interrogate IFF, then use the IFF and track attribute information to reach an identity decision. The identity decision was implemented by selecting the appropriate identity button located in the lower-right panel of the display and the decision criteria that was used to determine the identity.

Electronic signature (ES) detections were displayed in list form in the upper-centre panel of the display. ES detections could provide additional information about track identity, but only if they could be associated with a particular track. This was not always possible because ES detections only contained bearing information and there may have been more than one track along or near to a bearing that could have been the source of the ES detection. If ES detections could not be associated with a particular track they could be deleted, which removed them from the displayed list.

Manipulations

The experimental task required participants to maintain an accurate air-radar picture by identifying new air tracks, updating the identity of existing tracks if necessary due to changes in track behaviour, processing electronic signature (ES) detections and deleting stale tracks. The level of current task demand was therefore expected to be a function of the number of pending tracks, the number of active tracks, the number of ES detections and the number of stale tracks present on the display at any point in time. Task demand was manipulated by controlling the occurrence of pending tracks events, track behaviour change events where aircraft departed from an air-lane and began to approach own-ship, and ES detection events. The number of active and stale tracks was not directly manipulated but was influenced by pending track events, track behaviour, and participant actions. Five nominal levels of task demands were created by having the sum of pending tracks plus tracks with a behaviour change vary between one and five. The task demand profile used in the experiment started at one pending track, increased to five pending plus changed-behaviour tracks, reduced to two, increased to four and then reduced to two again. This manipulation meant that task demands went through two cycles where the task performance trajectory was initially negative but then changed to positive. Each level of task demand lasted for a block of six new pending or track behaviour change events. ES detections made up 20% of events and occurred randomly throughout the task.

This approach meant that the presentation of new pending tracks, track behaviour changes and ES detection events was not time-based, but was instead triggered by participants processing a pending track or updating the identity of a track with changed behaviour. Each participant therefore experienced the same task-demand profile irrespective of the speed with which they identified tracks, but this also meant that participants experienced a different number of events during the 50 minute experimental period and not all participants completed both demand cycles. The mean number of events across participants was $M = 65.15$, $SD = 13.64$.

The mean number of pending tracks, pending ES detections, active tracks and stale tracks across participants for the first 80 events are shown in Figure 12. The square black markers denote the end of each demand level block. Note that even though the manipulation of demand level was expected to vary the number of pending tracks between one and five, the mean number of pending tracks in each demand level block only varied between one and 3.5. This was because participants typically did not update the identity of tracks that had undergone behaviour changes. Given that task demand was calculated as the number of pending tracks plus the number of changed-behaviour tracks, failure to update the identity of changed-behaviour tracks inhibited the presentation of new pending tracks. The error bars shown for the number of pending tracks indicate that there was variability in the number of pending tracks present at each event across participants. All participants were presented with the same sequence of events controlled by the experimental script, but participants could choose from range of possible actions to perform at any point in time which influenced the specific state of the display at each event for each participant. Similar variance existed in the number of ES detections, stale tracks and active tracks but error bars are omitted from the figure for these variables to avoid clutter.

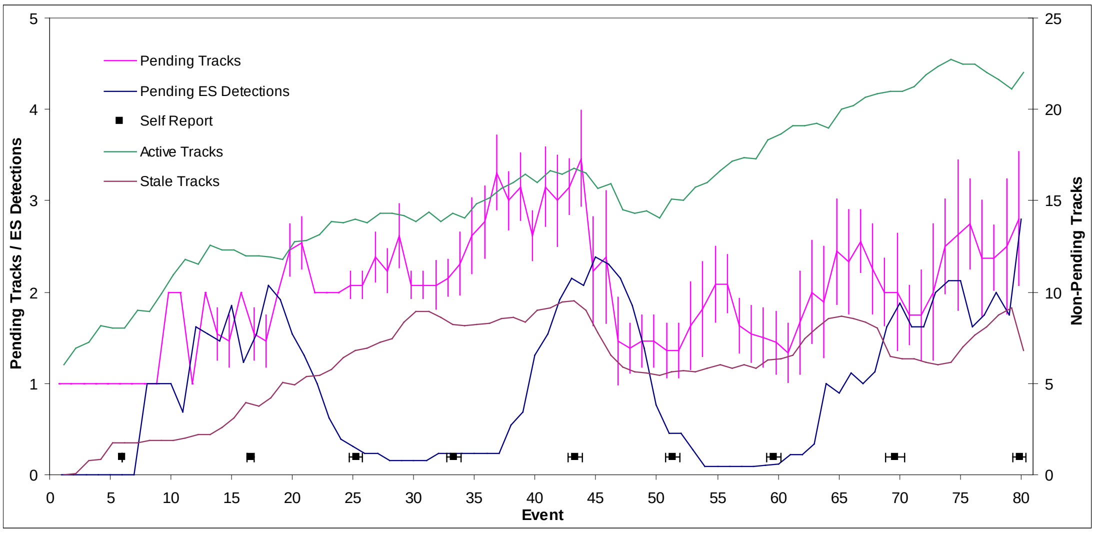

Figure 12. The mean number of pending tracks, pending ES detections, active tracks and stale tracks present at each event. To reduce clutter error bars are only shown for pending track and represent the 95th percentile confidence intervals.

Measures

Experiment 3 used the same self-report measures as Experiment 1, which were collected at the end of each demand level block. Pupil diameter was measured as the mean pupil diameter across each task demand level. The time taken to identify each new air contract was used to identify the effect of demand level on the speed of task performance.

Procedure

Participants were advised that they were to perform a simulated air radar task where the goal was to maintain an accurate air picture and that their task was to correctly identify new tracks as they appeared, make changes to the identity of existing tracks as necessary and to delete stale tracks. No specific task hierarchy was stipulated. The possible track identities and the identification criteria were explained and participants provided informed consent. A demonstration was provided of all elements of the task and participants then undertook a practice session where they were required to correctly identify tracks that corresponded to each of the possible identities. Participants were free to ask questions during this session in order to gain a full understanding of the task. After completion of the practice session participants completed a short demographic and experience questionnaire and the UMACL questionnaire. Participants then performed the experimental task for 50 minutes. After completion of the task they again completed the UMACL. Each experimental session lasted for approximately 1.5 hours. The UMACL results are not reported here.

Analysis strategy

A 3 level model was used to analyse the data, with Level 1 being the task demand level, Level 2 being the demand cycle level and Level 3 being the person level. A number of Level 1 variables were created to model the effects of task demands, performance trajectory and time on task. The variables of *PENDING*, *ES*, *ACTIVE* and *STALE* modelled the effects of task demands and were coded to represent the number of pending tracks, the number of ES detections, the number of active tracks and the number of stale tracks respectively. The variable of *POSPERF* modelled the effect of performance trajectory and was coded as 0 for periods of negative performance trajectory and 1 for periods of positive performance trajectory. The variable of *IDPERIOD* modelled the speed of task performance and was coded as the time taken (in seconds) to allocate an identity to a new air contact. BLOCK modelled the effects of time on task and was coded as 0 for the first demand level block and incremented by 1 for each subsequent block. *CYCLE* was entered as a Level 2 variable and was dummy coded as 0 for the initial negative and positive performance trajectory cycle and 1 for the second cycle. No variables were entered at Level 3.

Results

In line with the approach taken in the previous studies, the effect of current task demands on performance, the self-report measures and pupil diameter will be reported initially. The effect of prior task demands will then be presented, followed by an examination of the indirect effects of task demands on difficulty and valence.

The effect of current task demands

The effect of current task demands can be seen in the 'Initial Demand Cycle – Demand Level' block of Table 14. An inspection of column 1 of Table 14 reveals that during the initial demand cycle the time to identify a pending track (ID period) increased with the number of ES detections but no significant change was observed in ID period in response to the number of pending tracks, active tracks or stale tracks during the initial demand cycle. These results provide no evidence that participants increased the speed of task performance in response to increase task demands. However, the increase in ID period with the number of ES detections suggests that participants may have been attempting to incorporate ES information into the identification process which increased the time to perform the task.

Table 14. Models of the effects of demand level block, demand level, and demand cycle.

	ID Period			**Difficulty**			**Effort**		
Fixed effects	Coefficient	SE	*d* 95% CI	Coefficient	SE	*d* 95% CI	Coefficient	SE	*d* 95% CI
Initial Demand Cycle - Demand Level									
Intercept	59.13 ***	5.61	[2.53, 3.69]	4.42 ***	0.78	[1.38, 2.85]	4.84 ***	0.70	[1.43, 2.56]
Pending Tracks	-1.50	1.25	[-0.21, 0.05]	0.27 †	0.15	[-0.02, 0.27]	0.05	0.15	[-0.1, 0.14]
ES Detections	3.09 **	1.15	[0.04, 0.28]	0.17	0.11	[-0.02, 0.18]	0.03	0.11	[-0.07, 0.1]
Active Tracks	0.13	0.51	[-0.05, 0.06]	0.15 *	0.07	[0.01, 0.13]	0.27 ***	0.06	[0.06, 0.16]
Stale Tracks	0.14	0.23	[-0.02, 0.03]	0.08 *	0.03	[0.01, 0.07]	0.00	0.03	[-0.03, 0.02]
Initial Demand Cycle - Time on Task									
Demand Block	-4.27 ***	0.85	[-0.31, -0.14]	-0.25 *	0.10	[-0.21, -0.02]	-0.17 †	0.10	[-0.15, 0.01]
Repeat Demand Cycle - Demand Level									
Intercept	-5.80	14.52	[-1.8, 1.19]	3.56	2.24	[-0.39, 3.8]	1.38	2.10	[-1.13, 2.27]
Pending Tracks	-3.42	2.40	[-0.43, 0.07]	-0.27	0.32	[-0.43, 0.17]	-0.24	0.31	[-0.35, 0.15]
ES Detections	-0.54	2.12	[-0.25, 0.19]	-0.03	0.27	[-0.27, 0.24]	0.19	0.26	[-0.13, 0.29]
Active Tracks	-0.87	0.79	[-0.13, 0.04]	-0.27 *	0.11	[-0.23, -0.02]	-0.29 **	0.11	[-0.2, -0.03]
Stale Tracks	0.42	0.30	[-0.01, 0.05]	0.02	0.04	[-0.03, 0.05]	0.04	0.04	[-0.02, 0.05]
Repeat Demand Cycle - Time on Task									
Demand Block	4.36 *	1.81	[0.04, 0.42]	0.29	0.26	[-0.11, 0.38]	0.44 †	0.25	[-0.02, 0.38]
Model Fit									
Deviance	5176.0			361.2			347.4		
Parameters	15			15			15		

	Valence			**Activation**			**Pupil Diameter**		
Fixed effects	Coefficient	SE	*d* 95% CI	Coefficient	SE	*d* 95% CI	Coefficient	SE	*d* 95% CI
Initial Demand Cycle - Demand Level									
Intercept	1.93 †	0.93	[0.05, 1.57]	0.05	0.81	[-0.73, 0.78]	5.75 ***	0.30	[4.78, 5.87]
Pending Tracks	-0.03	0.14	[-0.12, 0.1]	-0.04	0.15	[-0.16, 0.12]	0.00	0.01	[-0.02, 0.01]
ES Detections	-0.08	0.10	[-0.12, 0.05]	0.21 †	0.11	[0, 0.2]	0.01 †	0.01	[0, 0.03]
Active Tracks	-0.04	0.06	[-0.07, 0.03]	0.19 **	0.07	[0.03, 0.15]	0.00	0.00	[0, 0.01]
Stale Tracks	-0.05 †	0.03	[-0.05, 0]	0.01	0.03	[-0.03, 0.03]	-0.01 **	0.00	[-0.01, 0]
Initial Demand Cycle - Time on Task									
Demand Block	0.01	0.09	[-0.07, 0.08]	-0.45 ***	0.10	[-0.31, -0.12]	-0.02 ***	0.01	[-0.03, -0.01]
Repeat Demand Cycle - Demand Level									
Intercept	-1.36	1.90	[-2.13, 0.99]	-3.12	2.06	[-3.39, 0.43]	-0.14	0.12	[-0.35, 0.08]
Pending Tracks	-0.23	0.28	[-0.32, 0.13]	0.05	0.30	[-0.25, 0.31]	0.03	0.02	[-0.01, 0.06]
ES Detections	0.31	0.23	[-0.06, 0.32]	-0.26	0.25	[-0.36, 0.11]	0.01	0.01	[-0.01, 0.04]
Active Tracks	0.12	0.09	[-0.03, 0.13]	0.05	0.10	[-0.07, 0.12]	0.00	0.01	[-0.01, 0.01]
Stale Tracks	0.06 †	0.03	[0, 0.05]	0.01	0.04	[-0.03, 0.04]	0.00	0.00	[0, 0.01]
Repeat Demand Cycle - Time on Task									
Demand Block	-0.19	0.23	[-0.27, 0.11]	0.37	0.25	[-0.06, 0.41]	0.01	0.01	[-0.02, 0.03]
Model Fit									
Deviance	349.1			355.4			-591.2		
Parameters	15			15			15		

† $p < .1$. * $p < .05$. ** $p < .01$. *** $p < .001$.

Considering next the effect of current task demands on perceived difficulty, it was predicted that increased task demands would predict increased perceived difficulty. Column 2 of Table 14 shows that during the initial demand cycle perceived difficulty increased with the number of active tracks and stale tracks. The increase in perceived difficulty with the number of pending tracks approached, but did not reach the criterion level of significance. Increased ES detections did not produce any significant change in perceived difficulty. These results broadly support the hypothesis and also support the above suggestion that ES detections may not have been considered to be an additional demand, but instead were considered to be an additional source of information to incorporate into the identification process.

Considering effort next, it was predicted that increased task demands would predict increased effort, but that this relationship may level out at high demand levels. Column 3 of Table 14 shows that during the initial demand cycle self-report effort increased with the number of active tracks but not the number of pending tracks, ES detections or stale tracks. This partially supports the hypothesis that increased task demands would predict increased self-report effort. A related hypothesis was that that increased task demands would increase pupil diameter, which was considered to be an index the level of resources allocated to a task. Column 6 of Table 14 shows that pupil diameter decreased with the number of active tracks. The increase in pupil diameter with increased ES detections approached, but did not reach, the criterion significance level. These results provide little support for the hypothesis but, as noted above, the effect of task demands on pupil diameter may have been masked by the associated increase in the number of visual elements which would have increased luminance and therefore decreased pupil diameter.

Considering valence next, it was predicted that increased task demands would predict decreased valence, but an inspection of column 4 of Table 14 shows that current task demands had little effect on valence. During the initial demand cycle the decrease in valence with the number of stale tracks approached, but did not reach, significance. The number of pending tracks, active tracks and ES detections had no significant effect on valence. These results offer only limited support to the prediction that increased task demands would be accompanied by reduced valence.

Considering finally the influence of task demands on the level of self-report activation, it was predicted that the level of activation would increase with task demands. An inspection of column 5 of Table 14 shows that the number of active tracks was a significant predictor of activation and the effect of the number of ES detections approached, but did not reach, the criterion significance level. The number of pending tracks and the number of stale tracks were not significant predictors of activation. These results partially support the hypothesis that increased task demands would predict increased activation.

The effect of prior task demands

The current experiment allowed two tests of the effects of prior task demands. The first was a direct measure of the effect of time on task, which was operationalised as the effect of demand level block. The second test was to examine whether the response to task demands or time on task during the repeat demand cycle differed from the response during the initial demand cycle. The effect of time on task can be seen in the 'Initial Demand Cycle – Time on Task' block of Table 14 and the effect of the repeat demand cycle can be seen in the 'Repeat Demand Cycle' blocks of Table 14.

Three predictions were made concerning the effect of prior task demands: it was predicted that activation would decrease with time on task, and it was predicted that the slope of the relationship between task demands and effort and task demands and pupil diameter would reduce with time on task. An inspection of column 5 of Table 14 reveals that demand level block predicted a significant decrease in activation, which supports the first hypothesis.

An inspection of column 3 of Table 14 shows that, while effort increased with the number of active tracks during the initial demand cycle, this relationship became non-significant during the repeat demand cycle, which indicates a reduction in the slope of the relationship between task demands and effort after sustained prior task demands and supports the second hypothesis. However, this result was not observed to occur for pupil diameter which did not support the third hypothesis.

The indirect effects of task demands on difficulty and valence

It was predicted that the level of activation would moderate the relationship between task demands and perceived difficulty, which was tested by examining whether the task demand x activation interactions were significant predictors of perceived difficulty. The model including the interaction terms is shown in column 1 of Table 15 from which it can be seen that none of the task demand x activation terms were significant. These results do not support the hypothesis.

It was also predicted that the current level of effort and the performance trajectory would mediate the relationship between task demands and valence. This was tested by adding effort and performance trajectory as additional predictors in the regression where task demands predicted valence. This model is shown in column 2 of Table 15 from which it can be seen that effort was a significant negative predictor of valence when included in the model. The effect of performance trajectory on valence was positive but just failed to achieve the criterion for statistical significance. However, the effect size was d = 0.64, which is a moderate effect size according to Cohen's criteria (Cohen, 1988) and is not consistent with a null effect. These results therefore provide support for the prediction that effort and the direction of change in task performance mediate the effect of task demands on valence. However the result that task demands were not significant predictors of valence does not support the prediction that the current level of task demands would also predict valence.

Table 15. Model of the moderating effect of activation on the relationship between task demands and difficulty.

	Difficulty			Valence		
Fixed effects	Coefficient	SE	*d* 95% CI	Coefficient	SE	*d* 95% CI
Initial Demand Cycle - Demand Level						
Intercept	4.61 ***	0.78	[1.48, 2.94]	2.27 †	1.06	[0.08, 1.82]
Pending Tracks	0.32	0.20	[-0.04, 0.35]	0.37	0.24	[-0.04, 0.35]
ES Detections	0.02	0.16	[-0.14, 0.16]	-0.05	0.10	[-0.1, 0.06]
Active Tracks	0.09	0.08	[-0.03, 0.11]	0.06	0.07	[-0.03, 0.08]
Stale Tracks	0.08 †	0.04	[0, 0.07]	-0.03	0.03	[-0.04, 0.01]
Pending x Activatio	0.00	0.06	[-0.06, 0.06]			
ES x Activation	0.05	0.05	[-0.02, 0.07]			
Active x Activation	0.02	0.01	[-0.01, 0.02]			
Stale x Activation	-0.01	0.01	[-0.02, 0.01]			
Effort				-0.21 *	0.09	[-0.16, -0.01]
Positive Trajectory				1.52 †	0.77	[0, 1.27]
Initial Demand Cycle - Time on Task						
Demand Block	-0.17	0.11	[-0.18, 0.02]	-0.45 *	0.22	[-0.37, -0.01]
Repeat Demand Cycle - Demand Level						
Intercept	4.35 †	2.16	[0.06, 4.11]	-2.38	0.77	[-1.63, -0.36]
Pending Tracks	-0.41	0.33	[-0.51, 0.11]	-0.73	0.66	[-0.85, 0.24]
ES Detections	0.19	0.28	[-0.17, 0.36]	0.27	0.23	[-0.07, 0.3]
Active Tracks	-0.29 *	0.11	[-0.24, -0.03]	0.04	0.12	[-0.09, 0.12]
Stale Tracks	0.01	0.04	[-0.04, 0.04]	0.04	0.04	[-0.02, 0.05]
Pending x Activatio	0.08	0.14	[-0.09, 0.18]			
ES x Activation	-0.10	0.13	[-0.17, 0.08]			
Active x Activation	0.00	0.02	[-0.02, 0.02]			
Stale x Activation	0.01	0.02	[-0.01, 0.02]			
Effort				0.10	0.16	[-0.09, 0.17]
Positive Trajectory				-1.95	2.27	[-2.68, 1.04]
Repeat Demand Cycle - Time on Task						
Demand Block	0.24	0.26	[-0.13, 0.36]	0.44	0.90	[-0.55, 0.92]
Model Fit						
Deviance	352.9			339.7		
Parameters	23			19		

† p < .1. * p < .05. ** p < .01. *** p < .001.

Discussion

The current study examined the effects of cyclic changes in demand level over a sustained period during a complex dynamic control task on cognitive, affective, motivation and physiological states. It aimed to identify whether a task that simulated the complexity, uncertainty and dynamics of some work environments would generate a similar pattern of psychological and physiological response as had previously been observed to occur in response to more structured cognitive tasks. The results will be discussed in terms of the effects of current task demands, the effects of prior task performance and the proposed indirect effects.

The effect of current task demands on the metacognitive variables and pupil diameter

The hypotheses developed in Chapter 2 proposed that increased current task demands would predict increased perceived difficulty, effort, activation and pupil diameter but reduced valence. Partial support was found for each of these predictions, but the effect of each aspect of task demands varied across the dependent variables.

Considering first the results relating to perceived difficulty, all aspects of task demands apart from the number of ES detections appeared to independently contribute to perceived difficulty. This was in line with expectations and replicates the results of the previous two experiments that perceived difficulty appears to be a sensitive measure of the level of demands posed by a range of tasks.

Changes in task demands had less effect on self-report effort than on perceived difficulty, with only the number of active tracks being a significant predictor of effort. This was also consistent with the results of the previous experiments which found that task demands had a smaller effect on effort than on perceived difficulty. The results of the current study may also support the proposal that the allocation of effort is not automatic, but rather is a volitional response that can be actively managed (Loft et al., 2007). As an example the number of stale tracks was a significant predictor of perceived difficulty but not effort. It may have been that, despite identifying that increasing numbers of stale tracks were contributing to additional task demands, it was more important to allocate resources towards the processing of pending and active tracks and therefore additional resources were not allocated towards the deletion of stale tracks.

However, as noted in the previous experiments, self-report effort may be prone to biases and failures of introspection. Pupil diameter was considered to be a physiological index of the level of resources allocated towards task performance which can be compared with the results obtained for self-report effort. The current experiment found that pupil diameter to be relatively insensitive to changes in task demands, and only exhibited a non-significant increase with the number of ES detections but not the number of active tracks, pending tracks, or stale tracks. As identified previously, this result can possibly be attributed to the increase in the number of visual elements that accompanied the increase in task demands which would act to reduce the size of the increase in pupil diameter in response to increased task demands. Given this, the true size of the increase in pupil diameter in response to task demands is likely to be larger than observed in the current experiment. While it is not possible to quantify this effect, it does suggest that the number of ES detections may have been a predictor of pupil diameter, which would suggest that increased levels of information processing resources were used to incorporate the ES information into the identification decision.

Considering next the affective response to increased task demands, the current study found that increased task demands were associated with increased activation but no change in valence. The increase in activation with the number of ES detections and active tracks was consistent with predictions and the results of the two previous studies which found that increased levels of cognitive processing demands were associated with increased activation. As noted above, the period to identify a pending track and, marginally, pupil diameter increased with the number of ES detections which suggested that additional information may have been processed during track identification as the number of ES detections increased. This result again suggests that information processing associated with task demands acts to increase the level of available resources.

The prediction that increased current task demands would be associated with reduced valence was not supported in the current experiment. This may in part be a sensitivity issue as the effect of changes to within-task demand level on valence in the previous studies was not large or reliable. However, it may also indicate that, as suggested by Carver and Scheier (1998), the current level of task performance is less important than the rate of change in performance. This issue will be revisited below in the discussion of the indirect effect of task demands on valence.

The effect of prior task demands

The second set of hypotheses considered the effect of prior task demands. These effects were examined by analysing the effect of time on task, as indexed by the demand level block currently being performed, and any differences in the response to task demands between the initial and repeat demand cycles.

It was predicted that activation would decrease with task block as resources were depleted due to the need for sustained attentional control (Muraven & Baumeister, 2000). The current study found that, as predicted, self-report activation decreased with demand level block across both the first and second demand cycles. This result is consistent with that of Experiment 2 and suggests that sustained task performance produces a reduction in the level of available resources, which is experienced as reduced levels of activation. The current results are also consistent with those of Experiment 2 in suggesting that it is attentional control, not information processing that is responsible for resource depletion. Evidence for this can be found in the above results that, while activation decreased with time on task it also increased with the additional information processing demands associated with the number of active tracks and the number of ES detections. This increase in activation in response to increased task demands combined with the decrease in activation in response to time on task supports the prediction that information processing acts to increase the level of available resources while attentional control acts to decrease the level of available resources.

The effect of prior task demands on the level of allocated resources was less predictable as effort may continue to be applied to maintain task performance. However, while effort may be maintained or increased under conditions of reduced resources at low and moderate levels of task demands, there may be a reduction in the maximum level of effort that is willing to be expended (Hockey, 1997; Meijman, 1997) so that the increase in effort in response to increased demands may become smaller after sustained task demands. Self-report effort followed the predicted pattern of results as it increased with the number of active tracks during the initial demand cycle but ceased to increase with the number of active tracks during the repeat demand cycle. Instead effort increased with time on task during the repeat demand cycle.

This pattern of results indicates that as time on task increased during the second negative goal period task more resources were perceived as being required and more resources were applied to maintain task performance. This suggests the application of compensatory effort, where tasks are perceived as being more difficult under conditions of depleted resources (Fairclough, 2001; Kanfer, 2011) and additional resources are applied in order to protect task performance. This pattern of response corresponds to a ‘strain control’ mode (Hockey, 1997) and suggests that participants were willing to protect performance goals at the cost of depleted resources. It also suggests that more regulatory, rather than computational resources may have been applied as the increase in effort during the second negative velocity phase was insensitive to increased task demands and not matched by increased activation, which appears to be sensitive to the application of information processing but not attention regulation resources.

A resource depletion account would also suggest that a similar, but smaller, effect of task block on perceived difficulty and effort should have occurred during the first task demand cycle, which was not observed. However, this may have been due to the effects of skill acquisition. It was previously noted that the period to identify a pending track decreased with task block during the first task demand cycle but did not change with task block during the second task demand cycle. This suggests that skill acquisition may have been occurring during the initial stages of the experiment in which case the resources required for task performance would decrease with task block which would counteract the effect of reduced resources and perhaps explain why difficulty and effort did not change with task block during the initial period of negative goal velocity.

The indirect effects of change in demand level

The hypotheses developed in Chapter 2 proposed that the level of activation should moderate the change in perceived difficulty in response to task demands, with reduced activation leading to increased perceived difficulty due to the reduced level of resources available to meet task demands. This prediction was not supported in the current experiment, which was consistent with the findings of Experiment 1 and Experiment 2 which also found that the level of activation did not appear to influence the level of perceived difficulty. These results stand in contrast to previous studies which have found that the experience of fatigue and resource depletion influence perceived task difficulty (Hagger et al., 2010; Wright et al., 2003; Wright et al., 2013). It may have been that the process of skill acquisition which appeared to be present during the initial demand cycle of the current experiment may have contributed to this result. The acquisition of skills is expected to mean that fewer resources are required in response to the same level of task demands. If the rate of reduction in required resources matches or exceeds the rate of reduction in available resources then it would be expected that reduced levels of activation would be associated with constant or reduced perceived difficulty, as was observed in the current results. Another possible reason that the current study failed to replicate previous results is that it compared repeated measures within a single task, rather than comparing measures across two different tasks. The use of a single task may have made task demand cues particularly salient when assessing perceived difficulty which may have had a greater influence on the appraisal than the effect of reduced resource levels. The use of different tasks could be expected to reduce this effect as the demand cues would not be as consistent between tasks as they were within a single task. Caution should therefore be used before arguing that the current results suggest that the level of available resources do not contribute to the assessment of perceived difficulty.

The second hypothesis concerning the indirect effects of task demands was that current effort and task performance trajectory would mediate the relationship between task demands and valence. The current study did not find that the current level of task demands predicted valence, but the results indicated that effort and performance trajectory did mediate the relationship between task demands and valence. The result that effort appeared to be a significant mediator is consistent with the results of Experiment 2 which found that the level of effort in response to task demand predicted valence, and extend the results of the previous studies which were not able to demonstrate any effect of the change in task performance levels on valence.

The result that valence increased under conditions of positive performance trajectory was consistent with previous work that a positive velocity towards goals is associated with a more positive mood and greater satisfaction (Chang et al., 2010; Elicker et al., 2010; Lawrence et al., 2002) and suggests that changes in the core affective state of valence may underpin mood and satisfaction changes. However, as discussed above and unlike these studies, the current study did not find that current performance levels, as measured by task demand level, made any incremental contribution to valence. This supports the proposal that the rate of change in performance levels may be a stronger influence on the affective response to task demands than instantaneous performance levels (Carver & Scheier, 1998).

Summary

The current experiment provides evidence that complex dynamic control tasks produce a broadly similar pattern of cognitive, affective and motivation responses as the simple cognitive tasks that are typically used in a laboratory environment. The current experiment also provided additional evidence that the application of information processing resources acts to increase the level of available resources but that the application of controlled attention acts to reduce the level of available resources. In addition, the current study replicated the result that the rate of change in performance levels is an important influence on the affective response to task demands and identified that the direction of performance chance influences the core affect state of valence. Finally, some inconsistent results were again observed in the responses of pupil diameter and self-report effort to task demands which suggested that pupil diameter may provide a more nuanced indication of the level of resources applied in response to task demands, but also highlight the potential difficulty in maintaining visual conditions that are conducive to the use of pupil diameter measurements.

CHAPTER 7: DISCUSSION

This thesis proposed a feedback control model which specified the effects of current and prior information processing and attentional control demands on the metacognitive states of perceived difficulty, effort, activation and valence, and the physiological state of pupil diameter. The model adopted a resources-based perspective and defined each state in terms of resource availability and resource allocation. The model attempted to synthesise several existing resource theories and control models which each emphasised different aspects of the cognitive, affective and motivational influences of task demands on the level of available and allocated resources (Brehm & Self, 1989; Carver & Scheier, 1998; Hendy et al., 1997; Hockey, 1997).

The model also sought to reconcile the potentially opposing predictions of ego depletion theory (Baumeister et al., 2007; Muraven & Baumeister, 2000), which proposes that self-regulatory demands associated with task performance deplete the level of available resources, and malleable resources theory (Young & Stanton, 2002b), which proposes that increased mental workload associated with task performance can increase the level of available resources. The proposed model attempted to reconcile these two predictions by suggesting that the information processing demands and attentional control demands of tasks have opposing effects on the level of available resources. It was proposed that information processing demands generate a short term increase in the level of available resources but attentional control demands produce a longer-term depletion in the level of available resources.

Eleven hypotheses were developed which related to different aspects of the model. The level of experimental support that each hypothesis received will be discussed first, which will be followed by a discussion of the theoretical, empirical and methodological implications of the results.

Experimental support for the hypotheses

These hypotheses fell into three broad categories: the effect of current information processing and attentional control demands, the effect of prior task demands, and the proposed indirect effects of task demands on perceived difficulty and valence. A summary of the level of support that each experiment provided for the hypotheses is shown in Table 16.

Table 16 Summary of the level of support provided to each hypothesis across the three experimental studies. The numbers inside the square brackets represent the 95th percentile confidence intervals of Cohen's *d* for each effect. The font represents the strength of evidence of each test. For non-null hypotheses bold corresponds to a 95th percentile CI of *d* that does not cross zero; italics corresponds to a 95th percentile CI that does cross zero but with mean $d > \pm 0.2$; grey corresponds to a *95th* percentile CI that does cross zero and with mean $d \leq \pm 0.2$. For null hypotheses bold corresponds to a 95th percentile CI that does cross zero with maximum $d \leq \pm 0.2$; italics corresponds to a 95th percentile CI that does cross zero maximum $d > \pm 0.2$ but with mean $d \leq \pm 0.1$; grey corresponds to a 95th percentile CI of *d* that does not cross zero or a 95th percentile CI that does cross zero and mean $d > \pm 0.1$.

Category	Hypothesis	Experiment 1	Experiment 2 CAdd Task	Experiment 2 N-back Task	Experiment 2 Fitts Task	Experiment 3
1	The effect of current information processing and attentional control demands					
1a)	Increased information processing demands will increase the level of self-report activation	**PASAT: [0.78, 1.95]** Level: [-0.17, 0.20]	**Task: [0.54, 1.39]** **Low-High change: [0.01, 0.30]**	**Task: [0.13, 0.99]** Low-High change: [-0.07, 0.22]	n/a n/a	n/a Pending: [-0.16, 0.12] **ES: [0.00, 0.20]** **Active: [0.03, 0.15]** Stale: [-0.03, 0.03]
1b)	Increased attentional control demands will not increase the level of self-report activation	n/a n/a	n/a n/a	n/a n/a	*Task: [-0.33, 0.53]* **Low-High change: [-0.14, 0.14]**	n/a n/a
1c)	Increased task demands will be accompanied by increased perceived difficulty	**PASAT: [2.80, 4.31]** **Level: [0.16, 0.56]**	**Task: [2.06, 3.34]** **Low-High change: [1.00, 1.64]**	**Task: [2.16, 3.44]** **Low-High change: [0.63, 1.26]**	**Task: [1.15, 2.44]** **Low-High change: [0.61, 1.25]**	n/a Pending: [-0.02, 0.27] ES: [-0.02, 0.18] **Active: [0.01, 0.13]** **Stale: [0.01, 0.07]**
1d)	Increased task demands will be accompanied by increased effort, but only up to a the point of maximum resource allocation after which effort will remain constant or decrease	**PASAT: [0.75, 1.64]** **Level: [0.01, 0.24]**	**Task: [1.85, 2.80]** **Low-High change: [0.51, 0.95]** Med deviation: [-0.18, 0.57]	**Task: [1.78, 2.73]** **Low-High change: [0.12, 0.56]** *Med deviation: [-0.08, 0.68]*	**Task: [1.41, 2.35]** **Low-High change: [0.07, 0.50]** Med deviation: [-0.43, 0.32]	n/a Pending: [-0.1, 0.14] ES: [-0.07, 0.1] **Active: [0.06, 0.16]** Stale: [-0.03, 0.02]

Category	Hypothesis	Experiment 1	Experiment 2			Experiment 3
			CAdd Task	N-back Task	Fitts Task	
1e)	Increased task demands will be accompanied by increased pupil diameter, but only up to the point of maximum resource allocation after which pupil diameter will remain constant or decrease	**PASAT: [0.72, 1.16]** Level: [-0.12, 0.05]	Pre-trial pupil Ø: **Task: [2.76, 3.86]** **Low-High change: [-0.11, 0.28]** **Med deviation: [0.34, 0.81]** Within trial change: **Task: [0.69, 1.56]** **Low-High change: [0.21, 0.62]** *Med deviation: [-0.32, 0.2]*	Pre-trial pupil Ø: **Task: [1.96, 3.00]** **Low-High change: [0.15, 0.23]** **Med deviation: [0.32, 0.48]** Within trial change: Task: [-0.47, 0.29] Low-High change: [-0.01, 0.06] Med deviation: [-0.08, 0.06]	Pre-trial pupil Ø: **Task: [2.61, 3.65]** Low-High change: [-0.08, -0.01] Med deviation: [-0.2, -0.09] Within trial change: Task: [-0.68, 0.09] Low-High change: [-0.12, -0.06] *Med deviation: [0.00, 0.09]*	Pending: [-0.017, 0.009] **ES: [0.000, 0.026]** Active: [-0.003, 0.011] Stale: [-0.008, -0.002]
1f)	Increased task demands will be accompanied by decreased affective valence	**PASAT:[-1.26, -0.06]** Level: [-0.26, 0.01]	**Task: [-0.76, -0.08]** Low-High change: [-0.14, 0.03]	*Task: [-0.65, 0.03]* **Low-High change: [-0.20, -0.02]**	*Task: [-0.65, 0.03]* Low-High change: [-0.14, 0.03]	n/a Pending: [-0.12, 0.1] ES: [-0.12, 0.05] Active: [-0.07, 0.03] **Stale: [-0.05, 0.00]**
2	The effect of prior information processing and attentional control demands					
2a)	Sustained attentional control demands will decrease the level of self-report activation	Count occasion: [-0.55, 0.19]	**Repeat phase: [-1.21, -0.41]**	**Repeat phase: [-1.18, -0.37]**	**Repeat phase: [-0.88, -0.08]**	**Demand block: [-0.31, -0.12]**
2b)	Decreased self-report activation will be accompanied by increased effort at low and moderate task demand levels and reduced effort at high task demand levels	*Count occasion: [-0.01, 0.43]*	Low-High x Repeat: [-0.56, 0.06]	Low-High x Repeat: [-0.27, 0.34]	Low-High x Repeat: [-0.4, 0.22]	Repeat x Demand block: Pending: [-0.35, 0.15] ES: [-0.13, 0.29] **Active: [-0.20, -0.03]** Stale: [-0.02, 0.05]

Category	Hypothesis	Experiment 1	Experiment 2			Experiment 3
			CAdd Task	N-back Task	Fitts Task	
2c)	Decreased self-report activation will be accompanied by increased pupil diameter at low and moderate task demand levels and reduced pupil diameter at high task demand levels	**Count occasion: [0.01, 0.37]**	Low-High x Repeat: Pre-trial pupil Ø: [-0.30, 0.24] **Within-trial change: [-0.70, -0.12]**	Low-High x Repeat: Pre-trial pupil Ø: [0.06, 0.18] **Within-trial change: [-0.12, -0.01]**	Low-High x Repeat: Pre-trial pupil Ø: [-0.03, 0.07] **Within-trial change: [0.00, 0.08]**	Repeat x Demand block: Pending: [-0.007, 0.057] ES: [-0.014, 0.038] Active: [-0.012, 0.013] Stale: [-0.002, 0.009]
3	The indirect effects of task demands on difficulty and valence					
3a)	The relationship between task demands and perceived difficulty will be moderated by the level of self-report activation	Count x activation: [-0.21, 0.28]	Low-High x Repeat: [-0.77, 0.14]	Low-High x Repeat [-0.59, 0.31]	Low-High x Repeat: [-0.65, 0.25]	Pend x Activate: [-0.06, 0.06] ES x Activate: [-0.02, 0.07] Active x Activate: [-0.01, 0.02] Stale x Activate: [-0.02, 0.01]
3b)	The relationship between task demands and valence will be mediated by the current level of effort, the current task performance level, and the rate of change in task performance	Effort PASAT: [-0.09, 0.28] **Perf PASAT: [-0.17, 0.00]** Effort Level: [-0.18, 0.11] Perf Level: [-0.13, 0.08] Perf Level Change: [-0.10, 0.07]	n/a	Effort Task: [-0.16, 0.01] Perf Task: [-1.24, 0.49] Effort High-Low: [-0.15, 0.03] Perf High-Low: [-1.41, 0.21]	n/a	**Effort: [-0.16, -0.01]** **Positive trajectory: [0.00, 1.27]**

Considering first the effect of current task demands, the proposed model predicted that an increase in the level of either information processing or attentional control demands would contribute to the perception of increased difficulty (Brehm & Self, 1989), generate increased effort (Hockey, 1997; Kahneman, 1973), and reduce affective valence (Carver & Scheier, 1998). The change in task demands could be produced in a variety of ways, including an increase in the complexity of information processing or manual control, a reduction in available response time, or an increase in the precision required by a task. In order to test these predictions this thesis examined the change that occurred in each variable between a low-load baseline task and several more demanding information processing or motor control tasks. It also examined the effect of changes in demand level within each task and also the effect of within-task demand level on a simulated air-radar task.

Considering first the increase in task demands between the low-load and high-load tasks, Rows 1c and 1d of Table 16 show that the PASAT, column addition, N-back, and Fitts' Law tasks each produced increased perceived difficulty and self-report effort compared to a low-load baseline. Row 1f shows that the PASAT and column addition tasks also reduced valence but that the N-back and Fitts' Law tasks offered only qualified support for the prediction that high task demands would reduce valence.

A similar pattern was observed in the responses to a change in demand level within these four tasks, with increased demand level producing increased perceived difficulty and effort in all tasks but only reduced valence during the N-back task. The air radar task of Experiment 3 also offered the opportunity to examine the effect of within-task changes in demand level, during which it was found that an increase in the number of active tracks and stale tracks predicted increased perceived difficulty, but only an increase in the number of active tracks predicted increased effort and only an increase in the number of stale tracks predicted reduced valence.

These results suggest that the effect of task demands on valence appear to have been weaker and less reliable than the effects of task demands on perceived difficulty and effort. One possible explanation for this outcome is that valence was not measured directly, but was instead derived from a transformation of self-report measures of energetic arousal and tense arousal. This transformation assumed that the scales used to measure these constructs indexed orthogonal dimensions with a 45 degree rotation relative to the core affect dimensions of valence and activation (Carroll et al., 1999). The accuracy of the transformation will be affected by the degree to which the measurement scales departed from bipolarity and deviated from the assumed degree of rotation. Large inter-individual differences have been observed in the location of specific mood adjectives on the affect circumplex (Kuppens et al., 2013; Yik et al., 2011) which may have contributed to error in the transformed value of valence. Future work examining the effect of task demands on valence would benefit by collecting a more direct measure of this variable.

Another possible explanation may be that valence is not driven by the general level of task demands, but instead different types or aspects of task demands may differentially affect valence. The level of performance and effort associated with task demands have been identified as possible additional influences which will be discussed further below. It may also have been that the tasks used in the current experiments may not have been sufficiently meaningful to participants to generate a strong emotional response. This possibility could be explored further by using simulations with higher contextual fidelity or by collecting data during actual work performance.

Considering in more detail the influence of current task demands on the level of effort, the decision to allocate resources is considered to be under volitional control (Loft et al., 2007) and it was predicted that a level of maximum effort may be reached after which further increases in task demands may either produce no further increase in effort or a withdrawal of effort if task demands are perceived as excessive (Gendolla & Richter, 2010; Hockey, 1997). However, no upper limit of self-report effort was observed during Experiments 1 and 2. Row 1d of Table 16 shows that self-report effort increased across the demand levels of the PASAT and that effort at the medium demand level of the column addition, N-back and Fitts' Law tasks did not significantly differ from the expected value if a linear trend existed between the low and high demand levels in each task.

A different pattern of results was observed for the effect of task demands on pupil diameter. Row 1e of Table 16 shows that, in contrast to self-report effort, pupil diameter did not increase across PASAT demand levels. Pupil diameter also often exhibited a non-linear response to task demands, with pupil diameter during the medium demand level of the column addition and N-back tasks being larger than would be predicted by a linear trend and pupil diameter during the medium demand level of the Fitts' Law task being smaller than would be predicted by a linear trend. These inconsistent results between self-report effort and pupil diameter and raise the question of which measure provided the more reliable index of the level of resources currently allocated to meet task demands. While it is not possible to provide a definitive answer, self-report questions are potentially influenced by a wide range of limitations and biases (Annett, 2002) that may not influence physiological measures which may provide a more direct measure of resource allocation (Kahneman, 1973). Of course difficulties can arise when interpreting physiological measures as they exhibit a many-to-one relationship where a number of different psychological states can influence the same physiological measure (Cacioppo & Tassinary, 1990). Emotional stimuli have been shown to generate a pupil diameter response that has a similar size and time constant to that of task demands (Bradley, Miccoli, Escrig, & Lang, 2008; Henderson, Bradley, & Lang, 2014), which makes it difficult to definitively separate the effects of information processing and emotional response on pupil diameter. A substantial body of evidence has accumulated which suggests that pupil diameter is a sensitive measure of instantaneous task demands (Beatty & Lucero-Wagoner, 2000; Brouwer, Hogervorst, Holewijn, & van Erp, in press; Klingner et al., 2011) but this may reflect a combination of information processing resources, attentional control resources and the resources associated with the affective response to task demands. However, while acknowledging this potential ambiguity, pupil diameter appears to be a more sensitive index of changes in the aggregate level of resources allocated to meet task demands than self-report effort which may have been influence by task characteristics, demand cues and errors of introspection.

A novel proposal of the model was that tasks which had an information processing component would have a different effect on the level of available resources than tasks which did not require information processing. It was predicted that both types of tasks would require the application of attentional control and deplete the level of available resources but that only tasks with information processing demands would produce a short term increase in the level of available resources.

Experiments 1, 2 and 3 all provided evidence that information processing demands increased self-report activation, which was considered to be an index of the level of available resources. Row 1a of Table 16 shows that self-report activation was higher during each of the three information-processing tasks used in Experiments 1 and 2 than during the low-load baseline tasks. Self-report activation also increased with within-task demands during the column addition and air-radar tasks but not during the PASAT or N-back tasks. As discussed above the lack of an increase in activation across PASAT demand level may have been because participants did not actually increase the level of information processing performed. The reason that no increase was observed across the N-back demand levels is less clear, but it may have been that the continuous nature of the task caused any increase in activation due to increased information processing to be masked by a reduction in activation due to sustained attentional control.

The prediction that non-information processing tasks would not increase self-report activation was tested in Experiment 2 which, as shown in Row 1b of Table 16, provided qualified support for the prediction. Although the size of the confidence interval of activation during the Fitts' Law task was too large to provide complete support for the hypothesis, the mean size of the effect was small (d = 0.1) and significantly less than for the column addition and N-back tasks. In addition, the change in demand level within the Fitts' Law task had no effect on activation.

These results broadly support the prediction that information processing, but not attentional control, acts to increase the level of available resources. In this they offer further support to the proposal of malleable resources theory that the level of available resources vary in line with current task workload (Young & Stanton, 2002b). They also identify a possible boundary condition of the theory, in that current task demands may need to have an information processing component to produce this effect. However, before a firm conclusion can be made regarding this, further work is required to replicate the result and test the prediction using additional tasks.

Considering next the effect of prior task demands, the proposed model drew on existing evidence that the sustained performance of a wide range of tasks may deplete the level of resources available for current task performance (Hagger et al., 2010) and predicted that the prior demands of both information processing and attentional control tasks would reduce the level of available resources. Typical tests of this effect use a reduction in performance levels to infer resource depletion, but this approach is potentially problematic as compensatory effort may be mobilised in order to protect performance from the effects of reduced resource levels (Hockey, 1997). In order to address this concern, this thesis attempted to index the level of available resources more directly by measuring self-report activation. Row 2a of Table 16 shows that Experiment 1 offered no direct evidence that prior task demands reduced the level of activation, but Experiments 2 and 3 found that sustained task demands produced reduced levels of activation in all tasks. Self-report activation was significantly lower during the repeat task performance phase than during the initial task performance phase of Experiment 2, and self-report activation exhibited a significant decrease with time on task during Experiment 3.

If it is accepted that self-report activation does index the level of available resources, these results provide direct evidence for the proposal that the need to exert attentional control contributes to resource depletion (Kaplan & Berman, 2010). The relationship between self-report activation and available cognitive resources is of course difficult to establish conclusively due to both being psychological constructs that can only be measured indirectly, but are they considered to be adequately, if imperfectly, linked (Humphreys & Revelle, 1984; Matthews, Davies, et al., 1990; Mracek, Arsenault, Day, Hardy, & Terry, 2014; Young & Stanton, 2002a). However, the use of a resources construct to explain the effect of sustained task demands on performance is not universally accepted. Motivation has also been proposed as an alternative explanation for the effect (Boksem & Tops, 2008; Hockey, 2013; Inzlicht et al., 2014; Kool & Botvinick, 2014) and it is possible that self-reported activation may also partly reflect motivation constructs in addition to resource constructs.

This makes it difficult for the current results to clearly distinguish whether sustained task performance influenced available resources or motivational levels but this may not be an important distinction as both may be involved in the effects of sustained task performance. It seems plausible to assume that individuals rarely operate at maximum possible resource capacity except under exceptional circumstances so that under most conditions incentives and other motivational manipulations are likely to have some effect on performance. This is inconsistent with a strict resource-limited interpretation of the effect of sustained task demands but the level of available resources may provide an upper limit of performance capacity where motivation may have less effect on performance (Vohs, Baumeister, & Schmeichel, 2012). However, in the absence of specific motivational manipulations, reduced resource availability may also be accompanied by reduced motivation levels, in which case any ambiguity in which construct was being measured by self-report activation would be less important.

The proposed model identified that the level of effort allocated to meet current task demands will be influenced by the current level of available resources, which is influenced by the level of prior task demands. It was predicted that reduced levels of available resources would be accompanied by increased effort at low and moderate task demand levels and reduced effort at high task levels. However, it also was noted that these predictions may not hold under all conditions as the level of resources allocated to meet task demands is considered to be under volitional control and can be actively managed (Loft et al., 2007).

The results of the three experiments provide mixed support for the hypothesis. Rows 2b and 2c of Table 16 show that in Experiment 1 pupil diameter was significantly larger and self-report effort was marginally higher during the second count occasion than during the first. This may offer support for the prediction that reduced available resources would generate increased effort a low levels of task demands, but it is difficult to interpret the result conclusively as no significant change in self-report activation was observed across count occasion.

The clear reduction in self-report activation between the initial and repeat performance phases of Experiment 2 provided a less ambiguous opportunity to examine the effects of reduced available resources on the level of allocated resources across several tasks. No significant change in self-report effort across demand level was observed during the repeat phase for any task but changes were observed in pupil diameter. The increase in within-trial pupil diameter across demand level during the initial phase of the column addition task did not occur during the repeat phase. This may have reflected a reduction in the maximum level of effort that participants were willing to expend at high demand levels under conditions of reduced resource availability which is consistent with the hypothesis. However, a corresponding increase in response time was also observed and error rates did not increase. Participants therefore appeared to be compensating for the reduced level of maximum effort by taking longer to perform each calculation so as to still produce a correct response. This suggests the active management of effort, but it is not possible to determine whether this was caused by reduced available resources or was a learning effect due to participants becoming more familiar with the length of time available for them to complete the task.

A somewhat complicated result was obtained for the effect of resource availability on the pupil diameter response to task demand level during the N-back task. The increase in pre-trial pupil diameter with demand level was larger during the repeat phase, which was inconsistent with the predicted effect, but the increase in within-trial pupil diameter with demand level was smaller during the repeat phase which was consistent with the prediction. This suggests that, under conditions of reduced resources, additional effort was allocated to the encoding and maintenance of the word list in memory as task demands increased but that comparatively less effort was allocated to recall of the target word. This suggests that in this task participants were prepared to invest compensatory effort to protect against the performance effects of resource depletion even under high task demand levels.

During Experiment 3 a reduction in effort with time on task was observed during the initial task demand cycle, which was also accompanied by a reduction in the level of available resources. However, task completion times also reduced over the cycle and, as in the column addition task, it is difficult to attribute the reduction in effort levels as being entirely due to the reduction in available resources. It may also have been due in part to a learning effect where practice enabled the task to be performed with greater automaticity which required reduced levels of controlled processing in order to achieve the desired outcomes. However, the decrease in effort continued during the repeat task cycle but the reduction in task completion times did not, which is more consistent with a withdrawal of effort in the face of reducing levels of available resources. In addition, the increase in effort with the number of active tracks became smaller with increasing time on task, which also supports the hypothesis that reduced available resources would limit the increase in effort in response to increased task demands.

These results demonstrate that the prediction that reduced available resources would lead to the application of increased effort at low and moderate demand levels but the application of reduced effort at high demand levels was supported during some, but not all of the tasks tested. This suggests that no simple relationship exists between the level of available resources and the level of applied resources which appears to be situation dependent. However, this thesis made no systematic attempt to identify the various factors that influence this relationship; additional work will be required to explore this further.

The final hypotheses to be discussed will be those relating to the indirect effects of task demands on perceived difficulty and valence. Considering first the indirect effects of task demands on difficulty, it was predicted that the current level of available resources would moderate the perception of task difficulty. This was based on prior work which has suggested that an individual’s capacity to perform a task will influence the perceived difficulty of that task (Hagger et al., 2010; Wright et al., 1986; Wright et al., 2003; Wright et al., 2013). However, Row 3a of Table 16 shows that this prediction received little support in any of the experiments. The statistical tests of moderation did not produce conclusive results and, in a more direct test of the effect of available resources on perceived difficulty, there was no significant change in perceived difficulty between the initial and repeat phases of Experiment 2 despite a large reduction in the level of self-report activation.

This suggests that individuals may not have incorporated an assessment of their current capacity or resource levels into their assessment of task difficulty. Instead they may have used a more stable assessment of capacity for task performance and discounted the effects of short term fluctuations in resource availability. Alternatively, the result may reflect the result that even though the level of available resources may have been reduced, participants were still able and willing to continue to allocate the resources necessary to maintain task performance. It may be that the level of available resources has to reduce to a level which limits the level of resources allocated before the effect of available resources on perceived difficulty would be observed. Yet another possible explanation is that the nature of the tasks used in the experiments provided very clear demand cues, which may have overshadowed the influence of the level of available resources on the assessment of self-report difficulty. While it is not possible to identify the specific reason for the current results, they do not support the proposal that changes in the level of available resources makes a significant contribution the perception of task difficulty during the performance of the same task.

Considering next the indirect effects of task demands on valence, it was predicted that the current level of effort, current task performance and the direction of change in task performance would each mediate the relationship between task demands and valence. Row 3b of Table 16 shows that some, but not complete, support was found for this proposal. Experiment 1 suggested that error levels during the PASAT contributed to reduced valence. Because error level during the PASAT was the same as the change in error level between the counting task and the PASAT it was not possible to separate the influence of performance level and the influence of change in performance level. However, Experiment 1 provided no indication that valence was influenced by the level of current resource allocation. Experiment 3 did not support the prediction that current task performance level would be a significant predictor of valence but did find that the level of effort predicted reduced valence and that a positive performance trajectory predicted an increase in valence.

These results provide evidence that within-person changes in the direction of performance trajectory can influence the affective valence associated with task performance. This extends the results of earlier work which measured satisfaction, rather than valence, and used cross sectional, rather than longitudinal, designs (Chang et al., 2010; Elicker et al., 2010; Lawrence et al., 2002). However, only limited support was provided for the prediction that current effort levels influence affective valence. This could possibly have been because the levels of effort induced by the tasks were not high enough to produce the predicted result. However, self-report effort levels during Experiments 1 and 3 regularly exceeded 8 on the

10 point scale, which suggests that reasonably high levels of effort were being expended during these tasks but that this did not always translate into reduced valence.

Instead the experiments offer some indication that, in addition to being influenced by the level of allocated resources, valence may be influenced by the level of available resources. In Experiment 2 valence was lower during the repeat performance of the N-back task than during initial performance, and in Experiment 3 valence exhibited a significant decline with time on task, which was also associated with a reduction in the level of available resources. However, as valence was not significantly lower during the repeat performance of the column addition and Fitts' Law task in Experiment 2, this effect may be moderated by the type of demands imposed by the task. The N-back task and the simulated air radar task both required continuous attentional control and information processing, whereas the column addition and Fitts' Law tasks only required episodic application of these resources. These results raise the possibility that both the level of available resources and the length of time over which they need to be continuously applied need to be considered in order to predict the effect of task demands on valence.

Implications for the proposed model

The results of the three experiments provide mixed support for the proposed model outlined in Chapter 2 which aimed to identify the dynamic effects of task demands on key metacognitive and physiological states, which were expressed in terms of the levels of available resources and applied resources. An annotated version of the model is shown in Figure 13 which reflects the extent of empirical support provided for each pathway.

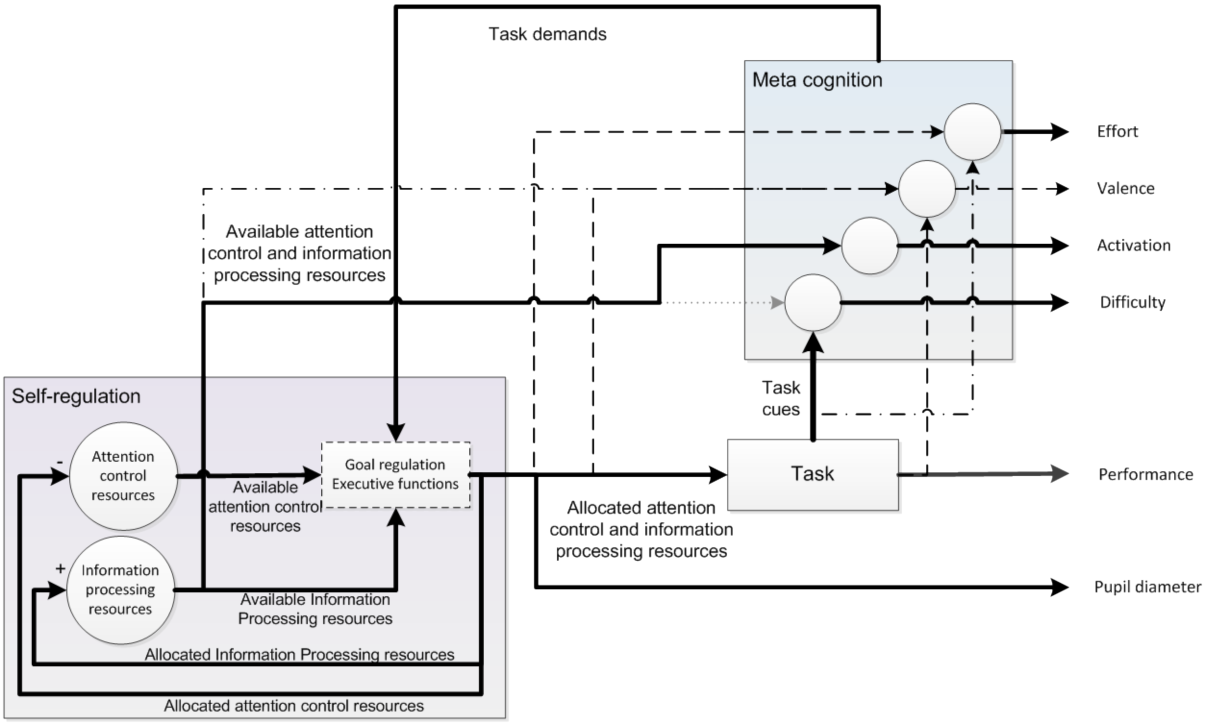

Figure 13 Model of the proposed relationships between available resources, allocated resources, metacognitive states and pupil diameter annotated to reflect the level of empirical support provided for each pathway. Heavy solid lines indicate strong support, dashed lines indicate qualified support, and dotted lines represent no support. Dash/dot lines represent a possible additional pathway.

An inspection of Figure 13 suggests that model was broadly successful in predicting the direct effects of task demands on the metacognitive states and pupil diameter. Valence was the only metacognitive state that did not consistently respond as expected to task demands, and it may be that the model needs to be refined to incorporate the result that continuous task demands may have a stronger effect on valence than episodic task demands. The distinction made by the model between the effects of information processing demands and attentional control demands on the level of available resources was also broadly supported, which indicates that resource-based theories of the human response to task demands may need to include consideration of each type of task demand in order to accurately predict the short and long term effects of different tasks. This result also has possible practical implications for the mitigation of and recovery from sustained attentional demands, which could possibly be enhanced if a series of short and intermittent cognitive tasks were performed either during breaks from the ongoing task or even possibly during the ongoing task provided they did not interfere with primary task performance.

However, the model was less successful in identifying how the level of available resources influenced the level of resources applied in response to changes in task demands or the factors that influenced each metacognitive state. The model predicted that the level of available resources would have a relatively simple effect on the level of resources applied to meet task demands, in that resource depletion would produce increased effort at low and moderate demand levels and reduced effort at high demand levels. However, the level of available resources had a more complicated and task-dependent effect on allocated resources than was predicted. In particular the pupil diameter results highlighted that potentially complicated and subtle patterns of resource allocation may be present even in relatively simple tasks such as those used in the first two experiments.

The predicted relationships between the levels of available and allocated resources and the metacognitive states also received only limited support that varied by task type. Self-report activation appeared to be a consistent indicator of the level of available resources, but difficulty did not appear to depend on the level of available resources, valence was only inconsistently influenced by the level of applied resources and may also depend on the level of available resources, and self-report effort appeared to be influenced by task cues in additional to, and perhaps to a greater extent than, the level of allocated resources.

These results suggest that the use of resource constructs to account for changes in metacognitive states arising from task demands may have only limited utility. While resource allocation does appear to deplete resource availability which can be sensed as reduced activation, it appears that the other metacognitive states considered in this thesis are more strongly influenced by external cues or other, non-resource-based, factors.

Methodological implications

This observed influence of task type appears to highlight the importance of context to an individual's self-regulatory response to task demands which has methodological implications for future research in this area. McGrath (1981) identified that, while it is desirable for psychological research to (a) generalise to the target population; (b) to precisely measure and control variables; and (c) to maximise the realism for the participants, individual research designs will typically need to compromise one or two of these goals in the pursuit of the other(s). Laboratory studies tend to maximise precision of measurement while sacrificing context and field studies tend to maximise realism at the expense of measurement precision. Experimental simulations and field experiments can potentially balance the demands for precision and contextual realism but at the cost of maximising neither. The studies reported in this thesis used defence personnel to undertake laboratory experiments and an experimental simulation. Given the observed influence of task on self-regulatory processes within this population, it is suggested that future research that aims to describe and predict task-based self-regulatory processes should focus on experimental simulations and possibly field experiments rather than laboratory experiments. This may help to clarify the role of valence in the processes, which may be more apparent in situations with higher contextual fidelity. However, future research that aims to further explore the apparently opposing effects of information processing and attentional control on the level of available resources should utilise additional experimental studies to enable tightly controlled manipulations that isolate the contribution of each process.

Practical implications

A frequent aim of applied human factors studies is to identify impending task overload before performance degradation occurs in order to allow timely and appropriate interventions to be implemented. One practical objective of this thesis was therefore to explore the potential utility of using pupil diameter as an index of the current level of allocated resources instead of self-report measures which can only be collected relatively infrequently, are subject to a range of potential biases, and can sometimes be too intrusive to use in applied settings.

Self-report effort was collected using a single-item scale in order to minimise measurement obtrusiveness and maximise sensitivity (Hendy, Hamilton, & Landry, 1993). However, despite this the self-report effort scale appeared to be biased by task demand cues rather than the level of resources allocated to meet task demands and was not able to capture some of the subtleties of resource allocation that were reflected in the pupil diameter measurements during Experiments 1 and 2. However, these experiments used tightly controlled luminance conditions and the co-variation of luminance with task demands in Experiment 3 made interpretation of the pupil diameter data difficult.

These results suggest that, wherever it is possible to ensure stable luminance levels, pupil diameter should be considered as a metric that can provide a sensitive, real time index of the instantaneous level of allocated resources. This will be difficult to achieve in most applied environments but, even if it is not feasible to use pupil diameter data, the current results raise doubts about the benefits of attempting to collect data on self-report effort as an index to the level of allocated resources. Perceived difficulty was found to be a more sensitive index of task demands and, if the aim of a study is to compare the demands imposed by different systems or different versions of the same system a better approach may to measure task performance levels and perceived difficulty, rather than attempt to measure self-report effort, which may only be a muted reflection of perceived task difficulty.

Conclusions

This thesis developed and tested a resources-based feedback control model to explain the dynamic effects of task demands on the metacognitive states of perceived difficulty, effort, activation and valence and physiological state of pupil diameter. It proposed that a metacognitive process generates an assessment of task demands and that a self-regulatory process determines the amount of resources allocated to meet the task demands based on the current level of available resources. The level of available resources is influenced by the current level of information processing and prior levels of attentional control. Broad support was found for the prediction that current information processing demands increased the level of available resources and that prior attentional control demands decreased the level of available resources. This indicates that resource-based theories need to consider the separate effect of information processing and attentional control on resource availability. However, no simple relationship could be identified that described the influence of the level of available resources on the level of resources allocated to meet task demands. The levels of available and allocated resources also appeared to have only a weak influence on most of the metacognitive states which appeared to be more strongly influence by task characteristics.

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APPENDIX A: EXPERIMENT 1 MODEL EQUATIONS

Level-1 MODEL

$\mathrm{PUPIL}_{tij} = \pi_{0ij} + \pi_{1ij}{*}(OCCASION_{tij}) + e_{tij}$

Level-2 MODEL

$\pi_{0ij} = \beta_{00j} + \beta_{01j}{*}(PASAT_{ij}) + r_{0ij}$
$\pi_{1ij} = \beta_{11}{*}(\mathrm{PASAT}_{j}) + \beta_{12j}{*}(COUNT_{ij})$

Level-3 MODEL

$\beta_{00j} = \gamma_{000} + \gamma_{001}(LIGHT_{j}) + u_{00j}$
$\beta_{01j} = \gamma_{010} + \gamma_{011}(LIGHT_{j})$
$\beta_{11j} = \gamma_{110} + \gamma_{111}(LIGHT_{j})$
$\beta_{12j} = \gamma_{120} + \gamma_{121}(LIGHT_{j})$

APPENDIX B: EXPERIMENT 2 MODEL EQUATIONS

Level-1 Model

$$VALENCE_{tijk} = \pi_{0ijk} + \pi_{1ijk}*(LEVC_{tijk}) + \pi_{2ijk}*(MID_{tijk}) + e_{tijk}$$

Level-2 Model

$$\pi_{0ijk} = \beta_{00jk} + \beta_{01jk}*(CADD_{ijk}) + \beta_{02jk}*(NBACK_{ijk}) + \beta_{03jk}*(FITTS_{ijk}) + r_{0ijk}$$
$$\pi_{1ijk} = \beta_{10jk}*(CADD_{ijk}) + \beta_{11jk}*(NBACK_{ijk}) + \beta_{12jk}*(FITTS_{ijk})$$
$$\pi_{2ijk} = \beta_{20jk}*(CADD_{ijk}) + \beta_{21jk}*(NBACK_{ijk}) + \beta_{22jk}*(FITTS_{ijk})$$

Level-3 Model

$$\beta_{00jk} = \gamma_{000k} + u_{00jk}$$
$$\beta_{01jk} = \gamma_{010k} + \gamma_{011k}*(REPEAT_{jk})$$
$$\beta_{02jk} = \gamma_{020k} + \gamma_{021k}*(REPEAT_{jk})$$
$$\beta_{03jk} = \gamma_{030k} + \gamma_{031k}*(REPEAT_{jk})$$
$$\beta_{10jk} = \gamma_{100k} + \gamma_{101k}*(REPEAT_{jk})$$
$$\beta_{11jk} = \gamma_{110k} + \gamma_{111k}*(REPEAT_{jk})$$
$$\beta_{12jk} = \gamma_{120k} + \gamma_{121k}*(REPEAT_{jk})$$
$$\beta_{20jk} = \gamma_{200k}$$
$$\beta_{21jk} = \gamma_{210k}$$
$$\beta_{22jk} = \gamma_{220k}$$

Level-4 Model

$$\gamma_{000k} = \delta_{0000} + v_{000k}$$
$$\gamma_{010k} = \delta_{0100}$$
$$\gamma_{011k} = \delta_{0110}$$
$$\gamma_{020k} = \delta_{0200}$$
$$\gamma_{021k} = \delta_{0210}$$
$$\gamma_{030k} = \delta_{0300}$$
$$\gamma_{031k} = \delta_{0310}$$
$$\gamma_{100k} = \delta_{1000}$$
$$\gamma_{101k} = \delta_{1010}$$
$$\gamma_{110k} = \delta_{1100}$$
$$\gamma_{111k} = \delta_{1110}$$
$$\gamma_{120k} = \delta_{1200}$$
$$\gamma_{121k} = \delta_{1210}$$
$$\gamma_{200k} = \delta_{2000}$$
$$\gamma_{210k} = \delta_{2100}$$
$$\gamma_{220k} = \delta_{2200}$$

APPENDIX C: EXPERIMENT 3 IDENTIFICATION CRITERIA

ID		Reason	Visual ID	Country of Origin		IFF		ES	Position		Course, Speed, Height	Separation
Hostile	HA -	Hostile Fire Control ES Emission						Within 10 degrees of hostile fire control ES emission				
	HB -	Quick Response Range				Not valid M4 or No Response M4	*AND*		Within 30nm of ownship	*AND*	Speed > 500 knots Heading within 20 degrees of OS	
Friend	FA -	Visual ID	Belonging to Friendly Nation									
	FB -	IFF M4				Valid M4						
Assumed Friend	AA -	Correct M1 & M2 IFF				M1 10 - 30 M2 2000 - 4000						
	AB -	Country of Origin (non Civair)		Allied Nation	*AND*	No IFF repsonse						
	AC -	Friendly ES						Within 10 degrees of friendly ES emission				
	AD -	Civair (Meets 4 of 5 criteria)				No M1 or M2 M3 Present No valid M4		Within 10 degrees of neutral nav ES emission	Within Air corridor		Altitude > 20,000 feet and Speed between 350 & 450 knots	Horizontal separation > 3nm or vertical separation > 1,000 feet from any other aircraft
Neutral	NA -	Visual ID	Belonging to Neutral Nation									
	NB -	Country of Origin		Neutral Nation								
Suspect	SA -	Visual ID	Belonging to Threat Nation									
	SB -	Country of Origin (non Civair)		Threat Nation	*AND*				Not Civair			
	SC -	Non-Targetting Hostile ES emission						Within 10 degrees of Hostile Search or Nav ES emission				
	SD -	Outside of Air Corridor							Outside Air corridor			
	SE -	Flying in formation										In coordiation with other aircraft - within 3nm horizontally or 1000 feet vertically and similar course
Unknown	UA -	Unknown ES emission						Within 10 degrees of unknown ES emission				
	UB -	Does not fit any other criteria										