Cognitive predictors of a common multitasking ability: Contributions from working memory, attention control, and fluid intelligence

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Abstract:

Previous research has identified several cognitive abilities that are important for multitasking, but few studies have attempted to measure a general multitasking ability using a diverse set of multitasks. In the final dataset, 534 young adult subjects completed measures of working memory (WM), attention control, fluid intelligence, and multitasking. Correlations, hierarchical regression analyses, confirmatory factor analyses, structural equation models, and relative weight analyses revealed several key findings. First, although the complex tasks used to assess multitasking differed greatly in their task characteristics and demands, a coherent construct specific to multitasking ability was identified. Second, the cognitive ability predictors accounted for substantial variance in the general multitasking construct, with WM and fluid intelligence accounting for the most multitasking variance compared to attention control. Third, the magnitude of the relationships among the cognitive abilities and multitasking varied as a function of the complexity and structure of the various multitasks assessed. Finally, structural equation models based on a multifaceted model of WM indicated that attention control and capacity fully mediated the WM and multitasking relationship.

Keyword: multitasking | attention | working memory | fluid intelligence

Article:

One hallmark of human behavior is the ability to retrieve and carry out actions for multiple goals, in rapid succession. To successfully complete many daily activities, people retrieve previously learned information, establish the appropriate motor program given the current context, and plan future actions or intentions. Many individuals are able to perform such functions not only for the successful fulfillment of one goal, but also for multiple goals concurrently. This ability to *multitask* is important, and has been studied extensively in and out of the lab using various paradigms (for review, see Salvucci & Taatgen, 2008). However, several questions remain unanswered, especially regarding individual differences, and we address these in the current research:

> *Research Question 1:* To what degree does a general multitasking ability exist, such that certain people are more successful (and others are less successful) multitaskers across different contexts?
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> *Research Question 2:* What is the relative importance of working memory (WM), attention control, and fluid intelligence abilities to multitasking performance?
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> *Research Question 3:* Does the nature of the multitasking situation affect the relative importance of these cognitive constructs?
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> *Research Question 4:* Does the power of WM to predict multitasking depend on how the WM construct is measured?

To address these questions, we adopted an approach whereby multiple computerized tasks were used to assess cognitive abilities relevant to multitasking performance (WM, attention control, and fluid intelligence). In addition, we approached the construct of multitasking using a varied set of complex tasks. Finally, we administered the measures to a large and diverse sample of young adults, to generate a wide range of individual differences in the abilities assessed.

Defining Multitasking

There are varied perspectives among both researchers and laypersons about what constitutes multitasking. For present purposes, we adopt the definition of multitasking provided by Oswald, Hambrick, and Jones (2007). Multitasking requires (a) performing multiple tasks, (b) consciously shifting from one task to another, and (c) performing the component tasks over a relatively short time span. In the current work, we do not measure aspects of multitasking such as media multitasking (Ophir, Nass, & Wagner, 2009), which assesses via self-report one's frequency of concurrently engaging in multiple computerized technologies. Indeed, multiple studies have observed that one's self-reported frequency of, or preference for, multitasking is not a positive predictor of actual multitasking performance (Poposki & Oswald, 2010; Sanbonmatsu, Strayer, Medeiros-Ward, & Watson, 2013). In addition, we do not measure multitasking with traditional laboratory-based techniques such as dual tasks designed to measure the psychological refractory period (for review, see Meyer & Kieras, 1997).

Previous multitasking research has typically taken one of two approaches. One method has been to administer a specific multitask to novice subjects and examine multitasking performance after extensive practice (e.g., Ackerman, 1988, 1992; Salthouse, Hambrick, Lukas, & Dell, 1996). Another, more applied approach, has examined the differences among individuals that work in a particular multitasking environment, such as emergency medical doctors (Ledrick, Fisher, Thompson, & Sniadanko, 2009) or airtraffic controller trainees (Ackerman & Kanfer, 1993). While these research approaches have been informative about how multitasking performance changes over time, they have limitations that an alternative research tactic may overcome. First, understanding expertise in multitasking is appropriate for some research goals, but may not be beneficial for applications where extended practice is neither feasible nor practical. Second, and most importantly, investigation of one particular multitask context may provide information that is applicable mainly to that particular context, and not multitasking more generally. For example, many studies on multitasking have used the Multiattribute Task Battery (MATB; Comstock & Arnegard, 1992) as the multitasking measure; in brief, the MATB requires subjects to perform tasks similar to those performed by airline pilots (monitoring, tracking, communication, fuel management, and scheduling future tasks). However, MATB performance may not be indicative of multitasking ability more broadly. Perhaps the MATB relies more heavily on spatial versus verbal abilities, or perhaps the number of component tasks within the MATB drives any associations with other constructs, compared to a multitask with just two component tasks. While the MATB may be relatively insensitive to effects of sleep deprivation (Lopez, Previc, Fischer, Heitz, & Engle, 2012), research using other multitasks such as SynWin (Elsmore, 1994) has demonstrated that sleep deprivation has a considerable detrimental effect on performance. An analogy can be drawn with the literature on executive functions— choosing one particular executive control task (e.g., Stroop) may provide different results than if another executive control task (e.g., random number generation) is used (Friedman & Miyake, 2004; Miyake et al., 2000).

One novel goal of the current study, then, was to examine performance across a variety of multitasks, to assess multitasking in multiple dimensions and also to see whether we could measure, at the latent-variable level, a general multitasking ability that was independent of the method-variance used in any one multitask measure. The multitasks are described in more detail in the Method, but we highlight the varying nature of the multitasks below:

> *SynWin:* simultaneous performance of four unrelated tasks varying in self- and externally paced timing; visual and auditory information processing; verbal and numerical stimuli
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> *Control tower:* primary speeded, self-paced task with externally paced interruptions; visual and auditory information processing; verbal, numerical, and symbolic stimuli
>
> *Air traffic control-lab:* speeded decisions while accounting for multiple sources of dynamically updating information; visuospatial and temporal processing; verbal and numerical stimuli

By measuring multitasking using multiple measures, we were able to examine whether a general multitasking ability was represented across the three tasks. Note that previous research has not always obtained significant correlations between multitasking measures. For example, Logie, Trawley, and Law (2011) administered the Edinburgh Virtual Errands Test and the cooking breakfast task (Craik & Bialystok, 2006) to a large sample of healthy young adults and observed no correlation between performance on the two tasks.

In addition to our interest in a general multitasking ability, we also sought to treat each multitask as a separate criterion by which to examine the relative importance of different cognitive abilities in relation to each multitask. For example, Ackerman and Beier (2007) observed that WM, intelligence, perceptual speed, and psychomotor measures were strongly correlated with performance on two different simulated air-traffic control multitasks. However, Ackerman and Beier (2007) additionally observed that spatial abilities predicted unique variance (beyond other ability measures) in one multitask but not the other, whereas WM abilities showed the exact opposite pattern. Similarly, Logie et al. (2011) observed that both verbal and spatial WM significantly correlated with performance on one multitask (Edinburgh Virtual Errands Test) but were not correlated with performance on another (cooking breakfast task). Such findings indicate that using one particular multitask measure can influence the interpretation of how important certain cognitive and noncognitive abilities are in predicting individual differences in multitasking, and may limit the generality of such results.

Cognitive Correlates of Multitasking

Previous research on multitasking has shown that while there are numerous predictors of multitasking performance, WM accounts for significant multitasking variance beyond that predicted by intelligence, attention, perceptual speed, polychronicity (self-preference for multitasking), extraversion, and videogame experience (Ackerman & Beier, 2007; Bühner, König, Pick, & Krumm, 2006; Colom, Martínez-Molina, Shih, & Santacreu, 2010; Hambrick, Oswald, Darowski, Rench, & Brou, 2010; Hambrick et al., 2011; König, Bühner, & Murling, 2005; Morgan et al., 2013). Germane to the current study is the finding that individual differences in WM account for multitasking performance beyond that measured by attention and fluid intelligence. WM, attention control, and fluid intelligence are strongly interrelated constructs (Engle, 2002; Kane, Conway, Hambrick, & Engle, 2007; McCabe, Roediger, McDaniel, Balota, & Hambrick, 2010), although they are not identical (Heitz et al., 2006; Unsworth, Redick, Heitz, Broadway, & Engle, 2009; but see Martínez et al., 2011). The finding that WM accounts for incremental variance in multitasking after accounting for fluid intelligence (e.g., Ackerman & Beier, 2007; Colom et al., 2010; Hambrick et al., 2010) is important given the ubiquitous role that intelligence plays as a predictor of human behavior (e.g., Hunter, 1986). Indeed, Hambrick et al. (2010) suggested "that [WM capacity] is more fundamental than [fluid intelligence] in accounting for individual differences in multitasking" (p. 1160), and Colom et al. (2010) concluded that "intelligence is a weaker predictor [of multitasking] than working memory" (p. 550). It is probably less surprising that WM is a stronger predictor of multitasking than attention is (Hambrick et al., 2011; König et al., 2005), given the relative complexity of WM tasks (see below). We note, however, that the type of attention tasks used in those studies (e.g., task-switching) has been shown to be only weakly related to individual differences in WM (Kane et al., 2007; Redick, Calvo, Gay, & Engle, 2011), in contrast to other attention control measures such as the Stroop and Eriksen flankers tasks (e.g., Unsworth, Spillers, & Brewer, 2009). In the current study, we therefore simultaneously assessed WM, attention control, and fluid intelligence using multiple indicators of each construct and assessed their relative importance to individual differences of various types of multitasking criterion measures. In addition, we assessed each of the cognitive predictors using a combination of verbal and nonverbal stimuli, in contrast to, for example, Morgan et al. (2013), who used only a verbal WM task.

Measurement of Working Memory

Another question assessed in the current study was how the measurement of the WM construct might affect its observed relationship with multitasking. Several studies that have shown strong correlations between WM and multitasking measured WM using only complex span tasks (Colom et al., 2010; Hambrick et al., 2010; Morgan et al., 2013). An example of a complex span task is operation span (Turner & Engle, 1989), in which subjects alternately mentally solve math problems and encode letter sequences for later recall (for further discussion of complex span tasks, see Redick et al., 2012). An inherent limitation in using only complex span tasks to measure WM is that complex span tasks are dual tasks themselves, and in fact have even been used as a multitask criterion in the literature (Sanbonmatsu et al., 2013). Thus, the finding that a dual task (viz., operation span) strongly predicts performance on a multitask would not be particularly surprising, despite differences in the exact components of the measures.

The simple choice would seem to be to use measures other than complex span tasks to represent the WM construct. However, complex span tasks have been used in the bulk of the individual differences and aging literature showing that WM is strongly related to attention control and intelligence (Kane et al., 2007). In addition, other research has indicated some differences in what different types of WM tasks measure. First, a meta-analysis by Redick and Lindsey (2013) showed that the zero-order correlation between complex span tasks and *n*-back tasks is weak. Second, a latent-variable study (Shipstead, Redick, Hicks, & Engle, 2012) suggested that complex span and change detection measures, despite being strongly correlated, accounted for differential variance in fluid intelligence.[1]

However, other research has indicated that complex span tasks are not “special” measures of WM, and that the variance tapped in such tasks is very similar to the variance present in other WM measures. Colom, Shih, Flores-Mendoza, and Quiroga (2006) noted the overlapping variance between simple span and complex span measures of immediate memory, suggesting they largely reflect the same variance (see also Unsworth & Engle, 2007). In addition, Schmiedek, Hildebrandt, Lövdén, Lindenberger, and Wilhelm (2009) explicitly tested whether a WM factor composed solely of complex span tasks was separable from a WM factor composed of noncomplex span tasks such as n-back, memory updating, and alpha span. Schmiedek et al. concluded that the two WM factors were correlated at 1.0 and accounted for similar variance in fluid intelligence, suggesting that individual differences in WM as measured by complex span tasks are nearly identical to individual differences in WM as measured by other updating tasks. Likewise, previous research has shown that complex span tasks and noncomplex span tasks such as running span (Broadway & Engle, 2010; Cowan et al., 2005) and immediate free recall (Unsworth & Engle, 2007) measure largely (although not identical) overlapping variance. Given both the prevalence of complex span tasks as individual differences measures of WM, and their potential limitation as dual tasks to measure the role of WM in relation to multitasks, we included both complex span tasks and noncomplex span tasks as measures of WM.

In addition, we conducted analyses to further specify which aspects of WM are important for the prediction of multitasking. Previous work has mostly looked at WM tasks as multitasking predictors in an a theoretical nature, without adopting a particular framework to decompose the WM–multitasking relationship. Based on a multifaceted WM model (Unsworth, Fukuda, Awh,

& Vogel, 2014) that suggests individual differences in WM are due to (a) differences in capacity limits, (b) attention control, and (c) secondary memory, we examined a series of models investigating whether attention control and/or capacity limits mediated the WM–multitasking relationship. This analysis approach has been useful for investigating the relationship between subcomponents of WM and fluid intelligence (Shipstead, Lindsey, Marshall, & Engle, 2014; Unsworth et al., 2014) and goes beyond previous research that solely examined whether or not WM is a predictor of multitasking.

Method

Subjects

A total of 586 subjects (226 male, 354 female, gender information missing for six subjects) were tested at four universities: Georgia Institute of Technology, University of Georgia, Michigan State University, and University of North Carolina at Greensboro. All subjects were healthy young adults between the ages of 18 and 30. In addition to testing college students, 117 of the subjects tested at the Georgia Tech site were community volunteers not attending Georgia Tech. These subjects included both students at other metropolitan Atlanta colleges and nonstudents. Five hundred thirty-four subjects completed all three test sessions (9% attrition). Of these 534 subjects, due to experimenter error, computer error, and other issues, data for all tasks were not available for 91 subjects (missing data for 0.80% of all possible dependent variable cases). Cases of missing data were imputed using a maximum likelihood parameter estimation algorithm, which is generally regarded as a better alternative to listwise deletion of subjects with missing data (Schafer & Graham, 2002). All analyses reported are based on $N = 534$ subjects.

Working Memory–Complex Span[2]

All complex span tasks were automated, presenting stimuli onscreen and collecting responses via mouse click. Each task first presented a brief practice block on the memory portion, then on the processing-task portion (in which response times were measured), and then on the combined processing-plus-memory task. In the experimental task blocks, the processing portion had an individualized response deadline, corresponding to the subject's processing practice mean reaction time (RT) plus 2.5 *SD* (exceeded deadlines counted as processing errors). In each task, the list lengths were randomly intermixed, meaning that the number of to-be-remembered items was unpredictable on each trial, given research demonstrating the increased predictive validity in contrast to sequential presentation (St. Clair-Thompson, 2012). Each task presented three trials of each list length. The complex span tasks are available for download from http://englelab.gatech.edu/tasks.html.

Operation span (Redick et al., 2012; Unsworth, Heitz, Schrock, & Engle, 2005). Subjects must solve a math equation, and then encode a to-be-remembered letter. After three to seven math–letter elements, subjects are required to recall the letters in the order in which they were presented. The score was the number of letters recalled in the correct order (maximum = 75).

Reading span (Redick et al., 2012; Unsworth et al., 2009). Subjects must make a veridical decision about the semantic content of a sentence, and then encode a to-be-remembered letter.

After three to seven sentence-letter elements, subjects recall the letters in serial order. The score was the number of letters recalled in the correct order (maximum = 75).

Symmetry span (Redick et al., 2012; Unsworth et al., 2009). Subjects must make a vertical symmetry judgment about a black-and-white grid figure, and then are presented with a red-square location within a 3 × 3 matrix that is to be remembered. After two to five symmetry–square elements, subjects are required to recall the squares in serial order. The score was the number of squares recalled in the correct order (maximum = 42).

Rotation span (Kane et al., 2004; Shah & Miyake, 1996). Subjects must make a normal-mirror decision about a rotated letter, and then are presented with a to-be-remembered short or long arrow pointing in one of eight specific orientations. After two to five rotation–arrow elements, subjects are required to recall the arrow directions in serial order. The score was the number of arrows recalled in the correct order (maximum = 42).

Working Memory–Other[3]

Keeping track (Engle, Tuholski, Laughlin, & Conway, 1999; Yntema & Mueser, 1962). Preceding each list of words, subjects are presented with two to six different categories (metals, animals, colors, distances, countries, relatives). Then, a list of 16 words is presented, with each word shown onscreen for 1,500 ms (and a 250-ms blank screen between each word). After the final word in the list is presented, the subject must recall the last exemplar of each category when probed. At recall, six exemplars are presented for each category cued before the list, and subjects use the mouse to click on the most recently presented exemplar for each category. Each list includes at least one exemplar from each of the six categories. Each category occurred equally often as a cued category across trials. The practice section presented two trials each of one- and two- category lists; the experimental block presented three trials each of two-, three-, four-, five-, and six-category lists (randomly intermixed). The number of correctly recalled final exemplars across the 15 experimental lists is used as the dependent variable (maximum = 42).

Matrix monitoring (Salthouse, Atkinson, & Berish, 2003). Subjects are presented with either one or two 4 × 4 matrices with a single cell highlighted for 2,500 ms. Next, a series of one to four arrows are presented, indicating the movement of the highlighted cell within the matrix. A probe matrix is displayed and the subject has to indicate whether the probe cell is the correct location of the target cell based on the series of arrows. In the experimental block, eight of the 16 trials presented one matrix, while the other eight trials presented two matrices simultaneously. On half of the trials, the probe cell matched the updated location of the target cell, and the other half of the trials, the probe cell location was in an adjoining cell of the updated location of the target cell and thus did not match. Four trials each of one, two, three, or four arrow updates are presented. The proportion of correct probe decisions is used as the dependent variable.

Continuous counters (Garavan, 1998; Unsworth & Engle, 2008). Subjects are instructed to keep a running count of each of the number of squares, circles, and triangles presented on a given trial (15 trials total). Shapes are presented individually, and subjects must add to the existing count for each type of shape. This is made difficult by randomly switching shape type six or seven times within each trial, and presenting an unpredictable number of stimuli for each trial. At the end of the trial, subjects are asked to report in order the number of squares, circles, and triangles presented. The correct final counts on each trial varied between three and seven on each trial. The correct proportion of correct final counts is used as the dependent variable.

Change detection (Morey & Cowan, 2004; Shipstead et al., 2012). Subjects are presented for 250 ms with a display of four, six, or eight colored (white, black, red, yellow, green, blue, purple) squares on a light gray background. The display disappears for 900 ms, and then the array reappears with all squares in the same locations. One of the reappearing squares is circled, and subjects must report whether the circled squares is the same color as it was when originally presented. There were 60 total trials in the experimental block, evenly divided among the three set sizes (four, six, eight) and answer type (color change, color same). A bias-corrected measure of capacity (*k*; Cowan et al., 2005) is used as the dependent variable.

Visual brief report (Poole, 2012; Sperling, 1960). Subjects are presented with three to eight letters simultaneously in random locations within a 4 × 4 grid. The letters are presented for 100 ms, and the subject then is instructed to report as many letters in any order as possible, using the same mouse-click response procedure as operation span and reading span. After five practice trials, the experimental block contains four trials of each array size (three, four, five, six, seven, eight), for a total of 24 trials. The total number of letters correctly reported across 24 trials is used as the dependent variable (maximum = 132).

Attention Control

Antisaccade (Hallett, 1978; Kane, Bleckley, Conway, & Engle, 2001). In this task, subjects must identify a briefly presented letter. A variable duration fixation screen (200, 600, 1,000, 1,400, or 1,800 ms) displays a string of asterisks (***) in the middle of the screen. An equal sign (*) cues flashes (onscreen for 100 ms, blank for 50 ms, onscreen again for 100 ms), immediately followed by a backward-masked B, P, or R (for 100 ms). The subject's job is to indicate which letter was presented via key press, using the left, down, and right arrow keys with stickers marked as B, P, and R, respectively. First, in the 30 response-mapping trials, the cue and letter are presented in the center of the screen. Next, subjects complete 15 prosaccade trials, in which the cue and letter are presented on either the left or right side of the screen, but the cue and letter occur on the same side on a particular trial. On the critical anti-saccade trials, the cue and letter also are presented on the either the left or right side of the screen, but the cue and letter occur on opposite sides on a particular trial. This is made difficult by the fact that the flashed asterisk tends to capture attention to the opposite side of the screen from where the subsequent letter stimulus is presented. After completing 10 practice anti-saccade trials, the experimental block includes 60 anti-saccade trials, equally divided between left and right letter locations and among the three letter responses. The proportion of errors across 60 trials is used as the dependent variable.

Go/no-go (McVay & Kane, 2009; Robertson, Manly, Andrade, Baddeley, & Yiend, 1997). In the semantic version of the sustained-attention-to-response task, subjects must decide whether each backward-masked word (presented for 300 ms, up to 1,200 ms to respond) is an exemplar of animal or food. Only animal words required a key press of the space bar with the subject's dominant hand, and these “go” stimuli occurred on 88.9% of all trials (540 trials total). Food words required subjects to withhold the response, and these “no-go” stimuli occurred on 11.1% of all trials. The ability to withhold a response to no-go stimuli is made difficult by the high frequency of responding to go stimuli. Sensitivity (*d*=) and RT variability (individual standard deviations) on correct trials are used as the dependent variables, following McVay and Kane (2009).

Spatial Stroop (Daniels, 2002; Simon & Rudell, 1967). Subjects are instructed to ignore the location of the arrow (left, center, or right part of the computer screen) and instead respond only to the arrow’s pointed direction (left or right), using the z and / keys labeled with left and right arrow stickers, respectively. Subjects first complete 16 response-mapping practice trials, in which the arrows appear in the center location onscreen. In the experimental block, the decision is made difficult because on 75% of the 144 total trials, the location and direction information are congruent (e.g., a left-pointing arrow on the left side of the screen), whereas on 12.5% of trials, the location and direction information are incongruent (e.g., a left-pointing arrow on the right side of the screen), and on the remaining 12.5% of trials (neutral), the arrow appears in the center location onscreen. An equal number of left and right arrows were presented within each trial type. The mean RT difference between correct responses on the incongruent trials minus the congruent responses is used as the dependent variable.

Cued visual search (Poole & Kane, 2009). Subjects must decide whether an F located within a 5 × 5 array of 25 letters (comprising Es, backward Es, 90°-tilted Ts, 270°-tilted Ts) is mirror-reversed (facing left) or normal (facing right). Subjects make their responses using the z and / keys, labeled with left and right arrow stickers, respectively. Subjects complete eight response-mapping trials with a lone mirror-reversed or normal F before proceeding to the cued search section of the task. Each trial begins with a blank screen (500 ms), and then subjects are given an arrow cue (500 ms) indicating in which two or four of the eight possible array locations the relevant letter F may appear (always along the internal 3 × 3 “ring” of the array). A blank screen is then shown for 50 ms, before the 5 × 5 grid of 25 possible locations is shown for 1,500 ms. A blank screen of 50 ms is shown again, and the array of 25 letters is shown until the subject responds (up to 4,000 ms). Because other Fs are randomly presented in non-cued locations as irrelevant distractors, the subject must maintain the cue information to respond correctly. Subjects complete 12 practice trials and 160 trials in the experimental block. Cue type, target direction, and target location were randomly and equally presented in the experimental block. The mean RT for correct responses across the 160 experimental trials is used as the dependent variable.

Cued flankers (based on Eriksen & Eriksen, 1974). Subjects must decide whether an F located within a horizontal array of seven letters is mirror-reversed (facing left) or normal (facing right). Subjects make their responses using the z and / keys, labeled with left and right arrow stickers, respectively. Subjects complete 10 response-mapping trials with a lone mirror-reversed or normal F before proceeding to the cued flankers section of the task. Before each array, subjects see a blank screen (250 ms) and then are given a location cue (a digit presented for 500 ms) that indicates which of the following seven letters is the one on which the direction decision is to be made. The target was restricted to one of the middle five positions in the row (hence the digits used as cues ranged from 2 to 6). Another blank screen (250 ms) is shown, and then the horizontal grid of seven locations is presented for 1500 ms. Finally, after a blank screen for 50 ms, the letter array is displayed until the subject responds (up to 3,000 ms). After completing the response-mapping practice, subjects practice the cued flankers task with no flankers present for 10 trials. In the subsequent practice (20 trials) and experimental block (120 trials), there were four different trial types. On compatible trials (50% of trials), all of the letters face the same direction as the cued target letter. On incompatible-homogeneous trials (16.7% of trials), all flanker letters face in the opposite direction of the cued target letter. On incompatible-heterogeneous trials (16.7% of trials), the target is flanked by a variety of non-F stimuli (comprising Es, backward Es, 90°-tilted Ts, 270°-tilted Ts). Incompatible-lure trials (16.7% of trials) are very similar to incompatible heterogeneous trials, except that one of the irrelevant flanker letters adjacent to the cued target letter faces in the opposite direction as the cued target letter. As an example of an incompatible-lure trial, the cue indicates Position 2 is where the target appears, and when the array of seven stimuli is presented, the cued F facing to the right is flanked in Position 1 by a mirror-reversed *F*, along with Es and Ts in the other positions. The mean RT for correct responses to the 20 incompatible-lure trials is used as the dependent variable.

Arrow flankers (Redick & Engle, 2006; Unsworth et al., 2009). Subjects are presented with an arrow in the center of the screen pointing toward the left or right, and subjects must indicate the direction that the arrow points. Subjects make their responses using the z and / keys, labeled with left and right arrow stickers, respectively. Subjects first complete 10 response-mapping practice trials, in which the arrows appear in the center location onscreen without any distractors. On the subsequent practice (six trials) and experimental block (150 trials), the central target arrow is flanked on both sides by two arrows. A fixation cross is present at the center of the screen throughout the trial. After a 400-ms fixation display, an asterisk cue appears above fixation for 100 ms, followed by another fixation display for 400 ms. The five-arrow array then appears, with the central target arrow in the same position as the asterisk cue. The arrows are shown until the subject responds (up to 1,700 ms). There was a 400-ms intertrial interval. The practice and experimental trials were equally divided into three trial types. On compatible trials, all four of the distractor arrows point in the same direction as the central target arrow; on incompatible trials, all of the irrelevant flanker arrows point in the opposite direction as the target arrow; and on neutral trials, the central arrow was presented without flanking arrows. The mean RT difference between correct responses on the incompatible trials minus the compatible trials is used as the dependent variable.

Fluid Intelligence

Raven's progressive matrices (Kane et al., 2004; Raven, Raven, & Court, 1998). Subjects see abstract shapes presented in a 3 × 3 matrix. The shape in the bottom-right matrix location is missing, and the subject must select from the eight answer options the item that best completes the overall pattern and series vertically and horizontally. After completing three practice items, the number of correct responses (out of the original 18 odd-numbered items) solved within the 10-min time limit is used as the dependent variable.

Number series (Thurstone, 1938; Unsworth, Redick, et al., 2009). Subjects are presented on each problem with a series of numbers, and the subjects are instructed to identify the response option that is the next logical number in the sequence. After completing five practice items, the number of correct responses (out of 15) solved within the 4.5-min time limit is used as the dependent variable.

Letter sets (Ekstrom, French, Harman, & Derman, 1976; Redick, Unsworth, Kelly, & Engle, 2012). Subjects are presented on each problem with five sets of letters, with each set containing four letters each. Subjects are instructed to find the rule that applies to four of the five letter sets, and then indicate the letter set that violates the rule. After completing two practice items, the number of correct responses (out of 20) solved within the 5-min time limit is used as the dependent variable.

Paper folding (Ekstrom et al., 1976; Kane et al., 2004). Subjects are presented with a square piece of paper on the left of the problem. The markings indicate that the paper has been folded a certain number of times, and then a hole was punched through the paper. The subject must decide which one of the five response choices is what the piece of paper would look like if it was completely unfolded. After completing one practice item, the number of correct responses (out of the original 10 items on Part 1 of the test) solved within the 4-min time limit is used as the dependent variable.

Multitasking

SynWin (Elsmore, 1994; Hambrick et al., 2010). The Syn-Win test is a proprietary multitask designed to require simultaneous performance of up to four unrelated tasks. Visual and auditory information processing is necessary for task success. The task characteristics and method for addition and subtraction of points was the same as outlined in the baseline condition of Hambrick et al. (2010). Subjects are presented with a visual display with four simultaneous subtasks to complete (see Figure 1). (a) Probe-recognition: When the task begins, a six-letter list is presented for 5 s and then disappears. For the remainder of the task duration, a probe letter is presented every 10 s, and the subject must indicate via mouse click whether the probe letter was one of the six letters presented on the list. Ten points are added to the subject's score for correct responses, and 10 points are subtracted for incorrect responses, failing to respond within 5 s and if the subject clicks to present the memory set again. (b) Arithmetic: The subject must mentally add two three-digit numbers and report via mouse click the correct sum. The arithmetic subtask is entirely self-paced, in that a new math problem is only presented after the subject has submitted a response to the previous problem. Twenty points are added for correct responses and 10 points subtracted for incorrect responses. (c) Visual monitoring: The subject must monitor the level on a gauge and click on the gauge to "reset" it before it reaches "empty." Points are awarded each time the subject resets the gauge, with more (up to 10) points being added the closer to zero the gauge is before it is reset. However, 10 points are subtracted for every second that the gauge remains at zero before being reset. (d) Auditory monitoring: High (2,000-Hz) and low (1,000-Hz) frequency tones are presented every 10 s. The subject must click a button within the quadrant when the rarely occurring high-frequency tone is presented (20% of all tones). Ten points are added for hits, and 10 points are subtracted for misses and false alarms. Subjects completed three 5-min blocks of the task. The subject's score is determined by a formula that combines the points earned across all subtasks. This composite score is used as the dependent variable.

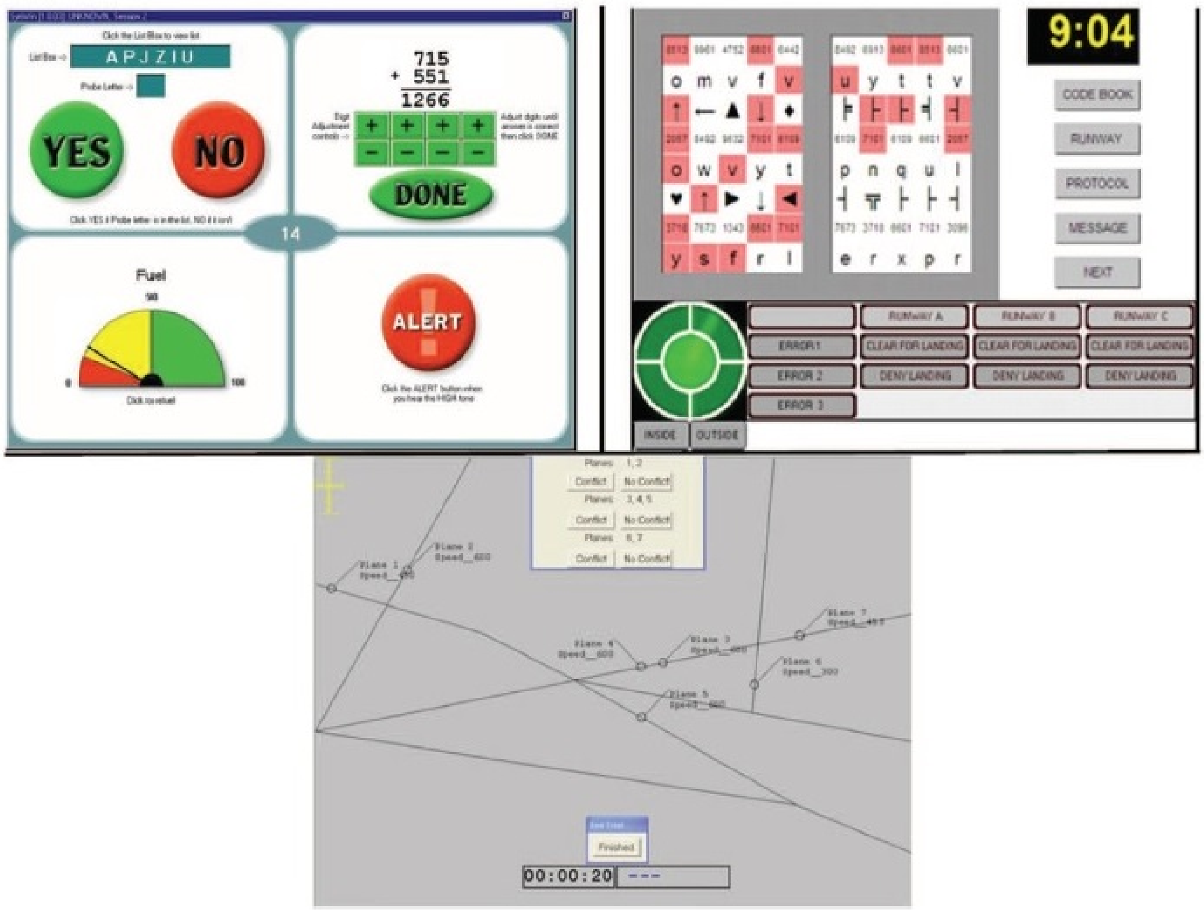

Figure 1. Screenshots of the multitasks. Clockwise from upper left: SynWin, control tower, air traffic control lab. See the online article for the color version of this figure.

Control tower (Redick et al., 2013). The control tower task is designed such that there is one, ongoing primary task while dealing with distracting interruptions from four other tasks. Visual and auditory information processing is necessary for task success. Subjects are presented with a visual display with various subtasks to complete (see Figure 1). For the primary task, subjects must search through an array of numbers, letters, and symbols on the left side of the screen and select the appropriate items from the array on the right side of the screen, as indicated by task instructions: for numbers, subjects click on the identical numbers in the right array; for letters, subjects click on the letter that precedes it alphabetically in the right array; and for symbols, subjects refer to a consistently mapped symbol *code book* and click on the relevant symbols in the right array. Subjects are instructed to complete as many array comparisons as possible over the duration of the task. Meanwhile, distractor tasks (radar, airplane, color, problem-solving) are presented visually and via headphones to reference items listed below the arrays at specific times or when specific colors are presented. For the radar task, subjects are instructed to click either the *inside* or *outside* button below the radar when a blip occurs. For the airplane task, requests for landing on one of three runways are presented via headphones and the subject either agrees to or denies the request, according to the availability listed in the button marked *runway*. For the color task, a color flashes briefly and the subject presses one of three "error" buttons according to the mapping presented in the button marked *protocol*. For the problem-solving task, trivia and general knowledge questions are presented via headphones, and subjects click on one of three possible answers presented at the bottom of the screen. Subjects completed one, 10-min block of the task. The subject's primary score is the mean of the number of correct number, letter, and symbol comparisons completed (no theoretical maximum score). The subject's distractor score is the sum of the correct decisions across the various distractor subtasks (out of 30). Both the primary and distractor scores are used as dependent variables.

Air traffic control lab (Fothergill, Loft, & Neal, 2009). The air traffic control-lab (ATC-lab) task is designed such that multiple, speeded decisions are required while accounting for multiple sources of visual information (see Figure 1). Across 15 unique trials, subjects are presented with a dynamic display highlighting four to 10 planes on various flight paths (some intersecting), traveling at various rates of speed indicated in the label for each plane. The screen refreshes the planes' locations every 5 s, and subjects have up to 1 min to make two to four yes/no decisions about whether each cluster of two or three probed planes are in conflict given their current locations, flight path, and speed. For the example trial presented in Figure 1, the correct response for the decision about Planes 3, 4, and 5 is "conflict," because Plane 5's flight path intersects too closely with Planes 3 and 4 given the speed of each plane. The proportion of correct potential conflicts detected is used as the dependent variable.

Procedure

All subjects completed the tasks in three sessions, with each session taking approximately 2 hr to complete. In addition to the measures described above, at the beginning of the first session, all subjects provided demographics information and completed a questionnaire about video game experience (Hambrick et al., 2010).[4] Subjects at the Georgia Tech site were compensated $30 for each session; subjects at all other sites received course credit in exchange for participation. All subjects completed the tasks in the same order (see Table 1). Tasks assumed to measure each construct were ordered such that they occurred in the early, middle, or latter stages of different sessions. For example, control tower occurred as the second task in the first session, ATC-lab occurred as the ninth task in the second session, and SynWin occurred as the fourth task in the third session.

Analyses

For the latent variable analyses, several fit statistics were evaluated.

A nonsignificant ($p > .05$) χ^2 value is desirable, although with sufficiently large sample sizes such as ours, a significant χ^2 value will be obtained and will not necessarily be indicative of poor model fit. Values of the non-normed fit index (NNFI) and the comparative fit index (CFI) greater than .95 indicate good model fit (Kline, 2011). Root mean square error of approximation (RMSEA) values and standardized root mean square residual (SRMR) values less than .06 indicate good model fit (Kline, 2011). χ^2, RMSEA, and SRMR provide an indication of the absolute fit of the model, while NNFI and CFI provide an indication of the relative fit of the model (Hooper, Coughlan, & Mullen, 2008). To statistically compare nested models, χ^2 tests of the difference ($\Delta\chi^2$) between the two models were used, with $p < .05$ indicating better statistical fit. In addition, the Akaike information criterion (AIC) was used to compare models, with the model associated with the smallest value representing the best statistical fit.

To address the relative importance of WM, attention control, and fluid intelligence in predicting variation in the general multitasking construct, and each multitask separately, multiple regression was used to provide estimates of (a) standardized regression coefficients (β), (b) incremental variance ($\Delta R2$), and (c) relative weight analysis (for a primer on the merits of relative weight analysis, see Tonidandel & LeBreton, 2011; for an example of its use in cognitive psychology, see Nairne, VanArsdall, Pandeirada, Cogdill, & LeBreton, 2013). Most germane to the current work, when there is high multicollinearity among predictors, relative weight analysis provides estimates of the regression weights that are more appropriate and interpretable than using other techniques such as standardized beta weights. Whereas beta weights provide information about how much the criterion variable will change with a unit change in the predictor variable, holding the other predictors constant, relative weights can indicate which predictor (if any) matters more than others when predicting the criterion variable (Tonidandel & LeBreton, 2011). Given that we anticipated possible multicollinearity among WM, attention control, and fluid intelligence based both on theoretical grounds (Kane et al., 2007) and empirical evidence from previous multitasking studies (Ackerman & Beier, 2007; Hambrick et al., 2010), our focus in the results is on the rescaled raw relative weights. The rescaled relative weights indicate the portion of the overall variance accounted for in the multitasking criterion that is attributable to each cognitive predictor—that is, for a particular outcome, the relative weights for each predictor variable sum to equal the total $R2$, which can then be converted to a percentage of the overall variance in the outcome accounted for by each predictor. Bootstrap-estimated estimates of confidence intervals [CIs] were used to test if two relative weights are statistically different from each other (Tonidandel & LeBreton, 2015).

Table 1. Test Orders Used for Three Sessions

Task number	Session 1	Session 2	Session 3
1	Operation span	Matrix monitoring	Antisaccade
2	Control tower	Visual brief report	Number series
3	Change detection	Letter sets	Rotation span
4	Paper folding	Cued search	SynWin
5	Arrow flankers	Keep track	Spatial DMTS
6	Continuous counters	Symmetry span	Dual n-back

7	Spatial Stroop	Go/no-go	Cued flankers
8	Reading span	Raven advanced	Math access
9		ATC-lab	

Note. ATC-lab = air traffic control lab; DMTS = delayed-match-to-sample. All subjects completed a demographics questionnaire before the first test in the pretest session.

Results

Descriptive Statistics and Bivariate Correlations

Descriptive statistics for all tasks are provided in Table 2; performance on operation, reading, and symmetry span was consistent with published normative data for young adults (Redick et al., 2012). Initially, the kurtosis values for a few dependent variables (SynWin, control tower distract, arrow flankers) were high. To conservatively influence the data, we screened each dependent variable and replaced values above +4 *SD*s or below -4 *SD*s for each variable with values equal to +4 *SD* or -4 *SD*, respectively. Seven of the 24 dependent variables were affected; in sum, 0.2% of all data points were trimmed. Although this trimming had little effect on the results and interpretation, the indices of normality of the trimmed data for all dependent variables reported in Table 2 are in line with recommended levels for the types of analyses used here (Kline, 1998). Reliability estimates (see Table 2) were generally high for the dependent variables, with a few exceptions (e.g., the spatial Stroop RT difference score). Inspection of the correlation matrix (see Table 3) indicates that zero-order correlations were generally moderate to high. Of note, the correlations among the three multitasking dependent variables (r = .27 to .48, all ps < .05) indicate that individuals' multitasking performance is consistent across different multitasking situations.

Table 2. Descriptive Statistics and Reliability Estimates for All Measures

Measure	M	SD	Range	Skew	Kurtosis	Reliability
WM–complex span						
1. Operation span	54.33	14.65	73	-.96	.54	.84[a]
2. Reading span	51.87	14.18	75	-.80	.47	.83[a]
3. Symmetry span	25.38	9.20	42	-.52	-.33	.81[a]
4. Rotation span	27.44	8.82	42	-.81	.40	.80[a]
WM–other						
1. Keeping track	34.76	8.98	47	-.67	.13	.85[a]
2. Matrix monitoring	.80	.15	.69	-1.06	1.14	.57[a]
3. Continuous counters	.82	.19	.91	-1.54	1.85	.91[a]
4. Change detection	3.40	1.29	5.80	-.97	1.01	.78[a]
5. Brief report	94.24	11.05	58	-.37	-.15	.73[a]
Attention control						
1. Antisaccade	.48	.16	.73	-.39	-.64	.86[a]
2. Go/No-go d´	1.63	1.10	9.09	-.79	1.55	.96[a]

3. Go/No-go RT ISD	174	57.01	334	.86	.67	.86[a]
4. Spatial Stroop	138	74.63	533	120	2.36	.48[b]
5. Cued visual search	1276	286.26	2067	.41	.83	.89[b]
6. Cued flankers	723	249.69	1634	1.41	2.55	.87[b]
7. Arrow flankers	101	67.95	796	1.07	4.00	.61[b]
Fluid intelligence						
1. Raven APM odd	8.97	3.68	17	-.32	-.54	.79[a]
2. Number series	8.66	2.98	14	-.18	-.32	.75[a]
3. Letter sets	10.14	3.18	17	-.01	-.30	.72[a]
4. Paper folding	5.86	2.67	10	-.46	-.59	.78[a]
Multitasking						
1. SynWin	5270.39	267.47	3108	-1.27	3.89	.86[b]
2. Control tower primary	30.24	11.38	58	-.43	-.11	.96[b]
3. Control tower distract	24.76	3.88	25	-1.82	4.05	.54[b]
4. ATC-lab	.68	.10	.60	-.43	-.17	.71[a]

Note. WM= working memory; RT = reaction time; ISD = individual standard deviations; APM = advanced progressive matrices; ATC-lab = air traffic control lab. Reliability estimates calculated using either a Cronbach's alpha or b Spearman-Brown formulas. *M*, *SD*, range, and reliability values based on data before trimming data points ± 4 *SD*s (see text). Skew and kurtosis values based on trimmed data, and represent data used in all correlational, regression, and latent-variable analyses.

Confirmatory Factor Analyses: One- or Two-Factor Working Memory?

To address the nature of the WM construct, we performed two confirmatory factor analyses, specifically comparing the fit between a one-factor WM model with loadings from all WM measures onto one factor, and a two-factor WM model consisting of separate but correlated complex span and noncomplex span factors. The models are depicted in Figure 2. Modification indices revealed that allowing the residuals between the operation and reading span to correlate would improve model fit. This modification is justified given that the memory recall parts of these two tasks are identical (serial recall of letters). The fit of the one-factor model was good, $\chi^2(26) = 106.801$, $p < .01$; NNFI = 0.962; CFI = 0.973; RMSEA = .0763; SRMR = .041, AIC = 3,317.591. In comparison, the fit of the two-factor model with the correlated error term was also good, $\chi^2(25) = 62.787$, $p < .01$; NNFI = 0.982; CFI = 0.987; RMSEA = .053; SRMR = .034, AIC = 3,275.577. The statistical fit of the two-factor model was better than the fit of the one-factor model, as evidenced by the smaller AIC value and significant chi-square test, $\Delta x^2(1) = 44.014$, $p < .01$. However, the correlation between the WM factors was .84 (95% CI [.81, .87]), indicating that the WM factors shared 71% of their variance. Thus, our interpretation is similar to that of Kane et al. (2004) – although statistically the best fit is achieved with the model with two separate WM factors, the high amount of shared variance indicates all of the WM measures tap primarily overlapping processes, with relatively little method-specific variance distinguishing complex span and noncomplex span tasks. Thus, a combined WM composite for complex span and noncomplex span tasks is used in further analyses.[5]

Regression Analyses: Relative Importance of Cognitive Abilities to General and Specific Multitasking

As mentioned above, given the presence of multicollinearity among the cognitive predictor variables and multitasking, we were unable to use structural equation models to assess simultaneously the relative contribution of WM, attention control, and fluid intelligence in the prediction of multitasking (for similar results, see Ackerman & Beier, 2007; Hambrick et al., 2010). Indeed, our attempts to use confirmatory factor analyses resulted in path coefficients not significantly different than 1.0 between WM and multitasking, and fluid intelligence and multitasking latent variables. Thus, we adopted a statistical approach common in the multitasking literature (e.g., Ackerman & Beier, 2007; Hambrick et al., 2010; König et al., 2005), namely, to use regression analyses to analyze the predictors' contributions to variance in multitasking. For the following regression analyses, we created factor composites for each construct. The factor composites were created by separately entering all specified tasks for a construct (e.g., Raven, number series, letter sets, and paper folding for fluid intelligence) into an exploratory factor analysis (principal-axis factor extraction) and specifying a one-factor solution. Factor scores for each subject, for each construct, were then used in subsequent analyses (for similar application, see Unsworth, Redick, et al., 2009). As seen in Table 4, all factor composite correlations were significant.

Table 5 provides the results of correlational and regression analyses with the multitasking factor composite as the criterion, and also each individual multitask as a separate criterion variable. As mentioned previously, our focus in interpreting the relative importance of WM, attention control, and fluid intelligence as predictors of multitasking will focus on the rescaled relative weights. These estimates provide a more interpretable, additive method of decomposing the total variance (R^2) when multicollinearity is present among the predictor variables, compared to hierarchical regression estimates of incremental variance such as ΔR^2 (Tonidandel & LeBreton, 2011). Examining the relative importance of WM, attention control, and fluid intelligence in the prediction of the multitasking construct, specific patterns emerged depending on whether the general multitasking composite or each individual multitasking dependent variable was used as the criterion (Table 5, Figure 3). First, all of the cognitive predictors had significant and moderate-to-strong correlations with the multitasking composite and each individual multitask. In addition, the combination of the cognitive predictors accounted for different amounts of variance in the multitasking criterion variable, ranging from 21% for the control tower primary score to an impressive 70% for the general multitasking composite. Within each multitasking criterion, there were also different patterns of the relative importance of the various cognitive predictors. For the general multitasking composite, examination of the rescaled relative weights showed that the WM and fluid intelligence composites accounted for equal amounts of the variance (39.8% and 38.4%, respectively), and attention control accounted for the remaining one fifth of the variance (21.8%). Thus, the conclusion from the general multitasking composite is that WM and fluid intelligence are equally strong predictors of the common multitasking ability, and both account for significantly more variance than attention control. Looking at the individual multitasks, for SynWin performance and the control tower distract score, WM and fluid intelligence were the strongest predictors, and attention control accounted for significantly less variance (Figure 3, Table 5). However, a different pattern emerged for the control tower primary score and the ATC-lab task. For the control tower primary score, fluid intelligence was the strongest predictor, and WM and attention control accounted for significantly less variance (Figure 3, Table 5). For ATC-lab performance, fluid intelligence accounted for significantly more variance than did attention control, and WM did not significantly differ from either fluid intelligence or attention control.

Table 3. Correlation Matrix for All Measures

Measures	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23
1. Operation span																							
2. Reading span	.64																						
3. Symmetry span	.39	.43																					
4. Rotation span	.40	.47	.58																				
5. Keeping track	.28	.42	.41	.42																			
6. Matrix monitoring	.26	.31	.37	.40	.39																		
7. Continuous counters	.39	.48	.43	.47	.55	.45																	
8. Change detection	.23	.30	.42	.42	.39	.42	.53																
9. Brief report	.30	.28	.25	.28	.24	.24	.26	.27															
10. Antisaccade	-.22	-.24	-.38	-.37	-.32	-.38	-.36	-.34	-.14														
11. Go/No-go d´	.13	.22	.29	.27	.47	.26	.40	.28	.16	-.30													
12. Go/No-go RT ISD	-.14	-.25	-.29	-.32	-.48	-.22	-.43	-.28	-.17	.30	-.70												
13. Spatial Stroop	-.12	-.12	-.15	-.20	-.12	-.12	-.20	-.18	-.15	.22	-.07	.11											
14. Cued visual search	-.11	-.15	-.25	-.22	-.14	-.16	-.22	-.14	-.05	.29	-.20	.22	.20										
15. Cued flankers	-.06	-.18	-.31	-.33	-.35	-.18	-.29	-.23	-.09	.33	-.25	.32	.11	.38									
16. Arrow flankers	-.04	-.02	-.15	-.15	-.04	-.04	-.11	-.07	-.03	.14	-.05	.10	.17	.24	.18								
17. Raven's APM odd	.27	.36	.46	.45	.54	.45	.58	.46	.28	-.39	.40	-.43	-.14	-.27	-.32	-.12							
18. Number series	.32	.34	.43	.45	.40	.44	.50	.40	.30	-.37	.30	-.30	-.07	-.25	-.24	-.09	.57						
19. Letter sets	.30	.34	.39	.38	.42	.39	.43	.34	.24	-.37	.34	-.34	-.18	-.27	-.22	-.08	.48	.55					
20. Paper folding	.26	.31	.40	.34	.28	.35	.35	.29	.17	-.29	.22	-.23	-.16	-.29	-.23	-.09	.44	.42	.39				
21. SynWin	.44	.45	.49	.56	.47	.45	.56	.42	.29	-.47	.38	-.42	-.18	-.28	-.34	-.09	.55	.57	.50	.38			

22. Control tower primary	.22	.25	.33	.29	.25	.27	.22	.28	-.28	.17	-.21	-.09	-.31	-.16	-.09	.29	.41	.41	.26	.35			
23. Control tower distract	.28	.32	.33	.33	.44	.40	.58	.41	.24	-.34	.31	-.31	-.14	-.23	-.27	-.10	.47	.45	.36	.35	.48	.10	
24. ATC-lab	.18	.26	.39	.40	.40	.40	.43	.38	.16	-.38	.27	-.29	-.12	-.19	-.30	-.16	.52	.43	.34	.44	.40	.27	.38

Note. RT= reaction time; ISD = individual standard deviations; APM = advanced progressive matrices ATC-lab; = air traffic control lab. N = 534. All correlations $r \geq .09$ and $\leq –.09$ are significant ($p < .05$).

Table 4. Correlations Among Factor Composites

Composites	WM	ATTN	GF
WM			
ATTN	.57		
GF	.72	.56	
MULTI	.77	.61	.76

Table 5. Regression and Relative Importance Estimates for Cognitive Composites Predicting Multitasking Composite and Individual Multitasks

	Raw importance estimates			
Variables	r	RW	ΔR^2	Rescaled RW
Multitasking composite (total R^2 =.70)				
Working memory	.77	.28[a]	.070*	39.8%
Attention control	.61	.15[b]	.020*	21.8%
Fluid intelligence	.76	.27[a]	.062*	38.4%
SynWin (total R^2 = .54)				
Working memory	.69	.23[a]	.068*	42.1%
Attention control	.55	.12[b]	.019*	23.0%
Fluid intelligence	.65	.19[a]	.033*	34.9%
Control tower primary (total R^2 = .21)				
Working memory	.39	.06[b]	.005*	29.7%
Attention control	.32	.04[b]	.003*	18.5%
Fluid intelligence	.45	.11[a]	.049*	51.7%
Control tower distract (total R^2 = .35)				
Working memory	.56	.15[a]	.047*	43.6%
Attention control	.42	.07[b]	.007*	19.9%

Fluid intelligence	.53	.13[a]	.024*	36.4%
Air traffic control lab (total R^2 = .33)				
Working memory	.50	.11[a,b]	.015*	33.2%
Attention control	.41	.07[b]	.008*	20.7%
Fluid intelligence	.55	.15[a]	.055*	46.1%

Note. RW= raw relative weights; Rescaled RW = rescaled raw relative weights as a proportion of R^2. All zero-order correlations and raw relative weights are significant ($p < .05$). Subscripts indicate relative weights that are statistically different from each other. *$p < .05$.

Structural Equation Models: Working Memory and Attention Control Predictors of Multitasking

Finally, although multicollinearity prevented us from using structural equation models when simultaneously considering all of the cognitive predictors of multitasking, we did test a series of specific structural equation models using the WM tasks and the attention control tasks to predict multitasking. In addition, our interest in examining these specific predictors of multitasking was driven by previous research (Engle, 2002; McVay & Kane, 2012) that proposed that the relationship between WM and higher-order cognition such as fluid intelligence and reading comprehension is primarily due to the shared attention-control processes among WM and attention tasks. Using alternative models, we examined the potential role for attention control to account for the shared variance between WM and multitasking (see Table 6).

We tested a series of structural equation models where multitasking was the criterion and WM and attention control were the predictors (for similar approach with fluid intelligence as the criterion, see Unsworth et al., 2009). Based on modification indices, correlated errors were allowed between (a) operation span and reading span, (b) go/no-go *d*= and go/no-go RT individual standard deviation, and (c) control tower primary and control tower distract scores, for these and all subsequent latent variable models. Although allowing these correlated error terms substantially improved overall model fit indices, the comparison of model fits among models without any correlated errors led to the same conclusion. In Model A (see Table 6), the correlation between WM and attention control, the path from WM to multitasking, and the path from attention control to multitasking were freed. Using Model A as a baseline model, we compared the relative fits of Model B (the path from attention control to multitasking was fixed to 0), Model C (the path from WM to multitasking was fixed to 0), and Model D (the correlation between WM and attention control was fixed to 0) to Model A. As can be seen in Table 6, the fit statistics for Model A were good. More importantly when comparing models, Model A also had a smaller AIC value, and provided a significantly better fit to the data, than Model B, $\Delta x^2(1) = 16.305$, $p < .01$, Model C, $\Delta x^2(1) = 37.805$, p _ .01, or Model D, $\Delta x^2(1) = 217.322$, $p < .01$.

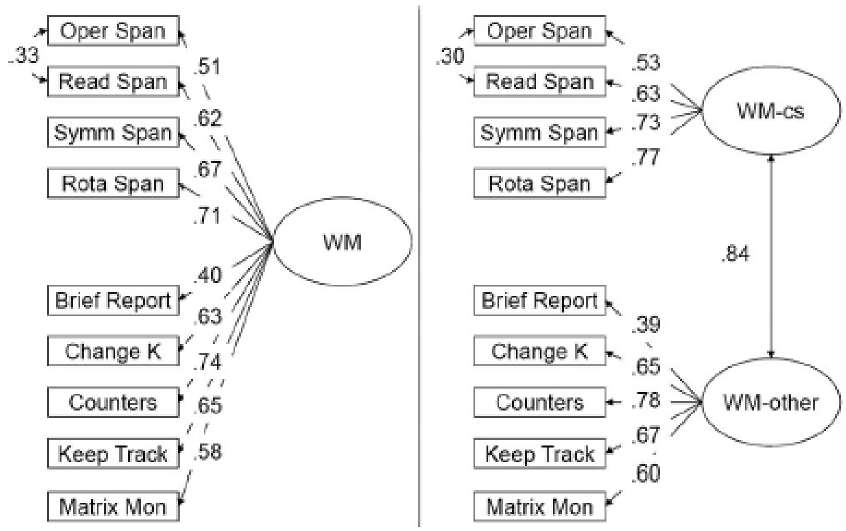

Figure 2. One- (left panel) versus two-factor (right-panel) working memory confirmatory factor analysis models are compared. Numbers appearing next to each manifest variable represent the loadings for each task on the latent variable. Numbers appearing next to the paths connecting the latent variables in the two-factor models reflect the latent-variable correlations. Numbers appearing next to the curved path between operation and reading span reflect the correlated error terms. WM = working memory; WM–cs = complex span working memory tasks; WM–other = working memory tasks that are not complex span tasks.

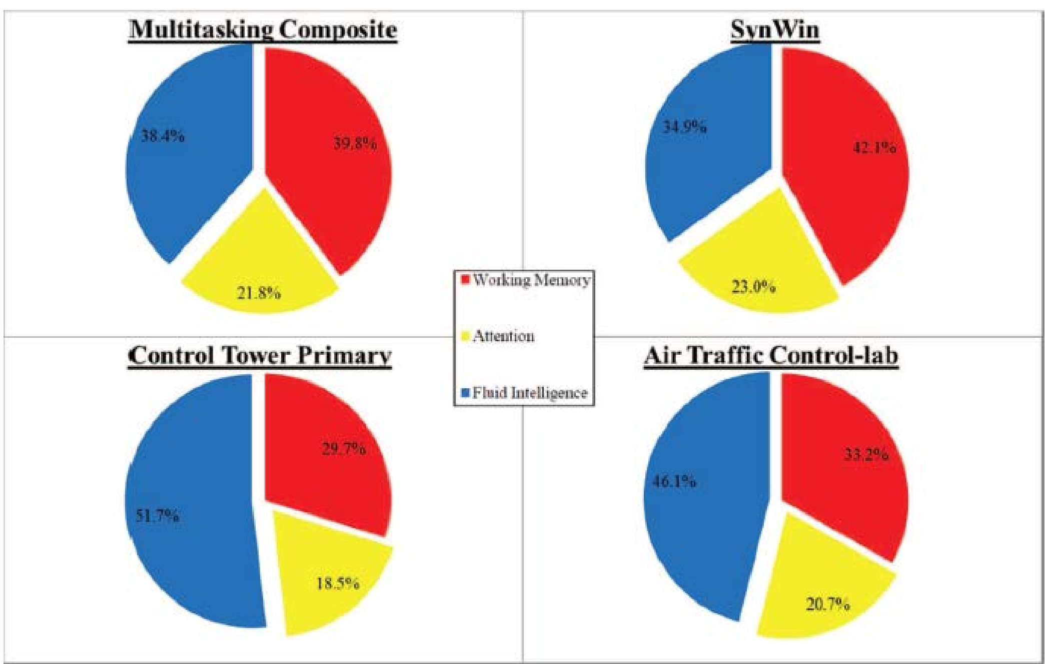

Figure 3. Rescaled relative weights for cognitive predictors of multitasking composite and individual multitasks. See the online article for the color version of this figure.

Finally, a fifth model (Model E) was tested (see Figure 4), in which the variance common to both the WM tasks and the attention control tasks loaded onto one variable, while the WM latent variable was composed of the common variance among the complex span tasks which was independent of the variance shared with the attention control tasks (similar to Unsworth et al., 2009). The fit for Model E was good (see Table 6), and the model is shown in Figure 4. Critically, compared to Model A, Model E had a smaller AIC value.

Table 6. Fit Statistics for Structural Equation Models (SEMs)

Model	χ^2	df	NNFI	CFI	RMSEA	SRMR	AIC
WM, ATTN SEM							
A: WM–multi and ATTN–multi free	497.685	164	.960	.966	.062	.051	7425.814
B: WM–multi free, ATTN–multi fix	513.990	165	.959	.964	.063	.052	7440.119
C: WM–multi fix, ATTN–multi free	535.490	165	.956	.962	.065	.053	7461.620
D: WM–ATTN fix, WM–multi & ATTN–multi free	715.007	165	.935	.943	.079	.154	7641.136
E: Common ATTN, residual WM	465.004	156	.961	.968	.061	.046	7409.134
WM–complex span, scope SEM							
F: One-factor WM	97.699	32	.970	.979	.062	.039	3795.525
G: Two-factor domain (WM–verbal, WM–spatial)	91.599	30	.970	.980	.062	.038	3793.425
H: Two-factor function (WMC)	84.985	30	.974	.982	.059	.037	3786.811
I: Three-factor (WMC–verbal, WMC–spatial, capacity)	83.105	28	.972	.982	.061	.037	3788.931
J: Two-factor function attention mediation	253.967	111	.970	.978	.049	.044	6605.157

Model E (see Figure 4) indicates that although attention control does account for substantial variance in multitasking, other processes that are common only to the WM tasks, are also important for the prediction of multitasking performance. Also, as shown in Figure 4, the loadings of the multitasking manifest variables were all significant, indicating there was sufficient common variance shared across all of the multitasks, independent of method-specific variance or measurement error.

To further explore which aspects of WM may account for the residual WM–multitasking relationship, we tested a structural equation mediation model in which WM capacity (as measured by complex span tasks and abbreviated here with WMC to delineate from previously defined latent variable) had indirect effects through both capacity and attention control to multitasking, and examined whether the direct effect of WMC and multitasking was significant. These analyses are based on multifaceted models of WMC indicating that variation in subcomponents all contribute to individual differences in WMC (Shipstead et al., 2014; Unsworth et al., 2014), and the relationship between WMC and fluid intelligence.

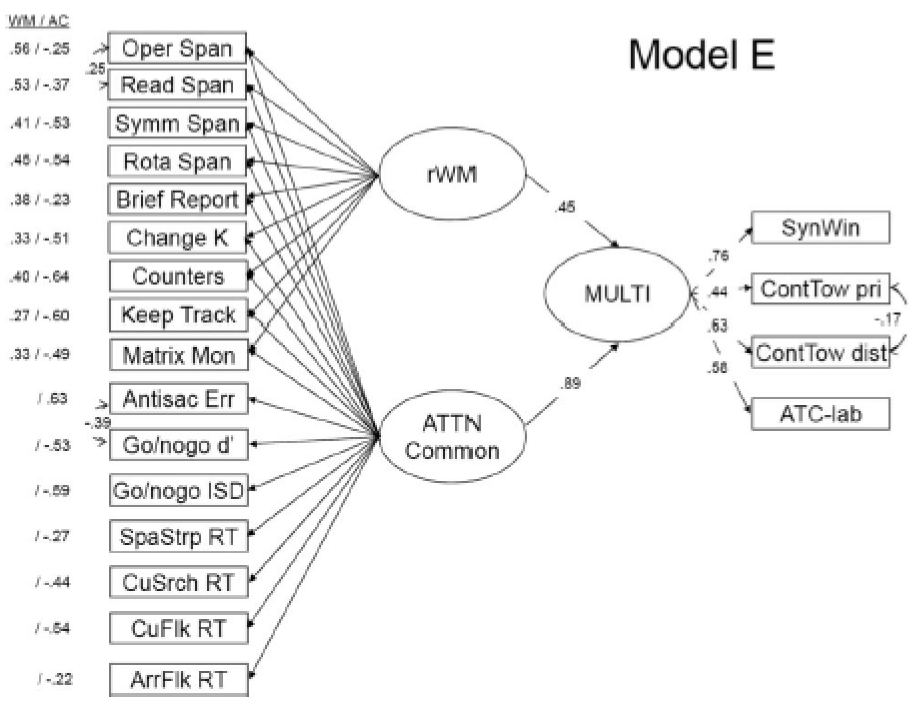

Figure 4. Structural equation models depicting relationships among working memory capacity, attention, and multitasking latent variables. All loadings, path coefficients, and correlations between errors are significant ($p < .05$). rWM = residual working memory variance after accounting for common attention control variance; ATTN common = attention common to all predictors; MULTI = multitasking.

First, we tested alternative models of the complex span (operation, reading, symmetry, rotation span) and capacity (change detection, Sperling brief report) WM tasks, in relation to multitasking (see Table 6). The baseline model (Model F) was a one-factor model in which all six WM tasks loaded onto one factor. We then contrasted the fit of this model with a two-factor model (Model G) based strictly on domain, in which the three verbal tasks loaded onto a verbal WM factor, and the three spatial tasks loaded onto a spatial WM factor; a two-factor model (Model H) with a domain-general WMC factor (with loadings from the four complex span tasks) and a domain-general capacity factor (with loadings from the two capacity tasks); and a three-factor model (Model I) based on domain and function (verbal WMC factor with operation and reading span loadings; nonverbal WMC factor with symmetry and rotation span loadings; capacity factor with change detection and Sperling brief report loadings).

Fit indices, which were good for all models, are provided in Table 6. Compared to the baseline, one-factor model (Model F), and to the two-factor domain model (Model G), the two-factor function model (Model H) had a smaller AIC value, and provided a significantly better fit to the data, than Model F, $\Delta x^2(2) = 12.714$, $p < .01$, and Model G (same degrees of freedom, but smaller χ^2). The three-factor model (Model I) had a larger AIC value and did not fit significantly better than Model H, $\chi^2(2) = 1.880$, $p = .39$, so the structure of Model H was retained for the subsequent mediation analysis.

The mediation (Model J) examined whether capacity and attention control together mediated the WMC–multitasking relationship. Specifically, we constructed a model in which WMC predicted capacity, attention control, and multitasking, and capacity and attention control separately also predicted multitasking. If capacity and attention control mediate the relationship between WMC and multitasking, WMC will significantly predict capacity and attention control, and these two intervening variables will in turn significantly predict multitasking, but the direct path between WMC and multitasking will no longer be significant. The resulting model is shown in Figure 5, and fit statistics, which were good, are provided in Table 6. The critical point to take away from Figure 5 is that full mediation was exhibited—the direct path between WMC and multitasking was not significantly different from 0 after accounting for capacity and attention control. Note that in the model shown in Figure the residual correlation between capacity and attention control is fixed to zero; freeing the residual correlation does not change the model fit or interpretation, given that it was estimated at $r = .07$.

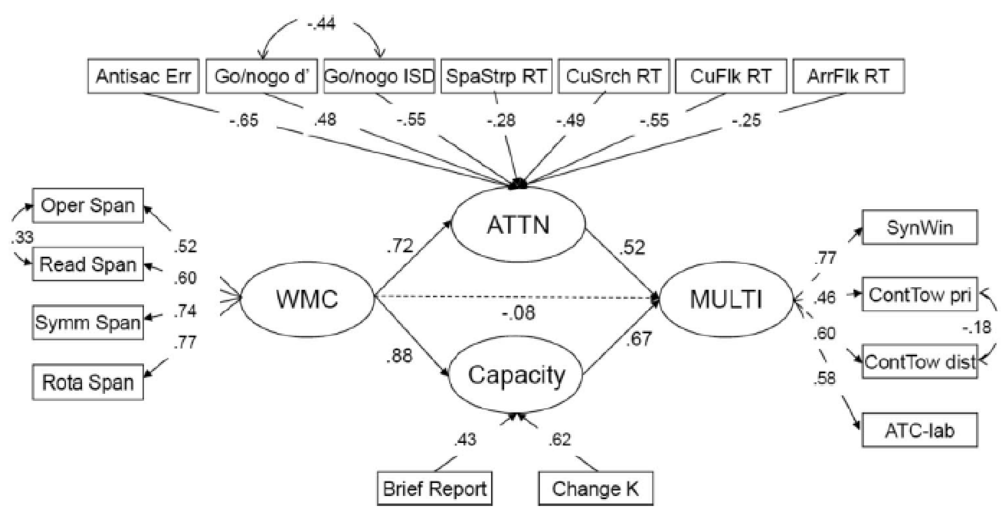

Figure 5. Structural equation model for working memory capacity (WMC), attention control (ATTN), capacity, and multitasking (MULTI). Single-headed arrows connecting latent variables (circles) to each other represent standardized path coefficients. Solid lines are significant (*p* _ .05); note that the capacity-to-multitasking path is only significant when one-tailed, due to a large standard error.

Finally, to investigate whether capacity and attention control could also mediate the relationship between fluid intelligence and multitasking, the same mediation structural equation model was constructed, except that the exogenous WMC factor derived from the four complex span tasks was replaced by a fluid intelligence factor derived from its four manifest variables. The resulting model (not shown) indicated excellent fit, $\chi^2(112) = 268.136$, $p < .01$; NNFI = 0.972; CFI = 0.977; RMSEA = .051; SRMR = .044, AIC = 6,526.336. Critically, and in contrast to the previous model with WMC, the direct path between fluid intelligence and multitasking was still strong (.55), and significant, $t = 2.960$, $p < .05$.

Discussion

The results are discussed below in relation to the four main questions outlined in the introduction.

Question 1: Is There a General Multitasking Ability?

One novel aspect of the current research was the attempt to measure a general multitasking ability using multiple indicators with varied demands and content domain. Previous research examining numerous cognitive predictors of multitasking has used at most two different tests to measure multitasking (Ackerman & Beier, 2007; Colom et al., 2010), but in both cases the tasks were highly similar in terms of content and abilities assessed (air-traffic control scenarios in Ackerman & Beier, 2007, and two visuospatial tasks involving moving colored dots to a particular location onscreen using the same response controls in Colom et al., 2010).

The pattern of correlations among the multitasks ($r = .27$ to .48), along with the moderate-to-high loadings of each multitask on the specified latent variable in the structural equation model (see Figure 4), confirm the presence of a general multitasking ability. Despite the numerous surface differences among the three multitasks, the significant correlations indicate that certain individuals are superior multitaskers across different contexts. This finding fits with recent work on “supertaskers” by Watson, Strayer, and colleagues (Watson & Strayer, 2010; Medeiros-Ward, Watson, & Strayer, 2015). We also note that the zero-order correlations among the multitasks did not approach 1.0, indicating separable but related aspects of multitasking that were tapped by each multitask. This conclusion is similar to that arising from executive function research by Friedman, Miyake, and colleagues (Friedman et al., 2006; Miyake et al., 2000), who observed separate but correlated factors representing different executive functions.

Question 2: What Is the Relative Importance of the Predictors of Multitasking?

Guided by previous research and theories based on individual differences in higher-order cognition, we examined three cognitive constructs – WM, attention control, fluid intelligence—to understand which abilities are most important for multitasking. As expected, WM, attention control, and fluid intelligence were highly related to one another. However, although the correlations between each cognitive predictor and multitasking performance were moderate-to-strong, application of relative importance analysis (via relative weights) revealed that, overall, WM and fluid intelligence accounted for more variance in general multitasking ability than did attention control. Because WM and fluid intelligence accounted for significant unique multitasking variance over and above the variance accounted for by each construct alone, the current results provide further evidence that WM and fluid intelligence are not isomorphic (Ackerman, Beier, & Boyle, 2005), despite the strong relationship between the two constructs (Kane, Hambrick, & Conway, 2005; Oberauer, Schulze, Wilhelm, & Süss, 2005). As multitasking is often used as a means to study the limitations of the human information-processing system (Kahneman, 1973; Meyer & Kieras, 1997), a focus on theories of WM instead of intelligence may provide a more tractable means to understand variations of multitasking performance between and within individuals.

The finding that WM accounts for as much variance in multitasking ability as fluid intelligence has practical implications, too. As suggested by Colom et al. (2010) and Hambrick et al. (2011), organizations whose personnel must perform in multitasking situations may be wise to use WM tests instead of, or in addition to, IQ tests in personnel selection to align employees' abilities with the appropriate occupation. The current data indicate that WM is an equally strong predictor of general multitasking, but it is also noteworthy that the WM tests used here are much shorter in duration than are typical IQ tests. From a practical standpoint, it may be desirable to predict multitasking performance as quickly and accurately as possible using a minimal amount of testing. While we have used multiple indicators to avoid the problems that can arise when using only one task to define and measure a hypothesized construct, in applied research and military settings, it may be necessary to administer as few measures as possible without sacrificing much in terms of predictive validity. Indeed, the recent development of reliable time-shortened measures of WM that have the same predictive utility may be particularly suitable for such applied situations (Foster et al., 2015; Oswald, McAbee, Redick, & Hambrick, 2015).

In the results described thus far, we used only the memory task component (e.g., remembering the order of letters) from the WM complex span tasks as the dependent variable for these tasks, which is the common practice in the literature (Conway et al., 2005). However, accuracy on the processing task (e.g., solving simple math problems) within the WM complex span tasks is also predictive of higher-order cognition (Unsworth, Redick, et al., 2009). If the goal is to predict as much variance as possible in a criterion variable, then including processing task accuracy can contribute additional unique variance. Processing and memory performance on symmetry span accounted for 46.7% of the variance in the general multitasking factor composite, more than any other individual task administered in the current study. Note that symmetry span (a) can be administered in 10–12 min, (b) is entirely automated using only the computer mouse, (c) is automatically scored at the end of the program, and (d) can be compared to the existing norms of thousands of scores obtained over the past 10 years (Redick et al., 2012).

Question 3: Does the Relative Importance of the Predictors Vary by Multitask?

Although WM and fluid intelligence equally contributed to the prediction of general multitasking ability, the results for each individual multitask indicate differential strength of WM and fluid intelligence as a function of the nature of the multitask. First, note that while the three cognitive predictors accounted for 54% of the variance in SynWin, only 21% of the control tower variance was accounted for, indicating that 79% of control tower performance is determined by other factors (see Table 5). Within each multitask, the relative importance of WM and fluid intelligence varied: for SynWin, control tower distract, and ATC-lab, WM and fluid intelligence were equally strong predictors, whereas for control tower primary, fluid intelligence was the stronger predictor. For all multitasks, attention control accounted for significantly less unique variance than fluid intelligence. Consistent with Ackerman and Beier (2007), who found that WM and reasoning alternated as the strongest predictors of performance on two multitasks, the current results provide direct evidence that the manner in which multitasking is operationally defined contributes to the relative importance of different cognitive abilities. Colom et al. (2010) and Hambrick et al. (2010) asserted that WM is a stronger predictor of multitasking than fluid intelligence is, based on the results of their respective studies. The current results show that such assertions may critically depend upon the particular multitasking contexts that serve as criterion variables in a study. Indeed, Sanbonmatsu et al. (2013) observed a negative relationship between operation span performance and *self-reported measures* of frequency of media multitasking and cell phone use while driving. We note that the current SynWin results do nicely replicate Hambrick et al. (2010), which was used as the lone multitasking measure in their study—WM accounts for substantial SynWin variance above and beyond the variance for which fluid intelligence accounts.

The differing relative importance of WM, attention control, and fluid intelligence across multitasks provides information about the cognitive processes that each type of multitasking taps. For example, WM is most strongly related to SynWin performance—one speculative interpretation is that WM is critically important when juggling the cognitive demands of multiple simultaneous, ongoing tasks. A question for future research is to investigate whether the number of ongoing tasks is necessary for WM involvement, or if the cognitive load imposed by SynWin is so taxing that higher levels of WMC are critical for an individual to avoid mind-wandering or lapses of attention that are critical for avoiding performance decrements (McVay & Kane, 2009; Unsworth, Mc-Millan, Brewer, & Spillers, 2012). Moreover, because our three multitasks differed from one another along multiple dimensions, testing hypotheses about the critical features predicted by different abilities will require designing multiple multitasks for each ostensible feature of interest. For example, to test whether the predictors of SynWin and control tower differed because SynWin presented four simultaneous subtasks whereas control tower presented a primary task interrupted by distractors, a future study would need multiple multitasks that presented several simultaneous subtasks and multiple multitasks that presented a primary task interrupted by distractors.

Question 4: How Similar Are Individual Differences in Various WM Measures?

A final question addressed the nature of the WM construct. Namely, at the latent level, how similarly do complex span tasks and other types of tasks measure individual differences in WM?

We observed moderate-to-strong correlations (see Table 2) among the complex span tasks (r = .39 to .64) and among the noncomplex span tasks (r = .24 to .55), as well as across the categories of WM tasks (r = .23 to .47). The confirmatory factor analyses (see Figure 2) revealed that a two-factor model statistically fit better than a one-factor model, although the correlation between the WM factors was strong, indicating the two latent variables shared 71% of their variance. In the interest of parsimony, we endorsed the one-factor model given the high degree of shared variance among the complex span and noncomplex span tasks, consistent with prior research (e.g., Broadway & Engle, 2010; Colom et al., 2006; Schmiedek et al., 2009).

One issue with previous studies of WM and multitasking is that the WM tasks were often dual tasks themselves, and thus our WM composite comprised both complex span and noncomplex span tasks reflects the variance common across tasks regardless of the method-specific variance. In addition, we conducted a supplemental analysis with separate WM composites (complex span and noncomplex span tasks). Critically, the WM composite based on noncomplex span tasks accounted for significant multitasking variance, indicating that previous studies that used only complex span tasks to represent WM did not observe strong relationships with multitasking solely because of the dual-task nature of complex span tasks.

Finally, the structural equation models (Figures 4, 5) with the WM, attention control, and multitasking tasks were both consistent and inconsistent with previous research using fluid intelligence as the criterion (Shipstead et al., 2012; Unsworth et al., 2009, 2014). Namely, the variance that is common to both WM and attention control tasks accounted for significant variance in general multitasking ability, but the residual variance unique to WM tasks also accounted for significant multitasking variance (see Figure 4). This result is similar to the fluid intelligence findings of Unsworth et al. (2009), who tested the same series of models and came to a similar conclusion about the role of attention control to account for some, but not all, of the WM–fluid intelligence relationship (note also the similarity between these models and the executive function literature—e.g., Friedman et al., 2008—who also observed significant relationships between common and unique executive function latent variables and intelligence).

Because residual WM still accounted for significant multitasking variance, even after removing the variance common to the WM and attention control tasks, the implication is that other WM processes are also important for successful multitasking performance. Therefore, we tested a structural equation mediation model examining whether capacity and attention control fully mediated the WM–multitasking relationship. In contrast to previous work demonstrating that capacity and attention control only partially mediate the WM–fluid intelligence relationship (Shipstead et al., 2014; Unsworth et al., 2014), the current results showed that the WM–multitasking relationship was fully mediated when accounting for capacity and attention control (see Figure 5).

A limited-capacity buffer is part of many influential WM theories, although it goes by different labels in different models: capacity (Fukuda, Awh, & Vogel, 2010); focus of attention (Cowan et al., 2005); primary memory (Shipstead et al., 2014; Unsworth & Engle, 2007); and region of direct access (Oberauer, Süβ, Wilhelm, & Sander, 2007). The mediation results indicate that the specific processes that make WM important for successful multitasking are the ability to actively maintain a number of task goals to guide behavior, and the ability to control attention to the currently relevant task. Critically, in support of the idea that WMC and fluid intelligence are closely related but not isomorphic (Heitz et al., 2006; Kane et al., 2005; Oberauer et al., 2005; but see Martínez et al., 2011), although the WMC–multitasking relationship was mediated by the subcomponents capacity and attention control, the fluid intelligence–multitasking relationship was still significant even after accounting for capacity and attention control. So, although WM and fluid intelligence contribute similarly to general multitasking, in terms of the absolute magnitudes, the mechanisms underlying their contributions vary.

Limitations and Future Directions

We note that despite the many strengths of our current approach to study multitasking, future work should address shortcomings identified here. First, although the mediation results give some specificity to the nature of the WM–multitasking relationship, future work could bring further clarity to why the other cognitive predictors account for multitasking variance. For example, a further decomposition of attention control may identify that selective, divided, or sustained attention is the critical attention component driving its relationship with multitasking. In addition, although the current work indicates that retrieval from secondary memory is not necessary to fully account for the WM–multitasking relationship, there could be multitasking situations where such processing is critical for successful performance. For example, the Edinburgh Virtual Errands Test used as a multitask in Logie et al. (2011) requires participants to remember the necessary errands to complete while navigating through a virtual environment. It seems that variation in an individual's ability to quickly and accurately retrieve information from secondary memory would be an important determinant of overall performance on the Edinburgh Virtual Errands Test, and indeed, immediate free recall was a significant predictor of multitasking performance in Logie et al. (2011). Thus, although we did not include measures of secondary memory in the current study, future work should include such measures to fully understand how individual differences in retrieval contribute to WM's relationship with multitasking.

Our approach focused on the aggregate scores on each multitask, to create a common multitasking factor across different multitasks. However, research analyzing a specific multitask, and examining performance on all of its subtasks in-depth, can be valuable in gaining further knowledge about particular multitasking situations. Examples in the literature include the detailed analyses of SynWin by Hambrick et al. (2010) and the Edinburgh Virtual Errands Test by Logie et al. (2011).

In addition, we note that although we measured multitasking broadly by using multiple indicators, we examined performance on each task with relatively little practice. Given the substantial literature on skill acquisition that demonstrates that the prediction of multitasking performance varies as a function of the amount of experience on the task (Ackerman, 1987, 1988), future work should examine if the patterns of relative importance and the amount of multitasking variance accounted for by the cognitive predictors are different after extensive multitasking practice. One could argue that labeling the ATC-lab task a "multitask" is a misnomer—compared to SynWin and control tower, the subject does not alternate between different tasks, but rather the subject must switch among different groups of planes, and different dimensions of their flight paths, in monitoring each display. However, ATC-lab performance was still significantly correlated with SynWin performance (r = .40) and the primary score from the control tower task (r = .27), suggesting an association between the kind of mental timesharing demanded by ATC-lab and that demanded by switching among discrete tasks in SynWin and control tower. Our use of ATC-lab was motivated by the desire to have a military-relevant, complex task, as in previous multitasking research (e.g., Ackerman & Beier, 2007), but future research using a more high-fidelity air-traffic control measure that requires the operator to switch between different kinds of tasks would be informative. Our results also do not speak to the underlying neural mechanisms involved in multitasking, including the intriguing result in previous work demonstrating that brain-injury patients and controls who showed equivalent fluid intelligence (as indexed by Raven's progressive matrices) nevertheless showed strikingly different profiles of multitasking performance (Burgess, Veitch, de Lacy Costello, & Shallice, 2000).

Finally, gender differences in multitasking have been a topic of great interest in the literature in recent years (e.g., Hambrick et al., 2010; Mäntylä, 2013; Stoet, O'Connor, Conner, & Laws, 2013; Strayer, Medeiros-Ward, & Watson, 2013). Although our study was not designed with the goal of examining gender differences, because our sample was so large and included a number of different multitasks, we have included gender analyses for the interested reader (see Table S1 in online supplementary material). None of the gender comparisons reach conventional statistical significance, and the effect sizes for all of the multitasking dependent variables fall below d = .20, which is the cutoff for an effect to be considered "small" (Cohen, 1992). Thus, gender differences in multitasking ability in the current sample are minimal, consistent with previously published work with the WM complex span tasks (Redick et al., 2012).

Conclusion

In a large sample of young adults, we observed strong relationships among WM, attention control, fluid intelligence, and multitasking. Although the three multitasks differed greatly in their task characteristics and demands, a multitasking construct of the variance common to the three tasks was identified. Although WM and fluid intelligence emerged as the constructs accounting for the most multitasking variance compared to attention control, the magnitude of the relationships among the cognitive abilities and multitasking varied as a function of the complexity and structure of the particular multitasking criterion. Finally, when analyzing the subcomponents of individual differences in WM that are critical for multitasking, we found that capacity and attention control fully mediated the WM and multitasking relationship.

Footnotes

[1] Note that Data Set A in Shipstead et al. (2012) is from the current study, and contained analyses specifically on the trial types within the change detection task in relation to WM and fluid intelligence. Unsworth et al. (2015, Experiment 2) contains analyses of a questionnaire about video game experience in relation to many of the tasks presented here. Otherwise, the data in the current study have not been previously published.

[2] In addition to the measures described here, three other measures were administered but removed from the final analyses. Math access (Oberauer, 2002; Salthouse, Babcock, & Shaw, 1991) was included as a measure of WM–updating, but due to a programming error, some trials had totals that violated the rules given to subjects (e.g., final counts were negative or greater than 10). A spatial delayed-match-to-sample task (Rowe, Toni, Josephs, Frackowiak, & Passingham, 2000; Rowe & Passingham, 2001) was included as a measure of WM–maintenance, but subjects had difficulty understanding the instructions, and the scoring method (mean squared error deviation from the correct location in the *x* and *y* planes) yielded widely varying values exceedingly higher than those obtained by subjects in Rowe and Passingham (2001). Finally, we also administered a non-adaptive version of the dual *n*-back (Jaeggi et al., 2007) as a measure of multitasking, but excluded the task from analyses because there was a relatively high rate of non-responders on the task. That is, out of the 530 subjects for which dual *n*-back data are available, 78 subjects (15% attrition) never made a button response to the auditory and/or visual component of the task. We are not sure why this task had such a high rate of nonresponse.

[3] Our initial intent with this category of tasks was to separately measure updating and maintenance to further elucidate the contributions of WM to the prediction of multitasking. However, initial analyses suggested very strong relationships among the intended updating and maintenance tasks, indicating there were measuring largely overlapping processes. In hindsight, given the results of other research using these tasks as either measures of WM or updating (Cowan et al., 2005; Engle et al., 1999; Poole, 2012), the lack of discriminant validity between the intended updating and maintenance tasks is not surprising. Therefore, in our analyses examining the WM construct, we combined the intended updating and maintenance tasks into a WM composite separate from the complex span tasks.

[4] Upon completion of all tasks, subjects were offered the opportunity to provide a saliva sample for genetics testing and an additional $10. The genetics collection was not mentioned during recruitment or until all behavioral tasks had been completed, and collection occurred at the Georgia Tech, University of Georgia, and University of North Carolina—Greensboro about halfway through data collection at each site. The genetics results are therefore not included in the current manuscript.

[5] We tested a second series of models without the correlated error terms, to ensure that including the correlated error term did not dramatically alter the conclusions of the comparison of the one- versus two-factor structure. The fit of the one-factor model was good, $\chi^2(27) = 227.998$, $p < .01$; NNFI = 0.910; CFI = 0.932; RMSEA = .118; SRMR = .059, AIC = 3,436.788. In comparison, the fit of the two-factor model with no correlated error term was also good, $\chi^2(26) = 160.299$, $p < .01$; NNFI = 0.937; CFI = 0.955; RMSEA = .098; SRMR = .050, AIC = 3,371.089. As in the models with the correlated error terms, the fit of the two-factor model was significantly better than the fit of the one-factor model, as evidenced by the smaller AIC value and significant chi-square test, $\Delta x^2(1) = 67.699$, $p < .01$. The correlation between the WM factors was .82 (95% CI [.79, .85]), indicating that the WM factors shared 67% of their variance, a result that was very similar to the model with the correlated error term. Thus, the inclusion of the correlated error term does not change the interpretation of the two models.

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