Attention and automation: New perspectives on mental underload and performance

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KEYWORDS: Attention; Automation; Mental Workload; Resources; Working Memory

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Abstract

There is considerable evidence in the ergonomics literature that automation can significantly reduce operator mental workload. Furthermore, reducing mental workload is not necessarily a good thing, particularly in cases where the level is already manageable. This raises the issue of mental underload, which can be at least as detrimental to performance as overload. However, although it is widely recognised that mental underload is detrimental to performance, there are very few attempts to explain why this may be the case. It is argued in this paper that, until the need for a human operator is completely eliminated, automation has psychological implications relevant in both theoretical and applied domains. The present paper reviews theories of attention, as well as the literature on mental workload and automation, to synthesise a new explanation for the effects of mental underload on performance. Malleable Attentional Resources Theory proposes that attentional capacity shrinks to accommodate reductions in mental workload, and that this shrinkage is responsible for the underload effect. The theory is discussed with respect to the applied implications for ergonomics research.

KEYWORDS: Attention; Automation; Mental Workload; Resources; Working Memory

Introduction

More than thirty years ago, the following warning was made to ergonomics researchers with respect to operators of automated systems:

> "They [human operators] will be on board for the versatility, adaptability and reliability they add to an automatic system. They will be expected to observe the environment and use 'programmed adaptive control' to change plans. They will monitor instruments and repair malfunctioning components. They will control in parallel with the automatic system and take over in the event of a failure. What is the extent of the theory for predicting man-machine behaviour in these situations? It is almost nil." (Young, 1969; p. 672)

It would be unfair and inaccurate to suggest that the current state of theory is the same. Nevertheless, it would also be optimistic to say that the theoretical waters are anything other than muddied. Explanations for human performance with automated systems have ranged from effort (Desmond, Hancock & Monette, 1998; Matthews, Sparkes & Bygrave, 1996), through situation awareness (Endsley & Kiris, 1995; Kaber & Endsley, 1997) and trust (Lee & Moray, 1994; Parasuraman & Riley, 1997), to vigilance (Molloy & Parasuraman, 1996; Parasuraman, Mouloua, Molloy & Hilburn, 1996) and mental workload (Stanton, Young & McCaulder, 1997). The general consensus (e.g., Wilson & Rajan, 1995) is that mental workload optimisation is crucial to maintaining effective task performance. Such optimisation inevitably involves a balancing act between demands and resources of both task and operator. This paper focuses upon some of the factors which can affect such a balance.

Theories of attention and mental workload are drawn upon in an effort to describe and explain the effects of automation on performance.

Background

Automation is defined as “the execution by a machine agent (usually a computer) of a function that was previously carried out by a human” (Parasuraman & Riley, 1997; p. 231). Designers of complex systems often use the technology at their disposal to aid operators, and even relieve them of their duties to some extent, in an attempt to eliminate error and improve performance. Since the vast majority of problems in safety-critical environments is popularly attributed to ‘human error’ (e.g., Coyne, 1994, estimates this majority at 90% for traffic accidents), substituting the weak link in the system (i.e., the human) seems the logical thing to do.

It is certainly true that automation can bring benefits of improved performance and efficiency in systems (Byrne, 1996, reports that automated flight decks are statistically safer than conventional aircraft). Previous experience, though, suggests that the solution for improved performance and safety is not as simple as the installation of automation. Modern technological systems are shifting the operator’s task burden to a psychological level, rather than a physical one. In automating a task, then, the operator’s role is qualitatively changed, and this introduces a plethora of new concerns and problems (Kantowitz & Campbell, 1996; Stanton & Marsden, 1996).

Performance problems with automation have variously been attributed to factors such as fatigue (Desmond et al., 1998; Matthews et al., 1996), vigilance (Molloy & Parasuraman, 1996; Parasuraman et al., 1996), or trust (Lee & Moray, 1994;

Parasuraman & Riley, 1997), to name but a few. These literatures are beyond the scope of the present review, but are all symptomatic of operators being ‘out-of-the-loop’ (Endsley & Kiris, 1995). It is believed that simply removing the human from active control can have a direct bearing on their performance. However, it is likely that there is a more general factor which can influence performance, since it is possible to find exceptions to all of these rules.

One particular problem associated with automation is that of mental workload (MWL). One of the purposes of automation is to reduce MWL, thereby improving performance. If an operator is overloaded with demands, performance is likely to falter. Intuitively, automation can help in such situations. However, in many domains MWL is only excessive in exceptional circumstances, and automation simply relieves the operator of demands s/he can quite readily cope with (Reason, 1998; 1990; Stanton & Marsden, 1996). Ironically, then, automated systems have the potential for imposing mental underload. It is precisely this problem which the present paper is concerned with. Underload is at least as serious an issue as overload (Leplat, 1978; Schlegel, 1993), and can be detrimental to performance (Desmond & Hoyes, 1996). However, its effects on performance, and the explanations for such, have not been fully documented as yet.

The theoretical impetus for this review comes primarily from MWL. This concept is inextricably linked with theories of attention. The opinion here is that excessively low MWL can adversely affect performance. The applied element of this research is concerned with how these potential effects on MWL and attention will affect performance. Ultimately, such research should be able to provide recommendations for the design of future systems. By discovering adverse effects of automation in the largely uncharted territory of mental underload, one may contribute to designing for the user and optimise the performance of the system as a whole.

The following literature review is structured to emphasise the theoretical elements of the research. Relevant research in <u>attention</u> is summarised, paying particular attention to the original formulation of attentional resources theory and how it differs from other theoretical positions, such as working memory. This provides the background for the ensuing discussions of <u>automation</u> and <u>mental workload</u>. Finally, the review is used to synthesise a new theory of attention in an effort to parsimoniously describe, explain, and predict the effects of mental underload on performance.

<u>Attention</u>

Background

The classic and often-cited early work is that of Kahneman (1973), who proposed a capacity model of attention as an alternative to bottleneck or filter theories (see Eysenck & Keane, 1990, for a review). Essentially, the capacity model proposes a single resource view of attention - that is, attention is viewed as one whole pool of resources. This pool has a finite limit, therefore the ability to perform two separate concurrent activities depends upon the effective allocation of attention to each. Interference between tasks depends upon the demands which each separately impose – when task demands drain the pool, performance will suffer.

Other researchers share the notion of a common resource pool. Norman & Bobrow (1975) described how performance may be constrained by the quality of input (data-limited) or by processing resources (resource-limited). Again, this view holds that if the demands of two tasks exceed the upper limit of resources, interference will occur and performance will deteriorate. Early researchers were of the opinion that the capacity limit may be susceptible to influences such as age, arousal, or mood (Hasher & Zacks, 1979; Humphreys & Revelle, 1984; Kahneman, 1973). Long-term variations in these factors could depress the limit, with concomitant effects on performance.

Later research found some major flaws with the single resource approach. For instance, Wickens (1984; 1992) described experiments whereby two tasks were perfectly time-shared (i.e., performed concurrently) even when the difficulty of either was manipulated. This was seen as a limitation of single resource theory, which predicted that difficulty manipulations should eventually lead to altered performance on one or both tasks. Thus, multiple resources theory emerged (Wickens, 1984; 1992; Wickens & Liu, 1988). Multiple resources theory posits that there are separate pools of resources along three dichotomous dimensions. The first dimension is processing stages – early vs. late. Perception and central processing (i.e., cognitive activity) are said to demand separate resources from response selection and execution. The second dimension is input modalities - auditory vs. visual. Performance of two simultaneous tasks will be better if one is presented visually and the other presented auditorily, rather than using the same modality for both. Finally, the theory states that there are separate resources for whether a task is processed verbally or spatially. This dichotomy also holds for response execution, whereby less dual-task interference occurs if one task is responded to vocally and the other demands a manual response. Thus, there will only be a trade-off between task difficulty and performance to the extent that two concurrent tasks share resources on these dimensions (Wickens, 1992) - interference is a joint function of difficulty (resource demand) and shared processing mechanisms (resource competition).

Multiple resources and working memory

To any student of cognitive psychology, there would seem to be a degree of overlap between multiple resources theory and models of working memory (as described by Baddeley, 1990; Wickens, Gordon & Liu, 1998). In particular, the verbal and spatial processing codes seem to correspond quite heavily with the phonological loop and the visuospatial sketchpad.

Traditional models of memory (see e.g., Baddeley, 1990; Eysenck & Keane, 1990, for basic explanations) view attention as a filter, a perceptual selection mechanism whereby whatever is attended to gets transferred to short-term memory. In contrast, working memory assigns short-term storage a more active role in cognition, acting as a kind of buffer between perception and long-term memory. Information from each source is coordinated by the central executive, and is used to carry out whatever task is at hand.

The distinction between working memory and attentional resources is therefore somewhat blurred, with both theories seeming to involve similar mechanisms. Multiple resources theory has moved the locus of attention from sensory and perceptual input to central processing and even response execution. As such, the theory is invading the territory of working memory. Furthermore, according to Wickens (1992), information processing draws upon separate resources depending on whether the task is verbal or spatial. By implication, this processing would involve the integration of information from the outside world and from experience. This integration is exactly the function of working memory, which also separates processing according to verbal or spatial elements (Baddeley, 1986; 1990). Finally, an additional element of confusion between multiple resources theory and working memory is introduced as the central executive component of working memory is often thought of as a supervisory attentional system (Baddeley, 1986; 1990). By specifically using the term ‘attentional’, working memory theorists have surrendered to the invasion of their territory, and are themselves implying that working memory and attentional resources are somehow related.

Unfortunately, there seems to be very little literature on distinguishing the two models. In the undergraduate textbook, Wickens et al. (1998) describe at different points both working memory and multiple resources, with only a brief mention of working memory related to Wickens’ definition of central processing. Furthermore, Baddeley’s own Working Memory book (1986) fails to mention multiple resources theory at any point, despite a self-admitted attempt to resolve concepts of working memory and attention. Apparently, attention researchers are content to work with resource models without acknowledging working memory, and vice-versa.

There are a few exceptions to this. Conway & Engle (1994) argued that working memory capacity is indirectly related to attentional resources. Retrieval from working memory depends upon the ability to inhibit irrelevant information, which is in itself resource demanding. This implies a distinction between the capacities of working memory and attentional resources, even though one is reflected in the other. Some support for this was found in a study of intelligence (Necka, 1996). Actual intelligence (as opposed to potential intelligence) was found to be determined by momentary values of attentional resources and working memory capacity. These are affected by arousal - as arousal increases, so do attentional resources, but working memory capacity decreases. Actual performance therefore depends on whether an optimal arousal level can be reached – the classic inverted-U curve of Yerkes & Dodson (1908).

One interesting paper directly pits multiple resources theory against working memory as alternative explanations of interference effects in timing (Brown, 1997). If a participant attempts to perform two similar tasks at the same time, their performance on each will be worse than when performing the tasks separately. Usually, in the absence of any instructions to prioritise one task over the other, the interference effect will be symmetrical; that is, both tasks will be equally affected. However, the interference effect when trying to maintain timing (i.e., make a response every 3s) with a concurrent nontemporal task (such as visual search, or tracking) seems to be asymmetrical. Brown (1997) found that performance on search or tracking tasks was not affected by a simultaneous timing task, but timing performance was adversely affected by these concurrent tasks. Mental arithmetic was the only concurrent task for which bidirectional interference was observed.

Brown's (1997) interpretation of multiple resources theory was that timing involves verbal resources at the perceptual/central stages, whereas search and tracking are spatial tasks. This argument, though, still fails to explain the asymmetry. If anything, there should be minimal interference, as the tasks draw on separate resource pools. In the event of an interference effect, it should affect both tasks in a similar manner, rather than affecting one task while leaving the other untouched. On the other hand, working memory, with its central executive, can offer an explanation. The central executive controls attentional and coordinational functions, such as allocating attention between dual tasks. Mental arithmetic and timing both draw on the central executive, which is why bidirectional interference occurs between these two tasks. Simple visual search or tracking tasks, on the other hand, only use the visuospatial sketchpad. Therefore, the nontemporal tasks do not suffer with a concurrent timing task, as the visuospatial sketchpad is essentially still dedicated to a single task. However, the mere introduction of a dual-task scenario draws on the coordination skills of the central executive, which also looks after temporal activities, hence the interference effect on timing. Brown (1997) concludes that working memory and multiple resources both attempt to explain similar phenomena and rely on similar concepts, but working memory is distinct in its provision for general purpose resources. Brown (ibid.) also hints, though, that there is some speculation on a general pool of resources in multiple resources theory, evidence for which has been cited elsewhere (see Matthews et al., 1996).

Thus we see that the two theories are in fact very similar, but were derived from different paradigms and never the twain shall meet. Most applications of multiple resources theory have been just that – applied, under the umbrella of ergonomics. Most theoretical work on attention focuses on selectivity or divided attention. In considering a review of three decades of attention research, Baddeley (1986) concludes that attention theories could not provide insights into the central executive, as most attention research is concerned with perception rather than the control of memory and action. It is perhaps not surprising then that there has been very little overlap between these two otherwise very related areas of cognition.

At present, then, there is very little to choose between multiple resources and working memory theories. There is an area of common ground, though, in that both are ultimately concerned with performance, which is mediated in each mechanism by physiological arousal. It is widely understood that there is a curvilinear relationship between arousal and performance (Kahneman, 1973; Yerkes & Dodson, 1908). There is some speculation that this is due to two competing processes: a positive linear relation between arousal and attentional resources, and an inverse relation between arousal and working memory (Humphreys & Revelle, 1984; Necka, 1996). If attentional resources are needed to make use of information in working memory (Conway & Engle, 1994; Hasher & Zacks, 1979), this would explain the inverted-U effect on performance. Now, a similar relationship exists between MWL and performance, which partly forms the crux of this paper. Before considering that, though, it is necessary to cover some background on MWL.

Throughout this paper, the terms ‘resources’ and ‘capacity’ will generally be used in reference to attentional resource theories. The working memory debate is left aside for a moment while the literature review continues, although it will be returned to at relevant points.

Attention and MWL

Attentional resource theories form a useful basis for describing MWL (see Young & Stanton, 2001b, for a full review and definition of MWL). These theories assume that individuals possess a finite attentional capacity which may be allocated to one or more tasks. Essentially, MWL represents the proportion of resources required to meet the task demands (Welford, 1978). If demands begin to exceed capacity, the skilled operator either adjusts their strategy to compensate (Singleton, 1989), or performance degrades. Such a view makes clear predictions about mental workload in any given situation, and observations of performance or behaviour provide simple indications of mental workload.

Although two tasks may impose different levels of mental workload, there may be little variation in the overt performance of each if both are within the total capacity of the operator. However, changes in behaviour or operator state can still provide information about the level of mental workload. Investing resources in a task is a voluntary and effortful process to meet demands, so performance can be maintained at the cost of individual strain or vice-versa (Hockey, 1997). Excessive load can also affect selective attention, leading to narrowed or inefficient sampling (Liao & Moray, 1993; Sanders & McCormick, 1993).

Resource models of workload can therefore provide a rational framework for defining mental workload. There is some debate, though, as to whether single resource models are more appropriate than multiple resource theory. Firstly, multiple resource explanations of MWL are context dependent, derived in dual-task laboratory settings, making it difficult to draw quantitative predictions for real-world design problems

(Hancock & Caird, 1993; Liao & Moray, 1993). In addition, multiple resource models do not consider nonattentional factors, such as experience (Selcon, Taylor & Koritsas, 1991). As an alternative, Liao & Moray (1993) posited that a single channel MWL model is of more use in real world situations, which generally have more than two tasks. However, they also stated that the multiple resource approach remains a superior model in purely dual task scenarios.

In terms of design, many authors agree that a key goal is to maximise the match between task demands and human capacity (e.g., Bainbridge, 1991; Gopher & Kimchi, 1989; Lovesey, 1995; Neerincx & Griffioen, 1996). For instance, Dingus, Antin, Hulse & Wierwille (1989) suggested some design improvements to reduce the demand of vehicle navigation displays (and hence their impact on the driving task). These were primarily aimed at improving the availability of information on the displays, to be more compatible with the driver's short glance strategy. Similarly, Selcon, Hardiman, Croft & Endsley (1996) designed a visuo-spatial display for threat assessment in combat aircraft, maximising resource compatibility with the primary task. It was found that this display increased spare attentional capacity compared to the previous text-based display. Computer-based decision support can also reduce attention on the primary task (Hoyes, 1994, uses air traffic control as an example, however the principle is applicable across domains). As modern technology in many working environments imposes more cognitive demands upon operators than physical demands (Singleton, 1989), the understanding of how MWL impinges on performance is critical. With that in mind, the review now turns to an in-depth analysis of MWL with respect to a particular class of technology – automation.

Automation and Mental Workload

Historically, the technological revolution has gradually removed the operators of many complex systems from front-line levels of control, to having their actions relayed via an intervening mass of computers and microprocessors. In the extreme, the operator's task is completely assumed by automation. Instead of actively controlling the system, the operator of an automated system now becomes a passive monitor. Intuitively, this should be an easier task and thereby facilitate performance improvements. As with many areas of research, though, intuition is often proved wrong. Seminal articles (Bainbridge, 1982; Norman, 1990; 1991; Reason, 1988; 1990) have criticised automation for being designed inappropriately and degrading the skills of operators, and empirical studies have supported this position. Active controllers have consistently demonstrated superior performance in failure detection than passive monitors (e.g., Desmond et al., 1998; Ephrath & Young, 1981; Kessel & Wickens, 1982; Wickens & Kessel, 1981; Young, 1969). Early research attributed this advantage to the availability of proprioceptive information for the active controllers, which may contribute to an improved internal model of system operation (Ephrath & Young, 1981; Kessel & Wickens, 1982). More recently, problems such as vigilance (Parasuraman, 1987), complacency (Parasuraman, Singh, Molloy, & Parasuraman, 1992), and trust (Lee & Moray, 1994; Muir & Moray, 1996) have been touted as causes for performance differences between manual and automated control. In particular, the effects of automation on MWL has been a well-explored avenue of research.

It may seem paradoxical, but automated systems can both reduce and increase MWL. For instance, it has been observed (Hughes & Dornheim, 1995) that glass cockpits in commercial aircraft have relieved workload in areas such as reduced display clutter, and more automated flight procedures. Increased trust in the automation also serves to relieve MWL, as the operator does not feel such a burden of monitoring the system (Kantowitz & Campbell, 1996). However, the same cockpit systems can increase workload by presenting operators with more options in their task and causing mode confusions (Hilburn, 1997). This can lead to mental underload during highly automated activities such as cruise flight, but mental overload during more critical operations such as take-off and landing (Parasuraman et al., 1996). Others have predicted that future systems could increase complexity (Labiale, 1997; Lovesey, 1995) or excessively reduce demands (Roscoe, 1992; Schlegel, 1993) in both aircraft and cars.

Extremes of MWL can create conditions of overload or underload, which may both be detrimental to performance (Wilson & Rajan, 1995). The notion of an optimal level of MWL is based on attentional resource theory, whereby overload or underload can each cause psychological strain due to a mismatch between demands and capabilities (Byrne & Parasuraman, 1996; Gopher & Kimchi, 1989). It is becoming accepted that optimal performance will be the reward for optimised demands (Hancock & Caird, 1993).

Overload occurs if the demands of a task are beyond the limited attentional capacity of the operator. This can be worsened if the operator becomes stressed, as stress is itself resource demanding and can compound cognitive interference (Matthews &

Desmond, 1995). Operators and automated systems are essentially members of the same team. Effective performance in any team is dependent upon good coordination and communication. However, automated systems are inherently bad at these tasks. The performance of the operator is hindered by the increase in processing load resulting from the additional task of collecting information about the system state. This is further complicated by the extent of the operator's knowledge about the system. In the event of manual takeover, the operator must be acutely aware of the system state, so as to match their actions to those which the computer is executing. If the user misperceives the state of the system, s/he could end up in a conflict with the computer for control. In sum, a lack of feedback, an increase in vigilance demands (Hancock & Verwey, 1997), and increased decision options in a given situation (Hilburn, 1997) are all ways in which automation can overload the operator.

Conversely, those susceptible to stress or fatigue may find their performance to be worse in conditions of underload, as there is a failure to mobilise compensatory effort appropriately to cope with the demands (Desmond et al., 1998; Matthews & Desmond, 1997). Underload has also been associated with passivity, with optimal MWL reflecting a need to exercise a level of control (Hockey, Briner, Tatersall & Wiethoff, 1989). The consequences of excessively low mental demands are not often given the consideration they merit, despite being at least as serious as those of mental overload (Hancock & Parasuraman, 1992). Indeed, underload is possibly of greater concern, as it is more difficult to detect than overload (Hancock & Verwey, 1997). There is some evidence that errors and workload are related according to a U-shaped function (Desmond & Hoyes, 1996). This suggests that operators might use less efficient strategies in such circumstances, and are failing to match their effort appropriately to the task. Although there is widespread concern about mental underload, and even some evidence to justify this, very few researchers seem to be actively involved in exploring the issue.

There has been a small amount of empirical work directed at automated vehicle systems, with implications for mental underload. A handful of studies (e.g., de Waard, van der Hulst, Hoedemaeker & Brookhuis, 1999; Desmond et al., 1998; Stanton et al., 1997) used driving simulators to explore the effects of automation failure on driver performance. Performance in the automated conditions was consistently inferior to manual control conditions, and was generally associated with reductions in MWL.

The curvilinear relation between MWL and performance is reminiscent of that between arousal and performance. However, where there is some explanation of the latter association (invoking attentional resources and working memory, discussed above), there is precious little theory underpinning the effects of MWL on performance. It could be, of course, that MWL and arousal are intimately related themselves, thus the same mechanism is responsible for performance variations. Indeed, many physiological measures of MWL depend on this link. However, the link is not perfect, and the measures may dissociate due to larger influences such as muscle movements or circadian rhythms. So, there must be a more direct connection between MWL and performance. Returning to the arousal issue, it was discussed previously that this may affect attentional resources and working memory, resulting in the inverted-U relation with performance. It could be, then, that MWL affects attentional resources in the same way. This premise is the basis for the theory which will be proposed in the closing section of this paper.

Malleable Attentional Resources Theory

On the basis of the literature review presented here, the authors offer a new hypothesis centred around the issue of mental underload with automation. The hypothesis states that mental underload can lead to performance degradation due to shrinkage of attentional resources. This hypothesis is encapsulated in a concept proposed here as malleable attentional resources theory (MART).

Thus far we have seen that automation can reduce MWL, and also that automation can adversely affect performance compared to manual control. Extrapolating from these results leads to the suggestion that mental underload can be detrimental to performance, just as mental overload can. Although a link between mental underload and performance has yet to be firmly established, there is a strong belief in the literature that underload should be considered at least as seriously as overload (e.g., Hancock & Parasuraman, 1992).

Many of the papers on MWL cited above describe the dangers of underload in terms of potential degradation of performance. With a few notable exceptions, though (e.g., Desmond et al., 1998; Matthews & Desmond, 1997), there is a gap in the literature for explanations of why mental underload should be detrimental to performance. Although we have not considered other explanations (such as situation awareness, vigilance, fatigue, or trust) in any detail, we believe that turning to the core literature in attention can provide a parsimonious answer which can encompass all of these.

Applied research on attention implicitly assumes that the size of resource pools is fixed. Capacity may change with long-term fluctuations in arousal, mood, or age (Hasher & Zacks, 1979; Humphreys & Revelle, 1984; Kahneman, 1973), but in most applied experiments on attention these factors are assumed to be stable within participants. Performance on primary or secondary tasks therefore simply depends on demand not exceeding some arbitrary maximum. There is a possibility, though, that this limit may change in the relatively short term, depending on task circumstances. This introduces the concept of <u>malleable attentional resource pools</u>. Evidence is accumulating that simply reducing demand is not necessarily a key to improving performance. It is proposed that resources may actually shrink to accommodate any demand reduction, in a converse of the ‘work expands to fill the time available’ tenet. This could explain the apparent degradation of attention and performance observed in low demand tasks. If the maximum capacity of an operator has been limited as a consequence of the task, it is not surprising that they cannot cope when a critical situation arises (see Figure 1). MART therefore potentially explains why mental underload can lead to performance degradation, whilst remaining grounded in established theories of attention.

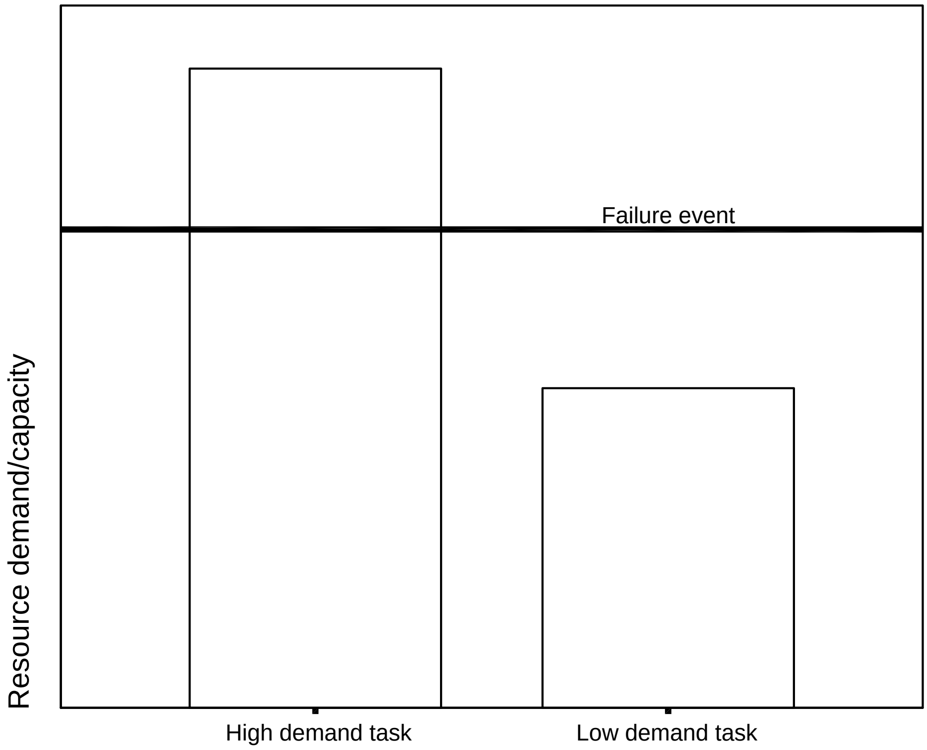

Figure 1: Pictorial representation of performance differences under a malleable attentional resources hypothesis.

In Figure 1, the bars represent the level of MWL and, by the logic of MART, the respective attentional capacity of the operator. The heavy line indicates the level of attentional resources a failure event would demand. As can clearly be seen, this is within the capacity of the high MWL operator, but beyond that at low MWL. It is for this reason that performance in responding to critical situations is predicted to be worse in conditions of mental underload.

Imagine someone driving a fully automated car. This is a situation which considerably reduces MWL. Assuming an attentional demand model of MWL (cf. Liao & Moray, 1993; Young & Stanton, 2001b), this translates to low demand on resources. Now, MART posits that the size of the relevant resource pool will temporarily diminish, as it is not required. This could result in poorer performance on any subsidiary tasks, or problems if the driver is suddenly faced with increased demand (e.g., if the automation fails).

The idea that the level of task demands can influence cognitive processing has been hinted at in previous research. Buck, Payne & Barany (1994) quoted the ‘par hypothesis’ to explain some of their results. This states that, as demands fluctuate, operators increase or decrease the amount of effort invested in a task to maintain performance at a set level. This level represents an operator’s personal par for that task. There is some support for this notion. Liao & Moray (1993) found that participants invest more effort with higher time pressure, which may increase capacity. Conversely, Desmond & Hoyes (1996) concluded that a decrease in performance at low levels of demand might be due to a failure to mobilise effort appropriately to match the task. MART reflects these attitudes, but is a little more parsimonious with respect to current knowledge. Being grounded in theories of attention, it does not have to appeal to extraneous concepts such as effort or motivation.

MART is also consistent with other theories of performance, such as working memory. The inverted-U relationship between arousal and performance was discussed previously as being due to competing processes of attentional resources and working memory. It has already been argued that MWL does not necessarily correlate with arousal directly, but the malleable resources perspective suggests that MWL can have the same influence, by affecting attentional capacity. In that respect, the hypothesis is by no means radical or novel, but simply taking existing ideas from the basic literature and applying them in a new domain.

A further implication concerns the traditional views of demand-performance relationships. Fixed capacity models assume that performance remains at ceiling, and is data-limited, as long as demands remain within the attentional capacity of the operator (Norman & Bobrow, 1975; Stokes, Wickens & Kite, 1990). Performance only begins to decline as the task demands approach the maximum resource availability. This is the very essence of the dual-task approach. Because two tasks can vary in objective difficulty, yet remain within the total capacity of the operator, overt performance differences will not be observed. A secondary task can assess remaining capacity once the primary task has taken its toll, and can therefore differentiate between such levels of difficulty. However, MART predicts that instead, performance is largely resource-limited for the full range of task demands. This would explain why some researchers (e.g., Roscoe, 1992) have found an inverted-U relation between task demands and performance. At low levels of demand, attentional capacity is reduced, artificially limiting the performance ceiling. If task demands exceed the maximum capacity of the operator, performance degrades. Only at medium levels of demand are resources (and hence performance) optimised. These ideas are best understood in figures 2 and 3.

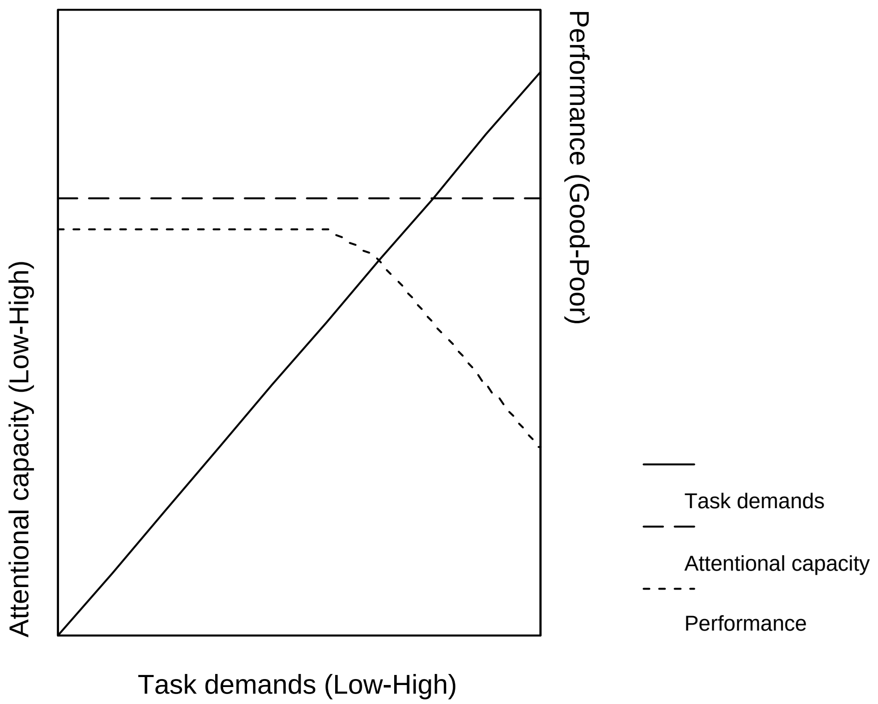

Figure 2: Relation between task demands and performance under a fixed capacity model (adapted from Stokes et al., 1990).

Figure 2 represents the textbook approach, in which performance remains constant until task demands begin to exceed capacity, reflecting the invariance of the capacity upper limit. However, in figure 3, the theory of malleable attentional resources has been applied to depress the upper capacity limit at lower task demands. This also limits the performance ceiling, effectively creating the classic inverted-U relation between task demands and performance.

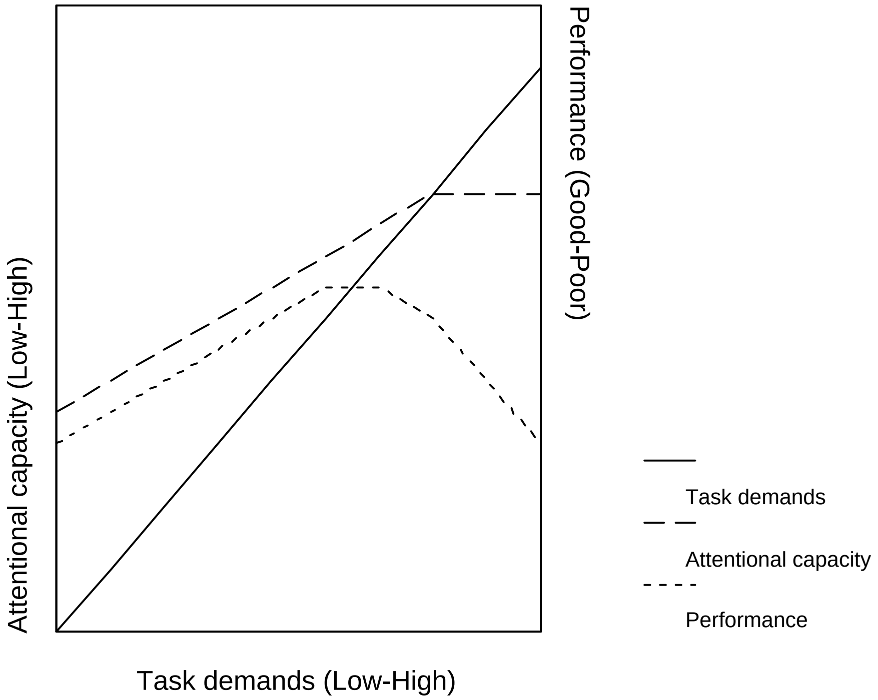

Figure 3: Relation between task demands and performance under a malleable attentional resources model.

Adopting a malleable attentional resources position would therefore help to explain the results from a number of studies in which performance and MWL are positively correlated (e.g., Moss & Triggs, 1997; Roscoe, 1992; Scallen, Hancock & Duley, 1995; Thornton, Braun, Bowers & Morgan, 1992). Indeed, even basic memory research reviewed by Baddeley (1986) could be interpreted as support for MART. A positive correlation between memory span and concurrent reasoning was explained in terms of the demanding influence of error-correction, but the results are also consistent with a change in resource capacity.

On the basis of MART, it is predicted that excessively low mental workload, such as may be presented by automation, could result in a reduction of attentional resources. Young & Stanton (2001a) used a neat measure of resource capacity (figure 4) to demonstrate that this was indeed the case. By comparing eye movements to responses to a secondary task, it was found that attentional capacity directly correlated with MWL. This was the first investigation into MART, and provided enough proof to warrant further investigations.

$$AR = \frac{ST_{cr}}{ST_t}$$ where AR = Attention Ratio
ST = Secondary Task
cr = correct responses
t = time

Figure 4: Derivation of Attention Ratio by Young & Stanton (2001a), used to infer attentional resource capacity. Number of correct responses on a secondary task were divided by total duration of glances directed at that task.

If enough support is found for MART, it will have far-reaching implications for both theoretical and applied researchers. Multiple resources theory (cf. Wickens, 1992), and many studies based upon it, have implicitly assumed that the size of resource pools is invariant across tasks. The conclusions of such studies often hinge upon the assumption that the total demands of primary and secondary tasks equals a constant. For instance, timesharing or multitasking experiments tend to infer that performance decrements are simply indicative of maximal capacity boundaries being exceeded (e.g., Brown, 1978; Buck & Ings, 1997; Harms, 1991; Liao & Moray, 1993; Liu, 1996). These inferences do not account for the possibility of the capacity limit adjusting to demands. Many such studies using dual- or multiple-task techniques to assess mental workload and performance may have to be reassessed. It may no longer be possible to directly compare different primary tasks against each other using the same secondary task. Although an increase in secondary task responses would still indicate an easier primary task, this cannot then be extrapolated to make absolute and quantitative deductions about the resource demands of the primary task. By virtue of the fact that the addition of primary and secondary task demands no longer equals a constant, the whole dual-task methodology is thrown into turmoil.

For applied researchers, there is now a parsimonious theoretical explanation for the effects of underload on performance. The idea of an optimal level of MWL (Hancock & Caird, 1993) is clearly supported, with performance suffering if demands are either too low (underload) or too high (overload). Starting with underload conditions, malleable attentional resources theory predicts that gradual increases in demands would facilitate performance. Such facilitation is particularly evident if suddenly required to assume additional tasks (or resume control of an automated system). The operator who had been working under higher demands (and therefore increased attentional capacity) will cope better with an emergency situation than the underloaded operator. Indeed, this is probably the single most important prediction of MART. If resources have shrunk in response to reduced task demands, a sudden increase in demand – even if it is within the ordinary capacity of the operator – cannot be tolerated. Given the initial support for MART under normal operations (Young & Stanton, 2001a), the logical next step would be to perform a structured investigation of performance when reclaiming control from automation in a failure scenario. Although many authors have tackled this (e.g., de Waard et al., 1999; Desmond et al., 1998; Nilsson, 1995; Stanton et al., 1997), the issue has not yet been specifically approached with malleable attentional resources in mind.

In sum, the present paper has taken a back-to-basics approach to analysing the theoretical literature, and used it to arrive at a new explanation for the effects of mental underload on performance. To the authors' knowledge, the connection between mental workload and attentional resource size has not been made previously, despite the fact that similar ideas have been echoed for physiological arousal. This is probably due to the fact that since the conception of a resource model of attention, applied research has simplified matters by implicitly assuming that resources are fixed, thus hindering theoretical progress. By considering basic theory, though, applied research will also benefit. Malleable attentional resources theory represents an effort towards that goal, in the hope of advancing knowledge in both theoretical and applied domains.

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