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The Relevance of Attention Control, Not Working Memory, in Human Factors

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Objective: Discuss the human factors relevance of attention control (AC), a domain-general ability to regulate information processing functions in the service of goal-directed behavior.

Background: Working memory (WM) measures appear as predictors in various applied psychology studies. However, measures of WM reflect a mixture of memory storage and controlled attention making it difficult to interpret the meaning of significant WM-task relations for human factors. In light of new research, complex task performance may be better predicted or explained with new measures of attention control rather than WM.

Method: We briefly review the topic of individual differences in abilities in Human Factors. Next, we focus on WM, how it is measured, and what can be inferred from significant WM-task relations.

Results: The theoretical underpinnings of attention control as a high-level factor that affects complex thought and behavior make it useful in human factors, which often study performance in complex and dynamic task environments. To facilitate research on attention control in applied settings, we discuss a validated measure of attention control that predicts more variance in complex task performance than WM. In contrast to existing measures of WM or AC, our measures of attention control only require 3 minutes each (10 minutes total) and may be less culture-bound making them suitable for use in applied settings.

Conclusion: Explaining or predicting task performance relations with attention control rather than WM may have dramatically different implications for designing more specific, equitable task interfaces, or training.

Application: A highly efficient ability predictor can help researchers and practitioners better understand task requirements for human factors interventions or performance prediction.

Keywords: attention control, working memory, ability/performance, multitasking

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PREDICTING AND EXPLAINING COMPLEX TASK PERFORMANCE (ABILITY-PERFORMANCE RELATIONSHIPS)

The ability to predict or explain how well an individual might perform in a complex task based on their performance in a simpler task (that purportedly measures a crucial task-relevant ability) has been the goal of applied researchers since at least the early 1900s, such as development of the early U.S. Army Alpha and Beta tests (circa 1917) to classify recruits for job placement (Murphy, 2007).

One example of the ability/performance measurement approach in human factors was a study by Sharit, Czaja, Nair, and Lee (2003) that found a measure of visuospatial attention (Trail Making Test Form B; Reitan, 1958) and working memory (Alphabet span; La Pointe & Engle, 1990), explained a 9.6% and 8.4% of the variance in older adult performance with an auditory voice menu system. This prompted the design of a cognitive aid to support those two cognitive processes. When tested in a second experiment, the aid mostly benefited older users experiencing age-related decrements in those abilities.

In other studies, individual differences in scores on WM measures explained performance variance when using automation (de Visser et al., 2010; McKendrick et al., 2014; Pak et al., 2017; Rovira, Pak, & McLaughlin, 2017). Consistent with the theoretical descriptions of automation (Parasuraman et al., 2000), individuals with lower WM benefited more from higher degrees of automation (designed to reduce WM demand; Rovira et al.). In that study of automation failures, scores on working memory tests predicted operator performance, whereas those with low scores were most adversely affected by automation failures. Relatedly, those with lower working memory scores reported higher trust in unreliable automation. After finding such ability/performance relationships, recommendations to enhance performance can be proposed (e.g., provide more automation for lower WM-ability individuals or adjustable automation levels for higher WM individuals).

Studies of how individual differences inform training designs or learning are still rare (see Szalma, 2009). However, one study using extreme age groups (where working memory scores significantly differed for younger versus older adults) found that training designs should provide informative feedback concerning cues that require working memory or attentional demands (e.g., cues in phishing emails) to the older learners. Cues relying on preserved abilities (e.g., crystallized intelligence) needed less feedback support while learning (Kelley & McLaughlin, 2012).

The problem with making inferences (and designing human factors interventions) based on significant WM-task relationships is that WM tests measure memory storage *and* controlled attention processes. Thus, while the significant WM-task relationship found in prior studies suggests the role of memory, it also implies the role of controlled attention. It may even imply the crucial role of another WM-correlated-factor, such as reasoning ability, also known as general fluid (G_f) intelligence (Horn, 1982). In light of recent findings on the nature of cognitive abilities and their measurement (Burgoyne et al., 2023), we argue that *attention control* is likely more crucial than either WM or reasoning for most tasks of concern to human factors researchers and practitioners.

Review of the Construct of Working Memory

Working memory (WM) capacity is the number of informational units one can maintain without rehearsal and under some simultaneous cognitive load. These units can be 'bits' of information or chunks based on experience (i.e., a, b, c or IBM, FBI, SAT). The concept of WM evolved from the earlier concept of short-term memory (Atkinson & Shiffrin, 1968; STM; Miller, 1956). However, it was soon realized that the concept of STM could not fully capture how memory was used to assist in ongoing mental activity (e.g., thinking, planning, and deciding). During mental activity, storage, processing, and maintenance of information occur in WM, but this was not reflected in measures of STM. To incorporate these processes, Baddeley and colleagues (Baddeley, 2000; Baddeley & Hitch, 1974) devised a model of WM comprising memory storage systems to hold phonological or visual information and a central executive that managed the flow of information to the storage systems; this model included modality-specific storage *and* active processing of information.

How is Working Memory Currently Measured?. To accurately measure WM, assessments should tap into both WM's storage and processing (attention control) functions (called complex span measures) and multiple measures should be combined. Most complex span measures involve remembering a sequence of items interspersed with an additional cognitive task (see Table 1). The most commonly used measure is probably the operation span (OSPAN) task (illustrated in Figure 1). Other examples of complex span tasks may vary the elements, (e.g., symmetry span replaces the math problem with a symmetrical shape and the letter with memorizing shape position), but the interweaving of the elements remains. Some of the tasks may be sensitive to acculturation (e.g., if language use is required in the test or instructions) while others may be more immune (e.g., symmetry span). However, none of these complex span assessments differentiate memory storage from attention control because they result in a single score that reflects both processes.

Memory Over-Emphasized?

The term "working memory" may erroneously imply that memory is the most important element of the construct. This is not necessarily a misunderstanding, as storage is an essential component of WM (e.g., Daneman & Carpenter, 1980); however, it is not the only component. Unfortunately, the attention-control component is rarely mentioned as an explanatory factor in

Table 1. Working Memory and Attention-Control Tasks

Task	Task Description	Relationship to Performance in an Sample Human Factors Study
	Working Memory Measures	
Backwards span (Wechsler, 1939)	Mental transposition of memoranda during recall (report in reverse serial order as stimuli were presented)	No use in Human Factors
Comprehension span (Waters & Caplan, 1996)	Participants judged whether sentences made sense while trying to remember the last word. After a variable number of sentences, tested on recall of last words.	[a]Correlated with multitasking baseline performance (r = 0.35) and several other conditions (rs between 0.36 and 0.65) using the MATB task.
Counting span (Case et al., 1982)	Interwoven processing task (simple counting)	No use in Human Factors
Letter-number sequencing	Mental transposition of memoranda during recall (report numbers in ascending order then letters in alphabetical order)	No use in Human Factors
Mental counters (Larson & Saccuzzo, 1989)	Continuous dropping of previously relevant information to accommodate new information	No use in Human Factors
N-back (Kirchner, 1958)	Continuous dropping of previously relevant information to accommodate new information	[b]Correlated with number of concepts (r = 0.35) and clusters (r = 0.29) generated on an association structure test for process control environments.
Non-selective visual arrays (Luck & Vogel, 1997)	Rapid visual presentation; attentional capture (with larger set sizes)	
Operation span (Turner & Engle, 1989)	Interwoven processing task (basic arithmetic)	[c]Higher scores on resulted in more auditory menu tasks completed and tasks completed faster, especially in a deep audio menu. Effect sizes not reported.
Rotation span (Kane et al., 2004)	Interwoven processing task (judge whether rotated letter is forward-facing or a mirror image)	No use in Human Factors
Running span (Pollack et al., 1959)	Continuous dropping of previously relevant information to accommodate new information	No use in Human Factors
Reading span (Daneman & Carpenter, 1980)	Interwoven processing task (reading comprehension)	[d]Explained time (r = − 0.44), pages viewed (r = − 0.35), and number of repeated pages per trial (r = − 0.36) in a web navigation task.
Selective visual arrays (Vogel & Machizawa, 2004)	Rapid visual presentation; attentional capture; selective attention	No use in Human Factors
Spatial span (Weschler, 1997)	A visual analog to simple digit span; shapes are presented and participant recalls order (forwards or backwards)	[e]Predicted situational awareness sensitivity for novice pilots (r = 0.52).

(Continued)

Table 1. (Continued)

Task	Task Description	Relationship to Performance in an Sample Human Factors Study
	Working Memory Measures	
Symmetry span (Unsworth et al., 2009)	Interwoven processing task (symmetry judgment)	No use in Human Factors
Attention control measures		
Antisaccade (Hutchison, 2007)	Letters are flashed very briefly (100 ms) on either side of the screen; a cue is presented on the opposite side of the screen prior to letter	No use in Human Factors
Visual arrays (Shipstead et al., 2014)	An array of colored shapes is flashed with one shape marked. After receiving a color cue, the participant confirms shape orientation from prior array display	No use in Human Factors
Attention network test (Fan et al., 2002)	Three tests evaluate the following functions of attention: Alerting, orienting, and executive attention. Individual tests are similar to anti-saccade and Flanker.	[f]Alerting ($r = -0.26$) and Orienting ($r = 0.31$) scores correlated with some vigilance sensitivity metrics on a vigilance task.
Stroop/Simon/Flanker (MacLeod, 1991)	Color (Stroop), arrow orientation (Flanker), or position (Simon) can be congruent or incongruent with cue	No use in *Human Factors*
Attentional Control Scale (Derryberry & Reed, 2002)	Survey used to assess perceived attentional control. Subjective measure.	[g]Predicted performance in supervisory control of multiple robots, particularly ratings of workload (effect size not reported), route-editing in some conditions ($\eta_p^2 = 0.25$), response time ($\eta_p^2 = 0.31$), and in multitasking ($\eta_p^2 = 0.35$).

Note. Not all of these commonly used tests were found in articles from *Human Factors* between 1992 and 2022. Search terms included the name of the test and returned 147 results. Articles were coded for whether ability-performance relationships were examined ($n = 32$), whether the ability test was used as a dependent variable for the study ($n = 10$), and whether the ability test was used to create cognitive load in an experimental design ($n = 21$). Most articles mentioned ability tests in an introduction or as part of a review ($n = 66$) and some mentioned the test in the introduction but did not include it in the study ($n = 18$).

[a]Morgan, D'Mello, Abbott, Radvansky, Haass, & Tamplin, 2013.

[b]Burkolter, Meyer, Kluge, & Sauer, 2010.

[c]Commarford, Lewis, Smither, & Gentzler, 2008.

[d]Laberge & Scialfa, 2005.

[e]Sohn & Doane, 2004.

[f]Craig & Klein, 2019.

[g]Chen & Barnes, 2012).

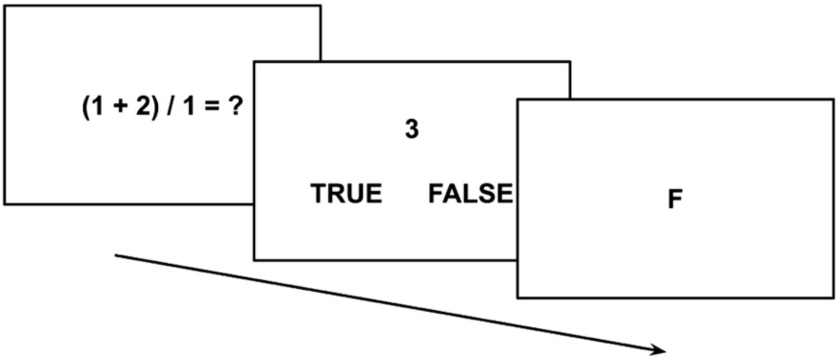


Figure 1. One sequence of the operation span (OSPAN) task. Complex span tasks interweave memory and processing tasks. In the OSPAN task, a math task is presented for a short duration. In the next screen, the participant is asked to verify whether the shown answer is correct. In the last screen, a to-be-remembered letter is briefly shown. This sequence is repeated until all of the letters in the trial are shown. A trial may contain up to 7 sequences (math problems/letters to be remembered, or "set size"). At the end of a trial, the participant is asked to report all the letters in the correct order. The measure of WM is the number of letter sequences recalled in the correct order.

WM-performance relations (Unsworth et al., 2009), even though it is critical, especially in applied and dynamic multitasking settings (Brewer et al., 2016; Burgoyne et al., 2019; Furley & Memmert, 2010; Kleider et al., 2009; Kleider-Offutt et al., 2016; Redick et al., 2016).

In examining the cognitive predictors of multitasking performance, Redick et al. (2016) found that measures of attention control explained more variance than working memory or fluid intelligence. We speculate that past use of WM measures rather than attention-control measures may have resulted in missed explanation of variance in the human factors literature. For example, in one study no relationship was found between performance on an air traffic control task with high multitasking demands and working memory measures (Durso, Bleckley, & Dattel, 2006). A measure of attention control may have better explained task performance.

Attention Control Explains the Relationship between WM and Reasoning Ability. Early applied psychologists studying the relationship between WM and reasoning ability (also known as fluid intelligence or G_f) noted strong correlations (Kyllonen & Christal, 1990). Engle (2002) proposed that the relation between WM and reasoning measures may be due to both relying on the ability to resist distraction in the service of primary goal maintenance. In other words, individual differences in the central executive component of WM, not the storage components, account for the strong relationship between WM and reasoning tasks and likely the relationship between WM and complex task performance (for an alternate view, see Oberauer, 2019). Both measures are likely influenced by a higher-order factor that functions similarly to the central executive: one that controls and directs attention. Figure 2 illustrates that the relationship between WM and G_f does not reflect that they are the same construct; instead, they are both affected by a third construct: attention control (see Table 1 for some commonly used attention-control measures).

How attention control influences or manifest itself in tests of WM or reasoning tests requires a "task analysis" of these tests and a discussion of two processes guided by attention control: maintenance and disengagement.

ATTENTION CONTROL VIA MAINTENANCE AND DISENGAGEMENT

In an elaboration of Engle's (2002) executive attention theory, Shipstead and colleagues (2016)

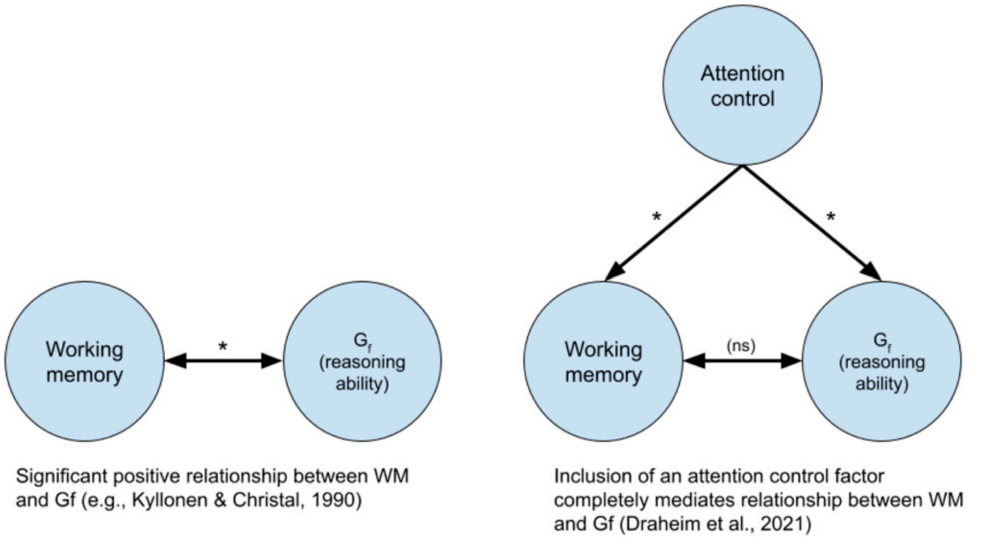


Figure 2. Explaining the relationship between WM and reasoning (G_f). Early research showed strong significant positive correlations (indicated by asterisks) between WM measures and reasoning measures leading many researchers to suggest that they were the same construct. However, newer research shows that when an attention-control factor is included in statistical analyses, the relationship between WM and reasoning ability is no longer significant (ns). The attention-control factor is significantly related to performance in *both* WM and reasoning tasks. More importantly, the attention-control factor fully mediates (or is responsible for) the relationship between WM and reasoning.

proposed that attention control facilitates goal-directed thought and behavior is through two processes: 1) *maintenance* of goal-relevant information and 2) *disengagement* of irrelevant or outdated information that interferes with goal-relevant behavior (Shipstead et al., 2016). This explains the significant correlations between WM and fluid intelligence tasks: both rely on the top-level attentional control factor (Figure 3). Tasks that measure WM primarily rely on the maintenance of goal-relevant information (maintaining the correct to-be-recalled items and in the correct order in the face of distraction from the cognitive task). Disengagement is less critical in these tasks (discarding interference from the intervening cognitive task and maintaining focus on the memory task). On the other hand, fluid intelligence tasks, such as Raven's progressive matrices (RPM; Raven & Court, 1998), primarily rely on disengagement; in RPM, the respondent is to determine the next shape in a sequence of shapes. Test takers may entertain several potential hypotheses for correct answers but must rapidly converge on a single solution by disengaging from irrelevant hypotheses. There is a minimal maintenance component in that they must remember the task instructions.

The construct of attention control may also provide one solution to one of the "Future Challenges in Multiple Resources" posed by Wickens (2008) regarding multiple resource theory (Wickens, 2002). Multiple resource theory describes how limited resources are controlled by a top-down policy that allocates (and reallocates) them. The challenge was that, outside the laboratory, how an individual allocated their limited resources often seemed to deviate from optimal. Wickens (2008) noted that, in the laboratory, this can be artificially imposed through task priority instructions. Individual differences in attention control may describe the ability to keep an optimal allocation policy in the face of overload or distraction. Successful maintenance of an optimal attention allocation policy in the real world would seemingly be affected by an individual's ability to focus and *maintain* their primary goal

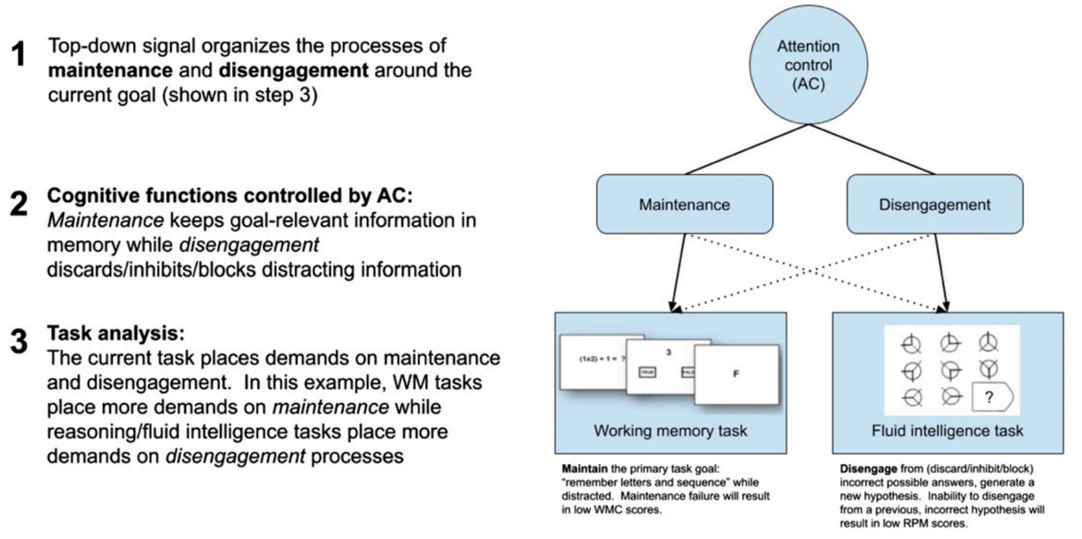


Figure 3. Attention control demands of WM and fluid intelligence tasks (adapted from Burgoyne & Engle, 2020). Attention control (1) is related to WM and reasoning task performance via attention control-controlled mechanisms of maintenance and disengagement (2). Each type of task places different demands on maintenance or disengagement (3), but the higher-level factor of attention control directs both processes (hence the AC-WM-reasoning relationship).

(e.g., vehicle steering), and *disengage* from distracting or irrelevant thoughts (e.g., new text message alert).

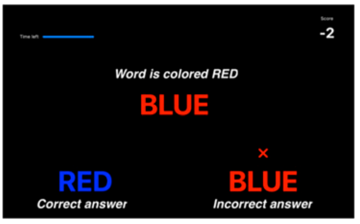
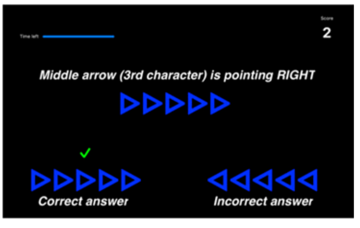
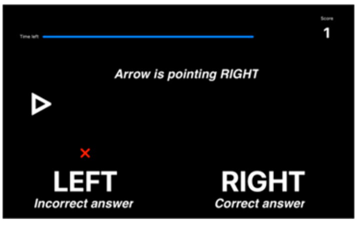
Efficiently Measuring Attention Control: Conflict Squared Tasks

In recent research, Engle and colleagues (Burgoyne et al., 2023) developed and validated a new measure of attention control that not only addresses critical theoretical and methodological flaws in existing attention-control measures (e.g., attention network test, antisaccade; see Table 1) but can each be administered in 3 minutes (compared to over 30 minutes for previous attention-control tests), making them well-suited for use in applied research in operational settings. The three tasks are illustrated in Table 2. For an in-depth review of the issues inherent in existing attention-control measures (i.e., the limitations of using tasks designed for use in an experimental approach designed to minimize individual differences, the use of reaction-time difference scores, low reliability, and speed-accuracy tradeoffs) see Draheim et al. (2019, 2021) and Redick and Engle (2006).

The measures are adaptations of the Stroop paradigm, a standard tool used in the study of selective attention (for a review, see MacLeod, 1991). In the Stroop test, a color word (e.g., green) can be printed either in a congruent color (e.g., green), incongruent color (e.g., red), or neutral (e.g., black). The participant's task is to report the color of the word as fast as possible. When the color and meaning of the word are congruent, the automatic processes of reading and color identification both result in a correct response. In the incongruent condition, there is a conflict between the two automatic processes making goal *maintenance* ("report the COLOR of the word and ignore the meaning") crucial. The conflict squared measures add an additional level of conflict at response time when *disengagement* is crucial (e.g., "discard COLOR of response choice word and interpret the meaning"). This double conflict (hence the term "squared") requires goal maintenance and disengagement.

The tests are reliable and valid whether administered in-lab or online (Burgoyne et al., 2023). The internal consistency (split-half reliability; correlation coefficient) was 0.93 for

Table 2. The Three Squared Tasks

Task Illustration	Description
Stroop squared	
	Participants are instructed to respond with the COLOR of the stimulus word (top) and ignore the meaning. The stimulus word can be congruent (the word RED colored red) or incongruent (the word RED colored blue). Response options can also be congruent or incongruent, but participants must ignore the color of the response options and focus on the MEANING. In this example, the word "BLUE" is colored RED, so the correct response is the word RED, which is incongruently colored in BLUE.
Flanker squared	
	Participants are instructed to respond with the direction of the CENTRAL arrow (in position 3) and ignore the outer arrows. The stimulus can be congruent (all arrows point in the same direction) or incongruent (central and outer arrows mismatch). Response options can also be congruent or incongruent, but participants must ignore the direction of the central arrow and focus on the direction of the OUTER arrows. In this example, the CENTRAL stimulus arrow is pointing right, and OUTER arrows are pointing left (incongruent). The first response (correct) is right OUTER arrows with an incongruent central left arrow. The second response (incorrect) is left OUTER arrows with a congruent central arrow.
Simon squared	
	Participants are instructed to respond with the DIRECTION of the arrow (left or right) and ignore its position on the screen. The arrow can be congruent (a right arrow on the right side or a left arrow on the left side) or incongruent (mismatch arrow direction with screen position). Response options can also be congruent (e.g., the word left on the left) or incongruent (e.g., the word right on the left), but participants must ignore the word's meaning and focus on its POSITION. In this example, the arrow points right but is on the left. The correct answer is RIGHT, which is congruently on the right side of the screen.

Note. Each task begins with 30 seconds of practice. Participants have 90 seconds to respond to as many trials as possible when the task begins. Score is the total number correct in 90 seconds (minus incorrect responses). The tasks are available for E-Prime, Windows, macOS (and after validation testing, on iOS) and are downloadable at: https://englelab.gatech.edu/attentioncontroltasks (labeled "Three-minute attention-control tasks"). When time is of the essence, one or more of the measures may be used to approximate attention control (at about 3 minutes of administration time each). Still, for maximal stability of construct measurement, all three tests should be administered (for a total administration time of about 10 minutes).

Stroop squared, 0.94 for Flanker squared, and 0.97 for Simon squared. To examine test-retest reliability, the tests were administered on three occasions in different settings (in-lab and remote). The correlations between the first and second administration (occurring in-lab, and on average, a month apart) were 0.53 for Stroop squared, 0.74 for Flanker squared, and 0.75 for Simon squared. Comparing scores from the second attempt (in-lab) with a third attempt (remotely; approximately 1.5 months apart) resulted in correlations of 0.55 for Stroop squared, 0.46 for Flanker squared, and 0.49 for Simon squared. Finally, construct validity, or the extent to which these new tests measured attention control, was very high (r = 0.80). Construct validity was examined by correlating a latent factor comprising the three Conflict squared measures to a latent factor comprising existing attention-control measures.

The Conflicts squared measures account for performance in complex multitasking activities (Burgoyne et al., 2023) better than existing measures. Participants were administered both sets of attention-control tasks (new and old) and a set of multitasking tests. Multitasking performance was measured as a composite of performance from four different synthetic work paradigms (each paradigm contained at least four simultaneous tasks): SynWin (Elsmore, 1994), two variations of a control tower task (Redick et al., 2016), and the Foster multitask (Martin et al., 2020). In each synthetic work paradigm, participants must carry out multiple tasks simultaneously (e.g., a memory task, auditory, and visual monitoring). While the older attention-control measures predicted 55.8% of the variance in multitasking performance, the new measures predicted 75.6%—while taking nearly two-thirds less time to administer. Finally, attention control (whether measured with the new or old tasks) accounted for more variance than measures of working memory.

CONCLUSION

Practitioners and scientists share the goal of trying to explain and predict complex task performance, whether it is an older adult using a smartphone or a pilot cooperating with an autonomous teammate. Prior research has shown that individual differences in attention control can predict complex task performance, beyond measures of working memory or reasoning ability. We encourage researchers and practitioners to incorporate elements of an individual differences approach, complementing the more common experimental approach, to discover inter-individual sources of complex task performance variance (e.g., Szalma, 2009). As illustrated by the studies in the introduction, discovering sources of individual differences that contribute to performance differences can be an important first step (e.g., Kelley & McLaughlin, 2012; Pak et al., 2017) in designing focused interventions to improve performance (e.g., Pak, Rogers, & Fisk, 2006; Pak, Pautz, & Iden, 2007; Pak & Price, 2008; Whitlock, McLaughlin, & Allaire, 2012).

Application

To understand how a human factors intervention might change depending on finding significant attention-control-relations versus significant WM relations, we can consider a hypothetical situation of finding significant relations between task performance (e.g., remotely operating a drone using an interface) and WM. If task performance relates to WM, one might believe the intervention should address the memory demands of the task. For example, an intervention could include more environmental support (for a review, see Morrow & Rogers, 2008). However, for complex task situations, the initial finding of a WM relationship attention control could be a better predictor suggesting a different kind of intervention. The finding of a significant attention control-task relationship would imply that memory is not the bottleneck in performance; rather, it is the need to control attention. A more focused human factors intervention that addresses attention control may be warranted, and the mechanisms of attention maintenance and disengagement might be informative. For example, interventions to enhance the operator's ability to *maintain* their current goal in memory such as highlighting the current task or task step, or interventions that enhance *disengagement* of irrelevant information or actions such as selectively removing parts of the interface or restricting their decision or action choices (e.g., scaffolding; Rosson, Carroll, & Bellamy, 1990) or removal of irrelevant information and replacement with attentional guides (Dehais, Causse, & Tremblay, 2011).

Another way in which the concept of attention control, and the mechanisms of maintenance and disengagement, are relevant to human factors research is that it may reveal how to precisely induce cognitive load in studies that thus far have used ability tests (e.g., OSPAN or N-back) to induce a secondary load. Researchers should also consider memory, maintenance, and disengagement when creating dual-task paradigms. These paradigms work best when the resource demands overlap (or do not overlap, depending on the research questions of the study). For example, in McLaughlin, Rogers, and Fisk (2009), a secondary game-like task was created using Multiple Resource Theory that overlapped with the task of interest (navigating an interface) to require visual-spatial attention but not visual-verbal attention. However, considering how much maintenance and disengagement of attention was allowed or demanded by the primary task could have also informed the design of the secondary task (to ensure appropriate levels of attention control were required by both). Related to this, human factors researchers sometimes leverage ability tests as dependent measures to discover the effects of some human factors intervention or treatment on that ability (e.g., the effect of a standing desk on working memory (e.g., Labonté-LeMoyne et al., 2020). A precise understanding of what these ability tests measure, and knowledge of how important attention control is to complex task performance, should guide future experimental designs.

Finally, there is preliminary evidence that, in the context of selection, the attention-control construct is less susceptible to *adverse impact* (Burgoyne et al., 2021) or unintentional discrimination against a protected group. However, even in a design or training context (the traditional domain of human factors), the use of a potentially less biased cognitive measure would make any resultant human factors intervention more equitable and widely effective.

KEY POINTS

- The use of cognitive measures, such as working memory, is common in human factors research
- The theoretical complexity of existing WM measures complicates interpretations of significant ability/performance relationships
- Prior research has shown that attention control predicts complex task performance, beyond measures of working memory or reasoning ability.
- Attention control is the domain-general ability to regulate information processing functions in the service of goal-directed behavior
- We present new attention-control measures that are brief, easy to administer, reliable, and valid, making them suitable for use in HF research

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