Title: Ultra-brief Ambulatory Assessment of Working Memory Capacity via Smart
Phones

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ABSTRACT

The development of mobile technology with substantial computing power (i.e. smart phones) has enabled the adaptation of performance-based cognitive assessments to remote administration and novel intensive longitudinal study designs (e.g. measurement burst designs). While an “ambulatory” cognitive assessment paradigm provides new opportunities to extend current psychological theories, the adaptation of conventional measures to a mobile format conducive to intensive repeated measurement involves balancing measurement precision, administration time, and procedural consistency. Across 3 studies, we developed mobile adaptations of computerized ‘complex span’ tasks to assess working memory capacity (WMC) and examined their validity, reliability, and sufficiency. Study 1 examined the convergent and criterion validity of a single administration of 3 ultra-brief complex span tasks on smart phones in a laboratory setting (ambulatory Operation Span, Symmetry Span, and Rotation Span tasks). Study 2 adapted the ultra-brief tasks to a 4-day measurement burst design where between- and within-person reliability was assessed over 16 repeated administrations (4 assessments/day). Study 3 involved the implementation of a single ultra-brief complex span task into a 7-day measurement burst design field study involving college students (5 assessments/day). Results of these 3 studies suggest that valid and highly reliable estimates of WMC can be obtained via smart phones, in the absence of intensive onboarding/training, in 3-6 minutes of total testing time (2 ultra-brief, mobile administrations). Considerations for future mobile cognitive assessment design and parameterization are discussed.

Keywords: EMA, mobile cognitive assessment, working memory capacity, measurement burst design

INTRODUCTION

The proliferation of mobile technology with substantial processing power has enabled a significant leap forward for intensive longitudinal study designs aiming to examine psychological and behavioral processes under naturalistic circumstances. This active area of research is often referred to as ecological momentary assessment (EMA) and leverages pervasive mobile technology (e.g. tablets and smart phones) to study how these processes, which have most often been well-studied under controlled, laboratory conditions, unfold over the course of daily life (Heron, Everhart, McHale, & Smyth, 2017; Shiffman, Stone, & Hufford, 2008). Recently, the translation of computerized cognitive assessments to administration on mobile devices has increased the potential for integrating performance-based measures of cognition into EMA study designs (Scott et al., 2015; Sliwinski et al., 2018). This emerging paradigm, often referred to as ‘mobile’ or ‘ambulatory’ cognitive assessment offers an opportunity to deploy studies of cognition at scale (through remote, phone- or tablet-based administration) and study the role of cognitive variation in processes that unfold over multiple timescales. Existing web- and mobile application-based platforms have confirmed the feasibility and validity of remote delivery in various populations (Allard et al., 2014; Koo & Vizer, 2019; Lee et al., 2012). However, a major hurdle in adapting performance-based assessments of cognition to intensive study designs involves the need to conform task/assessment parameters to unsupervised, ultra-brief administrations. In the current report, we present the results of three studies examining the feasibility of integrating “complex span” task assessments of working memory capacity (WMC) into intensive longitudinal study designs on mobile phones.

WMC describes an individual’s ability to maintain information in short-term memory while processing ongoing or new information (Engle, 2002). WMC is often approached as a domain-general cognitive construct indicated by performance on ‘complex’ short-term memory

span tasks covering multiple stimulus domains (e.g., verbal, visual, spatial; Kane et al., 2004). Individual differences in WMC are strongly associated with reasoning ability/fluid intelligence (Gf; Conway, Kane, & Engle, 2003; Kyllonen & Christal, 1990), indicators of attention and executive control (Engle, 2002; Kane & Engle, 2002; Redick, 2013; Unsworth, McMillan, Brewer, & Spillers, 2012), and the ability to retrieve information displaced from the focus of attention (Unsworth, Fukuda, Awh, & Vogel, 2014).

Recent applied research also suggests that WMC may play an important role in goal-directed behavioral processes. For example, in lab-based experiments, individuals with higher WMC have been shown to exhibit more successful self-regulation (e.g. behave more consistently with stated behavioral standards; Hofmann, Friese, & Roefs, 2009; Hofmann, Friese, & Wiers, 2011). In addition, studies linking lab-based assessment of WMC with EMA of stress-related processes indicate that individual differences in WMC may predict negative affective responses to stressor exposures over the course of daily life (Garrison & Schmeichel, 2020). Critically, these examples of work connecting WMC to complex behavioral processes are based on single lab-based assessments of WMC, which has limited examination of the role of WMC in these processes to the level of inter-individual differences. Recent evidence suggests that WM function may vary substantially within-individuals within- and between-days (Brose, Schmiedek, Lövdén, & Lindenberger, 2012; Riediger et al., 2014; Sliwinski, Smyth, Hofer, & Stawski, 2006), and the development of ambulatory assessments of WMC would enable investigations into the role of intra-individual variation in WMC in processes that unfold over time (e.g., behavior change processes; Hall & Fong, 2007).

Intensive longitudinal study designs represent a powerful framework for examining within-person processes (Bolger & Laurenceau, 2013). However, several validation steps and design considerations need to be taken into account to bridge well-studied experimental models to field-based research. WMC is most commonly assessed through automated, computerized administration of complex span tasks (Redick et al., 2012). The automated tasks begin with standardized instructions, opportunities for practice with each task phase (study item, secondary task, recall screens), and calibration of experimental parameters. Following this initial phase, a pre-determined number of trials at varying levels of set-size (# of study item-secondary task pairs) are administered. Primary outcomes for each complex span task are automatically generated and include estimated span scores, which are determined through one or more conventional scoring procedures (e.g. full- or partial-credit scoring; Redick et al., 2012).

While automated versions of these tasks offer a high degree of standardization across studies/labs, lengthy administration times (e.g. ~20-25mins per task) often discourage applied researchers from administering more than one task, despite the demonstrated utility of the multi-indicator/latent factor approach to WMC (Oswald, McAbee, Redick, & Hambrick, 2014). In view of promoting broader adoption of a multi-indicator approach, abbreviated versions of the automated tasks were recently validated, which greatly reduce administration times (Foster et al., 2014; Oswald et al., 2014). Results of these validation projects suggest that administration of fewer set-sizes and fewer trials per set-size, while retaining a multi-indicator approach (i.e. multiple tasks/stimulus modalities), yields valid and reliable estimates of WMC. Despite the reduction in administration time associated abbreviated tasks, the estimated 30-45mins of total administration time is still not ideal for repeated administration in intensive repeated measures designs.

Intensive longitudinal study designs commonly used in EMA research, such as the “measurement burst design,” involve sampling multiple times per day over multiple days in view of generating a rich description of contexts, behavior, or experiences under study (Nesselroade, 1991; Stawski, MacDonald, & Sliwinski, 2015). By deploying brief momentary assessments via mobile technology, information about context, behavior, and experience can be gathered as it occurs under naturalistic circumstances. This design offers several advantages over single or more periodic assessments. Sampling in close temporal proximity to an event or behavior may help reduce retrospective bias and other forms of confounding common to self-report methods (e.g. schematic responding), develop a more accurate description of experience through aggregation of momentary data, and allow researchers to unravel time-dependent associations between factors under study (Smyth & Stone, 2003). In addition, when repeated over time, measurement burst designs offer the ability to simultaneously monitor change at multiple timescales (moment-to-moment, day-to-day, year-over-year; Sliwinski, 2008).

The measurement advantages associated with EMA may also extend to ambulatory performance-based assessments of cognition. Aggregation of data over many ambulatory cognitive assessments can mitigate the influence of a single episode of poor or inspired performance, which may otherwise misrepresent an individual’s overall, average ability (i.e. reduce the impact of temporal sampling error; Salhouse & Nesselroade, 2010). The increased ecological validity associated with completing assessments in the context of a person’s natural environment (e.g. at home) may reduce negative effects of novel testing conditions (e.g. clinic, lab). High frequency cognitive assessments may provide valuable insight into cognitive development and disease by revealing the degree to which cognition systematically varies over moments, days, and contexts (Sliwinski, 2008). Finally, ambulatory cognitive assessment

promises the ability to liberate assessment procedures from the laboratory/clinic context and reach participant populations geographically separated from these resources and assessment opportunities (i.e. improve the generalizability of research by bringing data collection to participants, rather than the other way around). Achieving the goal of implementing performance-based assessments into EMA research designs, however, requires the ability to obtain valid and reliable estimates of cognition in just a few minutes through ultra-brief adaptations of cognitive testing paradigms. In the current set of studies, we sought to evaluate whether ultra-brief adaptations of complex span tasks could provide valid and reliable span estimates of WMC under different study design parameters and constraints.

This report is organized as follows. In the first study, we describe the results of a validation study designed to examine whether ultra-brief adaptations of the Operation Span, Symmetry Span, and Rotation span tasks can be administered on smart phones and provide valid estimates of WMC. In the second study, we describe the results of a measurement burst design study where we assessed the between- and within-person reliability of the three complex span tasks and composite WMC across intensive repeated administrations occurring over four days. In the last section, we describe the results of an EMA field study involving an ultra-brief Rotation Span task to illustrate task psychometrics in a context where participants received minimal in-lab practice/training with the task procedures.

STUDY 1

In Study 1, we conducted a cross-sectional study of performance on automated full-length Operation Span, Symmetry Span, and Rotation Span tasks and delayed performance on smart phone-based ultra-brief adaptations of each task (an average of 3 days later in a separate session). To determine the convergent validity of the ultra-brief tasks, we examined correlations

between point-estimates of performance on each task across administration modalities as well as the fit of latent factor models under different structural assumptions (one-factor, hierarchical two-factor). In addition, we examined the criterion validity of the ultra-brief tasks by fitting a measurement model including a fluid intelligence (Gf) factor indicated by performance on two reasoning tasks.

METHODS

Participants

A total of 132 younger adults (age $M = 19.12$, $SD = 1.05$, range = 18-23; 72% female) participated in the study. Participants were recruited from Pennsylvania State University's psychology undergraduate research pool. All participants provided written informed consent and received course credit for their participation. All experimental procedures were approved by Pennsylvania State University's Institutional Review Board for the ethical treatment of human participants.

Materials and Procedure

Experimental Measures

Participants completed three full-length, automated complex span tasks (Operation Span, OSpan; Symmetry Span, SSpan; and Rotation Span, RSpan) and two reasoning tasks (Ravens Progressive Matrices, RAPM; Letter Sets Task, Letters) in a 90-minute lab session. Tasks were administered in a fixed order across all participants: OSpan, SSpan, RSpan, RAPM, Letters. Following the initial lab session, participants were scheduled to return to the lab for a brief session, an average of 3 days later (range 2-4), where ultra-brief versions of the OSpan, SSpan, and RSpan tasks ("amb-OSpan," "amb-SSpan," and "amb-RSpan," respectively) were

administered on a lab-provided smart phone (Samsung Galaxy S5; Samsung Electronics, Seoul, South Korea).

Full-length Complex Span Tasks

Operation Span task (OSpan): OSpan involved memorizing a single letter at a time while performing interleaved arithmetic operations. After memorizing a set of letters and completing the interleaved arithmetic operations, participants were asked to recall all of the letters memorized throughout the current trial in order. Trials randomly varied in set-size. Set sizes (# of total letters tested on each trial) ranged from 3-7 with three repetitions of each set size throughout the task. The total number of item-operation pairs was 75.

Symmetry Span task (SSpan): involved memorizing highlighted locations in a 4×4 matrix one at a time while performing interleaved symmetry judgments on 8×8 mosaic pattern stimuli that were either symmetrical or non-symmetrical along the vertical axis. After memorizing a set of locations and completing the interleaved symmetry judgments, participants were asked to recall all of the spatial locations from the 4×4 matrices memorized throughout the current trial in order. Trials randomly varied in set-size. Set sizes (# of total locations tested on each trial) ranged from 2-5 with three repetitions of each set size throughout the task. The total number of location-symmetry pairs was 42.

Rotation Span task (RSpan): involved memorizing oriented arrows one at a time while performing interleaved mental rotation judgments on letter stimuli that were either forward or backward facing if oriented back to standard typeface orientation. Study arrows were oriented at 45deg increments around an invisible clock-face and were either short or long in total length, allowing for 16 possible orientation-length combinations. After memorizing a set of arrows and

completing the interleaved mental rotation judgments, participants were asked to recall all of the oriented arrows memorized throughout the current trial in order. Trials randomly varied in set-size. Set sizes (# of total arrows tested on each trial) ranged from 2-5 with three repetitions of each set size throughout the task. The total number of arrow-rotation pairs was 42.

Automated Task Procedures and Scoring: Each automated task contained self-guided instructions, practice, and timing parameters customized to the participant (for a full description of the development, parameters, and reliability of these automated procedures, see Conway et al., 2005; Redick et al., 2012). Each automated task was scored according to the partial-trial scoring method. The partial-trial scoring method involves counting each item recalled from memory regardless of whether all items within a trial were recalled. The partial-trial scoring method was selected to equate scoring methods between full-length and ultra-brief versions of the tasks, where only 3 trials were administered in the latter.

Reasoning Tasks

Ravens Advanced Progressive Matrices (RAPM): involved evaluating 3×3 matrices of patterned tiles with a tile missing in the lower right-hand corner of each matrix. For every matrix, participants were asked to select a sample tile from 8 possible choices located at the bottom of the screen that they believed would best complete the overall pattern present in the matrix (patterns included horizontal and vertical progressions). Participants were given 10 minutes to complete as many matrices as possible before the assessment timed-out. Number of correct responses obtained over the course of the 10 minutes served as the RAPM score.

Letter Sets (Letters): involved evaluating 5 groups of 4 letters each with a pattern/rule governing the association among 4 of the 5 groups. For every set of letters participants were asked to select

the group that violated the pattern/rule implied by the other 4 groups. Participants were given 10 minutes to complete as many sets as possible before the assessment timed-out. Number of correct responses obtained over the course of the 10 minutes served as the Letters score.

Ultra-brief Complex Span Tasks

Ultra-brief, smart phone-adapted versions of the full-length, automated complex span tasks used in Study 1 were programmed using Qualtrics survey software (Qualtrics, Provo, UT) and administered using the Qualtrics ‘Offline Surveys’ smart phone application (Qualtrics, Provo, UT) installed on the investigator-provided Samsung Galaxy S5 phones. The ultra-brief tasks were presented in a fixed order across participants, consistent with the order of the full-length task presentation in the first session: amb-OSpan, amb-SSpan, amb-RSpan. Participants completed 3 trials of each task, one at each set-size. Set-sizes for the amb-OSpan task ranged from 4-6 and set-sizes for the amb-SSpan and amb-RSpan tasks ranged from 3-5. The scale of set-sizes selected for the ultra-brief tasks (i.e. higher set-sizes for amb-OSpan than the other two tasks) was set to reflect the scale of the full-length tasks (see above). The ultra-brief tasks contained no practice phase and included only an instruction screen which reminded the participants of the respective task procedures. Due to limitations in the degree to which set-size randomization could be achieved using Qualtrics, within each task, set-sizes were presented in a pseudorandomized and counter-balanced order across all participants. Participants logged responses using the touch screen (see Figure 1).

Figure 1. Smart Phone-adapted Complex Span Tasks. (A) Ultra-Brief Rotation Span task (“amb-RSpan”). (B) Ultra-Brief Operation Span task (“amb-OSpan”). (C) Ultra-Brief Symmetry Span task (“amb-SSpan”). Images presented in the figure are screen captures of each task as presented via the Mobile Monitoring of Cognitive Change (“M2C2”) mobile application used in Studies 2 and 3.

Statistical Analyses

Confirmatory factor analyses and Structural Equation Modeling (SEM) Analysis used the Mplus software package (version 8.1; Muthén & Muthén, 2011) using maximum likelihood estimation.

Factor goodness of fit was evaluated using chi-square fit statistics, root mean square error of approximation (RMSEA), standardized root mean squared residual (SRMR), and comparative fit indices (CFI). Non-significant chi-square values, RMSEA values equal to or lower than 0.08, SRMR equal to or lower than 0.08, and CFI above 0.9 generally serve as indications of good fit (Hu & Bentler, 1999; Kline & B., 2005). All fit indices were considered when determining goodness of fit.

RESULTS

Descriptive Statistics

Means, standard deviations, and first-order correlations between each task can be found in Table 1. Significant correlations were observed between each of the full-length complex span tasks and respective ultra-brief phone-based tasks (e.g. OSpan and amb-OSpan; $r = 0.40-0.57, p < 0.05$). Generally, ultra-brief tasks were significantly correlated with non-matching domain full-length tasks (e.g. SSspan and amb-RSpan). However, a marginal correlation was observed between OSpan and amb-SSpan ($r = 0.15, p = 0.086$).

Table 1 about here

Convergent and Criterion Validity of Ultra-brief Tasks

To examine the validity of the ultra-brief, phone-based tasks two alternative measurement models were considered: Model 1 included a one-factor representation of WMC where the ultra-brief and full-length tasks were all considered as indicators of the same latent WMC factor, and Model 2 included a hierarchical factor representation where two latent factors (lab-WMC and amb-WMC) were indicated by respective full-length in-lab tasks and ultra-brief phone-based

tasks. In Model 2, lab-WMC and amb-WMC were modeled as latent indicators of a super-ordinate WMC factor. In each model, a latent reasoning (Gf) factor was included, indicated by RAPM and Letters, and correlations between Gf and the highest level WMC factors were estimated. Both models exhibited good fit to the data (Model 1: (X^2 [18] = 25.489, p = 0.011; RMSEA = 0.056, 90% CI = 0.000-0.103; SRMR = 0.049; CFI = 0.967); Model 2: (X^2 [16] = 24.241, p = 0.084, RMSEA = 0.062, 90% CI = 0.000-0.110; SRMR = 0.049; CFI = 0.964). In each case, consistent with previous research, WMC was highly associated with Gf (see Figure 2).

Figure 2. Convergent and Criterion Validity Measurement Models. (A) Model 1, one-factor model of WMC indicated by full-length in-lab and ultra-brief phone-based complex span tasks. (B) Model 2, hierarchical factor model of WMC indicated by two subordinate latent WMC factors representing full-length in-lab complex span tasks (lab-WMC) and ultra-brief phone-based complex span tasks (amb-WMC). WMC = Working Memory Capacity; Gf = fluid intelligence.

Sensitivity Analysis

Ceiling effects were observed in performance at the lowest set-sizes for each ultra-brief task (set-size 4 for amb-OSpan; set-size 3 for amb-SSpan and amb-Rspan). For set-size 4 of the amb-OSpan task 93% of all observations were at ceiling, for set-size 3 of the amb-SSpan task 74% of all observations were at ceiling, and for set-size 3 of the amb-Rspan task 70% of all observations were at ceiling. Performance on higher set-size trials yielded less skewed distributions. The

inclusion of low set-size trials was consistent with standard procedures for the automated full-length tasks. However, given the observation of ceiling performance on these trials, we conducted a follow-up sensitivity analysis to examine the fit of models removing the lowest set-size trial from each ambulatory task. We conducted a sensitivity analysis replicating Model 1, replacing ultra-brief assessment scores with performance on only the two higher set-size trails. This revised version of Model 1 exhibited good fit to the data ($\chi^2 [18] = 29.727, p = 0.04$, RMSEA = 0.07, 90% CI = 0.015-0.114; SRMR = 0.058; CFI = 0.940). Factor loadings and correlation between WMC and Gf in the revised model were highly consistent with Model 1 (all observed loadings and correlations were within 0.05 of Model 1 parameters).

INTERIM DISCUSSION

The results of Study 1 suggest that valid estimates of complex span task performance and WMC can be obtained via ultra-brief assessments performed on smart phones. Ambulatory adaptations of Operation Span, Symmetry Span, and Rotation Span tasks exhibited good construct validity in the measurement models. In addition, latent WMC factors indicated directly or by second-order relations to ambulatory task performance exhibited strong associations with a latent Gf factor, indicating strong criterion validity.

We examined two alternative measurement models in Study 1. In the first model, direct comparisons can be made between standardized factor loadings for full-length and ultra-brief, ambulatory tasks. Results of this model suggested that full-length administrations of Operation Span and Symmetry Span tasks are stronger indicators of WMC than the ambulatory counterparts. On the other hand, factor loadings for ambulatory Rotation Span were directly

comparable across formats. In addition, the rank order of task factor loadings as indicators of WMC was consistent across in-lab and ambulatory versions.

The second measurement model was designed to ensure that the criterion association between WMC and Gf was not biased by the presence of the previously validated full-length tasks as indicators of the single WMC factor. In order to dissociate the contribution of the full-length and ultra-brief formats, WMC was modeled as a second-order factor indicated by lower-order, format-specific factors. Results of this second model revealed an association of similar magnitude (numerically, greater) between WMC and Gf while the second-order factor was equally indicated by the format-specific factors. This finding suggests that the criterion association between WMC and Gf observed in the first, more parsimonious, model was not biased by the full-length format tasks.

Finally, results of our sensitivity analysis suggested that removal of the lowest set-size trials did not affect the pattern of associations observed. Removal of these trials equates to a reduction of almost 1/3 of overall administration length. Based on these findings, our data suggests valid estimates of WMC may be obtained in as few as 3 minutes of administration on smart phones (2 trials of each task). Building on this observation, in Study 2 we examined the psychometric properties of 2-trial, ultra-brief complex span tasks in context of a measurement burst study design.

STUDY 2

Results of Study 1 suggested that WMC can be validly assessed in an ultra-brief format, on smart phones, in as few as 2 trials per each of 3 complex span tasks. A primary motivation for the development and psychometric assessment of ultra-brief complex span tasks on smart phones

is to implement these tasks into EMA study designs (e.g. measurement bursts). Measurement burst designs typically involve intensive repeated assessments; e.g., 3-5 assessments per day, over a period of a few days to weeks.

Measurement bursts can be scheduled in a manner that allows for a comparable, or greater, amount of testing time/trials to be accumulated over repeated ultra-brief administrations as would be conducted during a single lab-based session. In support of cross-sectional study designs, in Study 2, we sought to examine approximately how many ultra-brief assessments would be necessary to generate reliable cross-sectional estimates of WMC (i.e. between-person reliability). As mentioned previously, another advantage of adapting performance-based assessments of cognition to EMA is the ability to capture and model short-term variation in cognition within-individuals, over time. Toward the goal of examining within-person processes that might depend upon, or interact with, WMC, it is essential to demonstrate that short-term within-person changes in WMC can be reliably detected. To estimate between- and within-person reliability of ambulatory, ultra-brief complex span task performance, in Study 2, we followed procedures described by Cranford, et al (2006) for conducting generalizability and decision studies based on Generalizability Theory (Cranford et al., 2006; Shavelson, Webb, & Rowley, 1989).

METHODS

Participants

A total of 39 younger adults (age $M = 20.64$, $SD = 3.01$, range = 18-30; 72% female) participated in the study. Participants were recruited from Pennsylvania State University's psychology undergraduate research pool and through local advertisement. All participants provided written informed consent and received course credit and/or compensation for their participation. All

experimental procedures were approved by Pennsylvania State University's Institutional Review Board for the ethical treatment of human participants.

Materials and Procedure

Experimental Procedures

Participants were acquainted with the task procedures for each complex span task by completing abbreviated versions of the automated complex span tasks used in Study 1 (OSpan, SSpan, RSpan; using parameters described in Foster et al., 2014; Oswald et al., 2014) during a 60-minute lab session. Tasks were administered in a fixed order across all participants: OSpan, SSpan, RSpan, and followed by full-length administrations of the RAPM and LETTERS tasks as described in Study 1. Following the lab session, participants were asked to carry a lab-provided smart phone for a period of 4 days. A custom prototype Android mobile application currently under development for the National Institutes of Health (NIH) Mobile Toolbox (the “Mobile Monitoring of Cognitive Change” or “M2C2” app; www.mobiletoolbox.org) was used to administer the battery of ultra-brief complex span tasks and generate 4 notifications per day requesting participants to begin the assessments. The first notification of each day was scheduled to occur within 2 hours of participant's self-reported average waking time. Subsequent notifications were separated by an average of 3.75 hours and pseudorandomly jittered around this interval by up to 30 minutes.

M2C2 Adaptation of Ultra-brief Complex Span Tasks

Ultra-brief (“amb-”) versions of the OSpan, SSpan, and RSpan tasks were programmed on the M2C2 platform and administered on Samsung Galaxy S5 smart phones (Samsung Electronics, Seoul, South Korea). The ultra-brief tasks were presented in a fixed order across participants,

consistent with the order of the full-length task presentation in the lab session: amb-OSpan, amb-SSpan, amb-RSpan. Participants completed 2 trials of each task, one at each set-size. Consistent with Study 1, set-sizes for the amb-OSpan task were 5 and 6, and set-sizes for the amb-SSpan and amb-RSpan tasks were 4 and 5. The ultra-brief tasks contained no practice phase and included only an instruction screen which reminded the participants of the respective task procedures. Within each task, set-sizes were presented in a random order. Participants logged responses using the touch screen.

Statistical Analyses

Correlations between Ambulatory and Lab-based Measures

Participants were highly compliant with the assessment protocol, completing $M = 15$ “sessions” (momentary administrations of the ultra-brief task battery) over the 4-day measurement burst. Accordingly, all correlational and psychometric analyses were conducted on the first 15 sessions. For the correlation analyses, performance on lab-based automated, abbreviated complex span task was first z-scored by task. Z-scores were then averaged across tasks to generate composite lab-WMC estimates. The same procedure was followed for the ultra-brief ambulatory complex span tasks to generate amb-WMC estimates. Performance on RAPM and LETTERS tasks was also z-scored and averaged to generate an estimate of Gf. Correlation analysis was conducted incrementally over the first 15 sessions. This procedure involved generating amb-WMC estimates derived from the first session, the first two sessions, the first three sessions, and so on, up to the 15th session. Amb-WMC estimates derived for each session increment were then correlated with lab-WMC and Gf.

Variance Decomposition and Psychometrics

First, as an initial descriptive stage of analysis, two-level random effects, intercept-only multi-level models (MLMs) were fit to composite amb-WMC and task-specific span scores to describe the proportion of variance between-persons relative to the total variance between- + within-persons (intraclass correlations, ICCs).

Next, toward estimation of between- and within-person reliability, generalizability studies (“G-study”) were conducted where burst-level (i.e. 15 session) data was decomposed into systematic and random variance components. The G-studies involved decomposing span score variance across 15 sessions into systematic and random components in a random effects repeated measures ANOVA in R (lme4 pkg; Bates, Mächler, Bolker, & Walker, 2015). Systematic variance associated with persons (p), occasions (o), items (i), and all two-way interactions ($p \times o$, $p \times i$, $o \times i$) were modeled in the repeated measures ANOVA, along with residual variance (the random component). Separate G-studies of amb-OSpan, amb-SSpan, amb-RSpan, and composite amb-WMC performance were conducted. For the G-studies of amb-OSpan, amb-SSpan, and amb-RSpan, within each session, scores could only vary across the 2 trials presented per task. Thus, the item (i) factor for each task-specific G-study was parameterized to account for *trial*-related variance. For the G-studies of composite amb-WMC, trials were first summed within each session by task so that the item (i) factor for the G-study of composite amb-WMC was parameterized to account for *task*-related variance. Two G-studies were conducted for composite amb-WMC, enabling examination of within-person reliability at different timescales, one defining occasion at the session-level (G-momentary), the other defining occasion at the day-level (G-daily). Decision studies (“D-study”), i.e. estimation of reliability at between- and within-person levels, were conducted using formulas described in detail in Cranford et al (2006; Equations 4 and 5; see also Scott et al., 2020).

Between-person reliability (R_{BP}) for each ultra-brief complex span task and composite amb-WMC was calculated in D-Studies of incremental epoch lengths of the measurement burst (similar to correlational analysis described above). R_{BP} of each ultra-brief task and of composite WMC was calculated based on the first 2 sessions, the first 3 sessions, the first 4 administrations, and so on, up to the 15th session based on the following formula (Equation 4 from Cranford et al (2006)):

$$(1) R_{BP} = \frac{\sigma_p^2 + \left(\frac{\sigma_{p*i}^2}{m}\right)}{\sigma_p^2 + \left(\frac{\sigma_{p*i}^2}{m}\right) + \left(\frac{\sigma_e^2}{km}\right)}$$

where σ_p^2 is the total systematic variance associated with persons, σ_{p*i}^2 is the total systematic variance associated with the interaction of persons $\times$ items (*tasks* for amb-WMC and *trials* for each ultra-brief span task), σ_e^2 is the random residual variance, m is the total number of items included in a single occasion (3 *tasks* for the amb-WMC D-Studies and 2 *trials* for the ultra-brief span task D-Studies), and k is the total number of sessions included in each D-Study.

Within-person reliability of change (R_{WP}) for composite amb-WMC was calculated at the level of momentary change (R_{WPM}) and daily change (R_{WPD}) using the following equation (*Equation 5 in Cranford, et al (2006)):

$$(2) R_{WP} = \frac{\sigma_{p*o}^2}{\sigma_{p*o}^2 + \left(\frac{\sigma_e^2}{m}\right)}$$

where σ_{p*o}^2 is the total systematic variance associated with the interaction of persons $\times$ occasions, σ_e^2 is the random residual variance, and m is the total number of items (*task* administrations) within the defined occasion. Results of G-Momentary were used to calculate R_{WPM} , and results of G-daily were used to calculate R_{WPD} . The total number of task administrations within o was 3 for

R_{WPM} (one administration of each ultra-brief span task) and 12 for R_{WPD} (3 tasks per session $\times$ 4 sessions per day).

RESULTS

Associations between Ambulatory and Lab-based Measures

Amb-WMC was significantly correlated with both lab-WMC and Gf after the first session (p 's < 0.05). Incremental correlation analysis between amb-WMC estimated from sessions 1 to 15 and lab-based estimates of composite lab-WMC and Gf suggested that ambulatory and lab-based administrations of automated complex span tasks are strongly correlated and reached an asymptotic level of correlation ($r = 0.66$, $p < 0.001$) after 7 sessions (< 2 days of burst administration in the current design). A similar pattern was observed between amb-WMC and Gf, where a correlation of $r > 0.5$ ($p < 0.001$) was observed by the 7th session (Figure 3).

Figure 3. Incremental Correlations between amb-WMC, lab-WMC, and Gf. After one session, amb-WMC was significantly correlated with lab-WMC and Gf. After 7 sessions (< 2 days of the measurement burst/ ~ 21 mins of total testing) amb-WMC reached an asymptotic level of correlation with the lab-based tasks ($r > 0.6$ with lab-WMC, $r > 0.5$ with Gf).

ICCs for Composite WMC and Task-specific Span Scores

Results of a random effects, intercept-only, MLMs on composite amb-WMC suggest that approximately 47% of the variance observed in amb-WMC over the measurement burst was within-persons, over time ($ICC_{amb-WMC}=0.53$). ICCs for task-specific span scores were overall lower than composite amb-WMC ($ICC_{amb-OSpan} = 0.30$; $ICC_{amb-SSpan} = 0.31$; $ICC_{amb-RSpan} = 0.39$), suggesting greater proportional within-person variance in task-specific span scores than composite amb-WMC.

Between-person Reliability

R_{BP} was calculated incrementally on task-specific span scores and composite amb-WMC (see Table 2 for amb-WMC G-study results). All tasks exhibited good between-person reliability, $R_{BP} > 0.7$, after 3 sessions, which is equivalent to about 9 minutes of administration during the first day of the measurement burst. Amb-WMC exhibited good between-person reliability after 2 sessions, which is equivalent to 6 minutes of testing ($R_{BP} = 0.76$; see Figure 4A).

Figure 4. Incremental Between-Person Reliability Estimates. (A) Between-person reliability for each ultra-brief complex span task and composite amb-WMC incremented by session in the measurement burst in Study 2. (B) Between-person reliability for the ultra-brief Rotation Span task incremented by session in the measurement burst in Study 3.

Within-person Reliability of Change

Within-person reliability of change in amb-WMC was examined at two levels: reliability of change across sessions (i.e. the “momentary” level; R_{WPM}) and reliability of change across days (R_{WPD}). Results of D-studies on reliability of change across sessions and days suggested low reliability at the momentary level ($R_{WPM} = 0.17$) and daily level ($R_{WPD} = 0.32$).

Table 2 about here

INTERIM DISCUSSION

The results of Study 2 suggest that reliable between-person estimates of composite WMC can be obtained in as few as 2 administrations of three ultra-brief complex span tasks on smart phones. Coupled with the positive validity results from Study 1, these findings suggest that valid and reliable estimates of individual differences in WMC can be obtained via smart phones in approximately 6 minutes of testing. Estimates of between-person reliability were, generally, lower for the individual complex span tasks than composite WMC, but all ultra-brief tasks exhibited good reliability after only 3 administrations, or ~9 minutes of testing.

While WMC is typically considered to be a stationary, domain-general cognitive construct, we observed considerable within-person variation in composite WMC and each ultra-brief task over the measurement burst. In Study 2, the proportion of total variance in task-specific scores attributable to within-person variation, over time was substantial, ranging from ~50% for composite WMC to 70% for the amb-OSpan task. Results of our incremental

reliability analysis, however, suggest that the tasks exhibit high between-person reliability with few administrations despite intra-individual variation in performance over time.

Intra-individual variation may be attributed to a number of systematic or random factors (Brose, Schmiedek, Gerstorf, & Voelkle, 2019; Cranford et al., 2006; Nezlek, 2017). In a second set of analyses in Study 2, we decomposed and parameterized systematic and random variance components in G- and D-studies. We estimated the reliability of within-person change in composite WMC at two timescales: momentary and daily. Results of each D-study suggested, based on our current design and administration characteristics (6 trials per session, 4 sessions per day), that composite WMC assessed via three ultra-brief complex span tasks exhibited low within-person reliability, particularly at the momentary level. In other words, the ability to detect systematic changes in WMC from moment-to-moment or day-to-day was limited with the current design.

It is critical to point out that these within-person reliability of change results do not suggest that ultra-brief complex span tasks are unreliable at the within-person level, *per se*. The value of Generalizability Theory in this context is that D-study results can be leveraged to prescriptively describe alternative study designs where psychometrics such as R_{WPD} can be brought to a level that generates sufficient power to detect within-person changes in future studies. Increasing the number of WMC indicators (*tasks*) from 3 to 4, and increasing the number of assessments per day from 4 to 6 would be expected to increase R_{WPD} to ~ 0.5 . Achieving higher within-person reliability in a burst design by administering ~ 4 -5 mins of testing at each of 6 sessions per day would remain consistent with recommendations for EMA design (Kirchner & Shiffman, 2013), but could invoke design trade-offs. For example, more lengthy assessments would be prohibitive of including additional forms of measurement during each assessment (e.g.

contemporaneous self-report EMA). In Study 3, we describe a study design aimed at increasing within-person reliability of ultra-brief complex span tasks while managing EMA measurement burden.

STUDY 3

In Study 2, set-size within each task and across tasks was variable, consistent with conventional practices. Typically, a wider set-size range is utilized in memory span tasks to improve measurement characteristics (e.g. avoiding ceiling and floor effects) and to help maximize between-person variance (Conway et al., 2005). However, ‘bracketing’ of set-sizes (attempting to remain sensitive to both higher and lower ability participants), by design, generates variance in span scores (trials have different total possible scores) and may also restrict person $\times$ occasion variance (the numerator in the R_C estimates above). This interaction term reflects the degree to which individuals differ from one another in how they differ across ‘occasions’ (momentary assessments, days). The goal of a well-powered study of within-person short-term change at these time scales is to maximize the variance accounted for by this interaction term and minimize the residual, error variance (the 2nd term in the denominator).

Assessments with bracketed set-sizes may not effectively distinguish a consistent participant (e.g. a participant who consistently remembers a few items) from one with an overall high degree of ability (where variance is only expected to be observed during the highest set-size trials). The latter participant may, in reality, be more variable across assessments, but the inclusion of low set-size trials for purposes of bracketing limits sensitivity to this fact (as they correctly respond to each trial at this level of difficulty across sessions). Designing around exclusively higher set-size trials may help maximize between-occasion variability for higher

ability participants while preserving sensitivity to performance of lower ability participants. For Study 3, we administered three trials at the highest set-size tested in Studies 1 and 2.

While the results of Study 1 and Study 2 were promising developments toward the deployment of ultra-brief complex span tasks into the field, these studies were also conducted under more controlled participant onboarding/training conditions than we expect researchers to employ in applied settings. In each of the previous two studies gold-standard, in-lab, automated, computerized versions of each complex span task were administered prior to mobile assessments. These in-lab sessions served two purposes: to establish convergent validity of the ultra-brief tasks and to familiarize participants with the task procedures ahead of the measurement burst. In practice, however, a major goal of ambulatory cognitive assessment is to liberate these procedures from the laboratory, and therefore, the reliability of these assessments in the absence of extensive pre-training needs to be established. In Study 3, we conducted a measurement burst study involving the ultra-brief amb-RSpan task in the absence of extensive task onboarding/training.

Finally, implementation of ambulatory cognitive assessments in future EMA studies, which may also involve contemporaneous self-report surveys, will require careful balance between measurement goals and participant burden. In Study 3, we sought to evaluate the psychometrics of ultra-brief complex span task performance under conditions that would closely approximate a prototypical research use case for future applied research: a study of stress and academic engagement in college-aged students. In view of striking a balance between optimizing the psychometrics of our ambulatory cognitive assessment protocol with other domains under study, we limited WMC assessment in Study 3 to the amb-RSpan task. The amb-RSpan task

exhibited the strongest loadings on latent WMC in Study 1, suggesting that it is among the strongest single indicators of latent WMC.

METHODS

Participants

A total of 102 younger adults (age $M = 21$; age $SD = 3.4$, range =18-44; 73% female) participated in the study. Participants were recruited from Pennsylvania State University undergraduate listservs. All participants provided written informed consent and received compensation for their participation. All experimental procedures were approved by Pennsylvania State University's Institutional Review Board for the ethical treatment of human participants.

Materials and Procedure

Experimental Procedures

Participants were asked to carry a lab-provided smart phone for a period of 7 days (Xiaomi Mi A1 model phones configured with Android One OS, v8.0; Xiaomi Corporation, Beijing, China). The prototype M2C2 application was used to administer EMA self-report surveys followed by 3 trials of the amb-RSpan task. M2C2 made a survey available each morning that participants were asked to self-initiate after waking and generated 4 pseudorandom notifications throughout each day to complete mid-day surveys. The morning and mid-day surveys each concluded with 3 set-size 5 trials of the amb-RSpan task (the highest set-size used in Study 1 and 2), and resulted in a total of five 3-trial amb-RSpan sessions per day. The first notification of each day was scheduled to occur within 2 hours of the participant's self-reported waking time. Subsequent notifications were separated by an average of 3.75 hours and pseudorandomly jittered around this interval by

up to 30 minutes. Data related to the self-report surveys is beyond the scope of the current study and will be reported elsewhere.

Onboarding/Training: Participants were given a visual overview of the amb-RSpan task via screenshots of the task presented in Microsoft PowerPoint slides (Microsoft Corporation, Redmond, WA). The slides contained a depiction of a single amb-RSpan trial and verbal instructions on how to respond to the secondary task and the recall phase using the phone touch screen. Following review of the slides, participants were asked to complete one amb-RSpan session (3 trials) on a lab-provided smart phone in the presence of the study coordinator. Participants were given an opportunity to ask questions after completion of the practice trials.

Ultra-brief RSpan task: Procedures for the amb-RSpan task were identical to Study 2 except that, based on results of Study 2, 3 trials of equal set-size (set-size = 5) were administered during each assessment.

Statistical Analyses

Between-person reliability and within-person reliability of change were calculated using the same equations as Study 2. Within-person reliability of change was estimated at momentary and daily levels. Similar to Study 2, the item (*i*) factor in the G-studies of amb-Rspan was parameterized to reflect *trial*-related variance.

RESULTS

Variance Decomposition of amb-RSpan Performance

Overall, participants were highly compliant with the assessment protocol, completing $M = 29$ sessions over the 7-day measurement burst (out of 35 possible sessions). All results reported

reflect analysis of the first 29 sessions. Results of a random effects, intercept-only, ANOVA on amb-RSpan suggest that approximately 49% of the variance observed in amb-RSpan performance over the measurement burst was within-persons, over time ($ICC_{\text{amb-RSpan}} = 0.51$).

Incremental Between-person Reliability

R_{BP} was calculated for session totals ranging from 2 to 29 sessions (the group mean of number of sessions completed over the measurement burst). Amb-RSpan exhibited good between-person reliability ($R_{BP} = 0.84$) after just 2 sessions (3 mins of testing) and excellent between-person reliability after 5 sessions ($R_{BP} > 0.9$; 1 days, 7.5 mins of testing; see Figure 4B).

Within-person Reliability of Change

Within-person reliability of change was examined at two levels: reliability of change across momentary sessions (R_{WPM}) and reliability of change across days (R_{WPD} ; see Table 2 for G-study results). Results of D-studies on within-person reliability of change across sessions and days suggested moderate, but higher estimates of within-person reliability at the momentary ($R_{WPM} = 0.37$) and daily levels ($R_{WPD} = 0.48$) than was observed for composite amb-WMC in Study 2.

INTERIM DISCUSSION

The results of Study 3 demonstrated that highly reliable between-person, single-indicator, estimates of WMC can be obtained on smart phones, in the absence of rigorous computerized training on the task procedures. In addition, limiting administration to one complex span task, increasing the number of trials per session, increasing/maintaining the set-size of each trial, and increasing the number of administrations per day increased within-person reliability of change estimates at momentary and daily levels compared to Study 2. The influence of study design

parameters over within-person reliability estimates are informative for future research.

Ultimately, these findings increase the promise and feasibility of conducting remotely-administered research via ambulatory cognitive assessment on smart phones.

GENERAL DISCUSSION

The results of the three studies reported here, evaluating the psychometrics of ultra-brief complex span tasks, suggest that valid and reliable estimates of WMC can be obtained in ~6 minutes on smart phones. Estimates derived from ~3 minutes of assessment on smart phones replicated the degree of association between WMC and reasoning task/Gf performance observed with full-length in-lab administrations (~75 mins of testing). Good between-person reliability of composite amb-WMC was observed after only two 3-minute sessions in Study 2 and two 1.5-minute sessions for a single indicator of WMC (amb-RSpan) in Study 3. Results from Study 3 also suggested that reliable single-indicator estimates of WMC can be obtained in the absence of rigorous training on the task procedures, opening the possibility for valid and reliable estimation of WMC in future research without face-to-face participant onboarding/training. Finally, estimates of within-person reliability in Study 2 and Study 3 highlighted important design considerations for future work.

Results of Study 2 and 3 suggest that highly reliable cross-sectional estimates of complex span task performance may be obtained in ambulatory study designs where data is collected on smart phones, over the course of everyday life. These findings are encouraging for efforts to engage under-represented populations in cognitive research (e.g. rural participants, participants in areas/communities without a strong connection to an academic institution). Moreover, the ability to leverage mobile tools to study WMC may help sharpen cross-sectional and long-term change estimates in future work by harnessing the measurement advantages associated with

intensive longitudinal study designs (Nesselroade, 1991; Salthouse & Nesselroade, 2010; Sliwinski, 2008; Stawski et al., 2015).

A second major goal for the current set of studies was to design measures that are sensitive to systematic changes in WMC that occur within-individuals, over short periods of time (within- and between-days). Results of multi-level, random intercept models suggested that at least 50-70% of the total variance in complex span task performance was observed within-individuals over repeated administrations (15 sessions over 4 days in Study 2; 29 sessions over 7 days in Study 3). The challenge for studies of within-person (i.e. ‘intra-individual’) variation is to parse and detect what is typically a fairly weak change signal (differences between individuals in variance across occasions; the $p*o$ interaction term in each G-Study) from a background of random noise (random measurement error; Brose et al., 2019; Cranford et al., 2006; Nezlek, 2017). Study 2 indicated low within-person reliability of composite WMC. Following this observation, several design parameters were considered when planning for Study 3 including number of trials per session, number of sessions per day, number of WMC indicators, and variation in set-size between trials.

After tuning design and task parameterization for Study 3, estimates of within-person reliability improved but still did not reach conventional rule-of-thumb benchmarks for ‘good’ reliability. Variance decomposition of amb-RSpan data in Study 3 into systematic and random components, based on Generalizability Theory, determined that ~11% of the total variance was due to how individuals differ in amb-RSpan performance over occasions (i.e. the $p*o$ numerator of the within-person reliability coefficient). While this was an improvement over Study 2, a substantial proportion of the total variance was determined to stem from random measurement error, which is summed with $p*o$ in denominator of the within-person reliability coefficient

equation (e.g. ~57% of amb-RSpan total performance variance over 3 trials $\times$ 29 occasions; see Table 2, Study 3, G-Study Momentary). One approach to maximizing sensitivity to within-person changes would be to simply measure more at each occasion (increasing the m term that scales the random error term in the denominator due to averaging). However, this approach risks dramatic increases in measurement burden. For example, it would require ~12 trials per session (or ~6 minutes of testing) to achieve good (0.7) within-person reliability this way.

An alternative approach to increasing within-person reliability would involve increasing the precision of each individual measurement (i.e. each trial). In the context of the G-Studies presented here, the trial-to-trial variation within each session remains unaccounted for by systematic components (including the ‘item’ factor, which only captures effects that are stable across sessions such as task difficulty, set-size differences, or order effects). Random error is unable to be partitioned from the 3-way interaction of person*occasion*trial (only 1 observation would exist per cell). By virtue of this, the ability to sensitively detect within-person changes is proportional to the degree of trial-to-trial variance within sessions. The implication for ultra-brief, ambulatory cognitive assessments is that any task where the lower-bound of trial-to-trial differences is substantially high by design (e.g. 20% changes in trial scores per item recalled, or X out of 5 items, as in the specific parameterization of amb-RSpan used in Study 3), random measurement error may be estimated imprecisely (potentially, artificially inflated). These barriers to the detection of short-term within-person cognitive change may attenuate within-person associations, but may not threaten detection of between-person differences or long-term change (Armstrong, 1998; Hutcheon, Chiolero, & Hanley, 2010). Given the increased focus on intra-individual variation in applied research, future development of ultra-brief ambulatory cognitive assessments should focus on tasks with high trial-level precision. An opportunity to

improve sensitivity to systematic within-person changes in WMC may stem from paradigms involving continuous report recall techniques, which were developed out of work evaluating competing theories of working memory representation (Ma, Husain, & Bays, 2014).

Ambulatory Cognitive Assessment of WMC in Applied Research

In Study 1 and Study 2, we evaluated mobile assessment of WMC through the lens of a multi-indicator approach to WMC. The multi-indicator, or latent factor, approach treats WMC as a domain-general construct, potentially reflecting the operation of attention/executive cognitive processes (Engle, 2002; Kane, Conway, Hambrick, & Engle, 2007; Kane et al., 2004, although see Mogle, Lovett, Stawski, & Sliwinski, 2008; Oberauer, Lewandowsky, Farrell, Jarrold, & Greaves, 2012). Applied research over the past 30 years has demonstrated that individual differences in WMC are strongly associated with important domains of higher-order cognition, development, and behavior including fluid intelligence/reasoning ability (Conway et al., 2003; Kyllonen & Christal, 1990), control of attention/cognitive control (Engle, 2010; Kane & Engle, 2003; Redick, 2013), mind wandering (McVay & Kane, 2009; Unsworth et al., 2012), and everyday skills such as driving (Wood, Hartley, Furley, & Wilson, 2016). Recent work has also focused attention on the possibility that WMC may index an individual's capacity to carry out goal-directed behavior, modifying how individuals respond in the presence of an environmental/contextual challenge (Hofmann, Gschwendner, Frieze, Wiers, & Schmitt, 2008; Hofmann, Schmeichel, & Baddeley, 2012; Garrison & Schmeichel, 2020).

While previous work has focused on individual differences (i.e. WMC as a trait/between-person factor), our current set of studies demonstrate that there is considerable short-term, within-person variability in WMC. The validation of ultra-brief complex span tasks suitable for repeated administration represents an important step toward examining the role of intra-

individual variation in WMC in psychological and behavioral processes that unfold under naturalistic circumstances. Goals for future research in these areas will need to include a description of *when* WMC predicts behavior (e.g. is behavior more well-regulated during moments when WMC is higher for that individual?). We assume that while individuals with higher WMC may excel at criterion tasks in the lab/under experimental conditions, they may not *always* engage in such successful patterns of behavior. Moreover, it seems unreasonable to assume that individuals lower in WMC would infrequently or *never* exhibit successful patterns of behavior. Moment-to-moment and day-to-day variation in cognitive function may be driven by a wide-range of contextual factors including, but not limited to, stress, fatigue, pain and negative affect (Brose et al., 2012; Brose, Schmiedek, Lövdén, Molenaar, & Lindenberger, 2010; Kratz et al., 2020; Schmitter-Edgecombe, Sumida, & Cook, 2020; Sliwinski et al., 2006). Future research should leverage intensive repeated designs to reveal *whether*, *how*, and *when* short-term variation in WMC impacts behavioral processes and the potential mechanisms through which higher/lower WMC confers an advantage.

The current set of studies leveraged a new mobile platform under development and sponsored by the National Institutes of Health/National Institute on Aging. The M2C2 platform is part of the NIH Mobile Toolbox project and currently undergoing development, validation, norming, and testing across a wide range of use cases and populations. An early prototype of the M2C2 platform was used to conduct Study 2 and Study 3, which was validated in other research involving middle-aged and older adult samples (Scott et al., 2015; Sliwinski et al., 2018). More information about the forthcoming NIH Mobile Toolbox can be found at www.mobiletoolbox.org.

Study Limitations and Deviations from Conventional Procedures

The complex span tasks developed for the current studies deviated in a few ways from the most widely-distributed, automated tasks (Redick et al., 2012). Choice of scoring approach (full-credit/partial credit) is always an important consideration. Partial-credit scores have been shown to have preferable psychometric properties to full-credit scores during full-length administrations (Redick et al., 2012). In the current 2-3 trial administration context, partial-credit scoring offers a significant advantage for measurement precision (in Study 3, span range = 0-15 in 1 point increments with partial-credit scoring vs 5 point increments with full-credit scoring). Second, we did not include ‘don’t know’ response options on the recall screens for each task. Smart phone screen real estate is at a premium, and in the absence of the ‘don’t know’ response option participants were allowed to submit fewer items than the set-size during recall. We also did not enforce a time-limit on the secondary tasks judgments. In the conventional automated tasks a response time distribution is generated for secondary task judgments during the practice phase and used to restrict response times during testing. Because we implemented the ultra-brief tasks without a practice phase on the smart phones, we did not include an upper boundary for secondary task judgments. Finally, the current study involved college-aged younger adults, and thus, the procedures/parameters chosen may need to be adapted for other research populations.

CONCLUSIONS

The results of the studies reported suggest that valid and reliable estimates of WMC can be obtained via ultra-brief adaptations of computerized complex span tasks, in a measurement burst design, via smart phones, under naturalistic circumstances. These findings present a new avenue for research on the role of WMC in psychological and behavioral processes that unfold over the course of daily life. Future work should also be focused on the optimization of ambulatory cognitive assessments for detecting short-term intra-individual variation in cognition.

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REFERENCES

- Allard, M., Husky, M., Catheline, G. L., Pelletier, A., Dilharreguy, B., Amieva, H., ... Swendsen, J. (2014). Mobile technologies in the early detection of cognitive decline. *PLoS ONE*, 9(12). <https://doi.org/10.1371/journal.pone.0112197>
- Armstrong, B. G. (1998, October 1). Effect of measurement error on epidemiological studies of environmental and occupational exposures. *Occupational and Environmental Medicine*. BMJ Publishing Group. <https://doi.org/10.1136/oem.55.10.651>
- Bates, D., Mächler, M., Bolker, B. M., & Walker, S. C. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software*, 67(1), 1–48. <https://doi.org/10.18637/jss.v067.i01>
- Bolger, N., & Laurenceau, J. P. (2013). *Intensive longitudinal methods: An introduction to diary and experience sampling research*. Guilford Press.
- Brose, A., Schmiedek, F., Gerstorff, D., & Voelkle, M. C. (2019). The Measurement of Within-Person Affect Variation. *Emotion*. <https://doi.org/10.1037/emo0000583>
- Brose, A., Schmiedek, F., Lövdén, M., & Lindenberger, U. (2012). Daily variability in working memory is coupled with negative affect: The role of attention and motivation. *Emotion*, 12(3), 605–617. <https://doi.org/10.1037/a0024436>
- Brose, A., Schmiedek, F., Lövdén, M., Molenaar, P. C. M., & Lindenberger, U. (2010). Adult Age Differences in Covariation of Motivation and Working Memory Performance: Contrasting Between-Person and Within-Person Findings. *Research in Human Development*, 7(1), 61–78. <https://doi.org/10.1080/15427600903578177>
- Conway, A. R. A., Kane, M. J., Bunting, M. F., Hambrick, D. Z., Wilhelm, O., & Engle, R. W. (2005). Working memory span tasks: A methodological review and user's guide.

- Psychonomic Bulletin & Review*, 12(5), 769–786. <https://doi.org/10.3758/BF03196772>
- Conway, A. R. A., Kane, M. J., & Engle, R. W. (2003). Working memory capacity and its relation to general intelligence. *Trends in Cognitive Sciences*, 7(12), 547–552. <https://doi.org/10.1016/j.tics.2003.10.005>
- Cranford, J. A., Shrout, P. E., Iida, M., Rafaeli, E., Yip, T., & Bolger, N. (2006). A procedure for evaluating sensitivity to within-person change: Can mood measures in diary studies detect change reliably? *Personality and Social Psychology Bulletin*, 32(7), 917–929. <https://doi.org/10.1177/0146167206287721>
- Engle, R. W. (2002). Working Memory Capacity as Executive Attention. *Current Directions in Psychological Science*, 11(1), 19–23. <https://doi.org/10.1111/1467-8721.00160>
- Engle, R. W. (2010). Role of Working-Memory Capacity in Cognitive Control. *Current Anthropology*, 51(1), 17–26. <https://doi.org/10.1086/650572>
- Foster, J. L., Shipstead, Z., Harrison, T. L., Hicks, K. L., Redick, T. S., & Engle, R. W. (2014). Shortened complex span tasks can reliably measure working memory capacity. *Memory and Cognition*, 43(2), 226–236. <https://doi.org/10.3758/s13421-014-0461-7>
- Garrison, K. E., & Schmeichel, B. J. (2020). Getting Over It: Working Memory Capacity and Affective Responses to Stressful Events in Daily Life. *Emotion*. <https://doi.org/10.1037/emo0000755>
- Hall, P. A., & Fong, G. T. (2007). Temporal self-regulation theory: A model for individual health behavior. *Health Psychology Review*, 1(1), 6–52. <https://doi.org/10.1080/17437190701492437>
- Heron, K. E., Everhart, R. S., McHale, S. M., & Smyth, J. M. (2017). Using Mobile-Technology-Based Ecological Momentary Assessment (EMA) Methods With Youth: A Systematic

- Review and Recommendations. *Journal of Pediatric Psychology*, 42(10), 1087–1107.
<https://doi.org/10.1093/jpepsy/jsx078>
- Hofmann, W., Friese, M., & Roefs, A. (2009). Three ways to resist temptation: The independent contributions of executive attention, inhibitory control, and affect regulation to the impulse control of eating behavior. *Journal of Experimental Social Psychology*, 45(2), 431–435.
<https://doi.org/10.1016/j.jesp.2008.09.013>
- Hofmann, W., Friese, M., & Wiers, R. W. (2011). Impulsive processes in the self-regulation of health behaviour: theoretical and methodological considerations in response to commentaries. *Health Psychology Review*, 5(2), 162–171.
<https://doi.org/10.1080/17437199.2011.565593>
- Hofmann, W., Gschwendner, T., Friese, M., Wiers, R. W., & Schmitt, M. (2008). Working Memory Capacity and Self-Regulatory Behavior: Toward an Individual Differences Perspective on Behavior Determination by Automatic Versus Controlled Processes. *Journal of Personality and Social Psychology*, 95(4), 962–977. <https://doi.org/10.1037/a0012705>
- Hofmann, W., Schmeichel, B. J., & Baddeley, A. D. (2012). Executive functions and self-regulation. *Trends in Cognitive Sciences*, 16(3), 174–180.
<https://doi.org/10.1016/J.TICS.2012.01.006>
- Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, 6(1), 1–55. <https://doi.org/10.1080/10705519909540118>
- Hutcheon, J. A., Chiolero, A., & Hanley, J. A. (2010). Random measurement error and regression dilution bias. *BMJ (Online)*, 340(7761), 1402–1406.
<https://doi.org/10.1136/bmj.c2289>

- Kane, M. J., Conway, A. R. A., Hambrick, D. Z., & Engle, R. W. (2007). *Variation in working memory capacity as variation in executive attention and control*. Oxford University Press.
- Kane, M. J., & Engle, R. W. (2002). The role of prefrontal cortex in working-memory capacity, executive attention, and general fluid intelligence: An individual-differences perspective. *Psychonomic Bulletin & Review*, 9(4), 637–671. <https://doi.org/10.3758/BF03196323>
- Kane, M. J., & Engle, R. W. (2003). Working-memory capacity and the control of attention: The contributions of goal neglect, response competition, and task set to Stroop interference. *Journal of Experimental Psychology: General*, 132(1), 47–70. <https://doi.org/10.1037/0096-3445.132.1.47>
- Kane, M. J., Hambrick, D. Z., Tuholski, S. W., Wilhelm, O., Payne, T. W., & Engle, R. W. (2004). The Generality of Working Memory Capacity: A Latent-Variable Approach to Verbal and Visuospatial Memory Span and Reasoning. *Journal of Experimental Psychology: General*, 133(2), 189–217. <https://doi.org/10.1037/0096-3445.133.2.189>
- Kirchner, T. R., & Shiffman, S. (2013). Ecological Momentary Assessment. In *The Wiley-Blackwell Handbook of Addiction Psychopharmacology* (pp. 541–565). Wiley-Blackwell. <https://doi.org/10.1002/9781118384404.ch20>
- Kline, & B., R. (2005). *Principles and practice of structural equation modeling, 2nd ed.* Guilford Press.
- Koo, B. M., & Vizer, L. M. (2019). Mobile Technology for Cognitive Assessment of Older Adults: A Scoping Review. *Innovation in Aging*, 3(1). <https://doi.org/10.1093/geroni/igy038>
- Kratz, A. L., Whibley, D., Kim, S., Sliwinski, M., Clauw, D., & Williams, D. A. (2020). Fibrofog in Daily Life: An Examination of Ambulatory Subjective and Objective Cognitive Function in Fibromyalgia. *Arthritis Care & Research*, 72(12), 1669–1677.

<https://doi.org/10.1002/acr.24089>

Kyllonen, P. C., & Christal, R. E. (1990). Reasoning ability is (little more than) working-memory capacity?! *Intelligence*, 14(4), 389–433. [https://doi.org/10.1016/S0160-2896\(05\)80012-1](https://doi.org/10.1016/S0160-2896(05)80012-1)

Lee, H., Baniqued, P. L., Cosman, J., Mullen, S. P., McAuley, E., Severson, J., & Kramer, A. F. (2012). Examining cognitive function across the lifespan using a mobile application. *Computers in Human Behavior*, 28(5), 1934–1946. <https://doi.org/10.1016/j.chb.2012.05.013>

Ma, W. J., Husain, M., & Bays, P. M. (2014). Changing concepts of working memory. *Nature Neuroscience*. <https://doi.org/10.1038/nn.3655>

McVay, J. C., & Kane, M. J. (2009). Conducting the train of thought: Working memory capacity, goal neglect, and mind wandering in an executive-control task. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 35(1), 196–204. <https://doi.org/10.1037/a0014104>

Mogle, J. A., Lovett, B. J., Stawski, R. S., & Sliwinski, M. J. (2008). What's So Special About Working Memory? An Examination of the Relationships Among Working Memory, Secondary Memory, and Fluid Intelligence. *Psychological Science*, 19(11), 1071–1077. <https://doi.org/10.1111/j.1467-9280.2008.02202.x>

Muthén, L. K., & Muthén, B. O. (n.d.). Statistical Analysis With Latent Variables User's Guide.

Nesselroade, J. R. (1991). The warp and the woof of the developmental fabric. In *Visions of aesthetics, the environment & development: The legacy of Joachim F. Wohlwill*. (pp. 213–240).

Nezlek, J. B. (2017). A practical guide to understanding reliability in studies of within-person

- variability. *Journal of Research in Personality*, 69, 149–155.
<https://doi.org/10.1016/j.jrp.2016.06.020>
- Oberauer, K., Lewandowsky, S., Farrell, S., Jarrold, C., & Greaves, M. (2012). Modeling working memory: an interference model of complex span. *Psychonomic Bulletin & Review*, 19(5), 779–819. <https://doi.org/10.3758/s13423-012-0272-4>
- Oswald, F. L., McAbee, S. T., Redick, T. S., & Hambrick, D. Z. (2014). The development of a short domain-general measure of working memory capacity. *Behavior Research Methods*, 47(4), 1343–1355. <https://doi.org/10.3758/s13428-014-0543-2>
- Redick, T. S. (2013). Cognitive control in context: Working memory capacity and proactive control. *ACTPSY*, 145. <https://doi.org/10.1016/j.actpsy.2013.10.010>
- Redick, T. S., Broadway, J. M., Meier, M. E., Kuriakose, P. S., Unsworth, N., Kane, M. J., & Engle, R. W. (2012). Measuring Working Memory Capacity With Automated Complex Span Tasks. *WMC Tasks European Journal of Psychological Assessment*, 28(3), 164–171. <https://doi.org/10.1027/1015-5759/a000123>
- Riediger, M., Wrzus, C., Klipker, K., Müller, V., Schmiedek, F., & Wagner, G. G. (2014). Outside of the laboratory: Associations of working-memory performance with psychological and physiological arousal vary with age. *Psychology and Aging*, 29(1), 103–114. <https://doi.org/10.1037/a0035766>
- Salthouse, T. A., & Nesselroade, J. R. (2010). Dealing With Short-term Fluctuation in Longitudinal Research. *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences*, 65B(6), 698–705. <https://doi.org/10.1093/geronb/gbq060>
- Schmitter-Edgecombe, M., Sumida, C., & Cook, D. J. (2020). Bridging the gap between performance-based assessment and self-reported everyday functioning: An ecological

- momentary assessment approach. *Clinical Neuropsychologist*, 34(4), 678–699.
<https://doi.org/10.1080/13854046.2020.1733097>
- Scott, S. B., Graham-Engeland, J. E., Engeland, C. G., Smyth, J. M., Almeida, D. M., Katz, M. J., ... Sliwinski, M. J. (2015). The Effects of Stress on Cognitive Aging, Physiology and Emotion (ESCAPE) Project. *BMC Psychiatry*, 15(1), 146. <https://doi.org/10.1186/s12888-015-0497-7>
- Scott, S. B., Sliwinski, M. J., Zawadzki, M., Stawski, R. S., Kim, J., Marcusson-Clavertz, D., ... Smyth, J. M. (2020). A Coordinated Analysis of Variance in Affect in Daily Life. *Assessment*, 27(8), 1683–1698. <https://doi.org/10.1177/1073191118799460>
- Shavelson, R. J., Webb, N. M., & Rowley, G. L. (1989). Generalizability Theory. *American Psychologist*, 44(6), 922–932. <https://doi.org/10.1037/0003-066X.44.6.922>
- Shiffman, S., Stone, A. A., & Hufford, M. R. (2008). Ecological Momentary Assessment. *Annual Review of Clinical Psychology*, 4(1), 1–32.
<https://doi.org/10.1146/annurev.clinpsy.3.022806.091415>
- Sliwinski, M. J. (2008). Measurement-Burst Designs for Social Health Research. *Social and Personality Psychology Compass*, 2(1), 245–261. <https://doi.org/10.1111/j.1751-9004.2007.00043.x>
- Sliwinski, M. J., Mogle, J. A., Hyun, J., Munoz, E., Smyth, J. M., & Lipton, R. B. (2018). Reliability and Validity of Ambulatory Cognitive Assessments. *Assessment*, 25(1), 14–30.
<https://doi.org/10.1177/1073191116643164>
- Sliwinski, M. J., Smyth, J. M., Hofer, S. M., & Stawski, R. S. (2006). Intraindividual coupling of daily stress and cognition. *Psychology and Aging*, 21(3), 545–557.
<https://doi.org/10.1037/0882-7974.21.3.545>

- Smyth, J. M., & Stone, A. A. (2003). Ecological Momentary Assessment Research in Behavioral medicine. *Journal of Happiness Studies*, 4(1), 35–52.
<https://doi.org/10.1023/a:1023657221954>
- Stawski, R. S., MacDonald, S. W. S., & Sliwinski, M. J. (2015). Measurement Burst Design. In *The Encyclopedia of Adulthood and Aging* (pp. 1–5). Hoboken, NJ, USA: John Wiley & Sons, Inc. <https://doi.org/10.1002/9781118521373.wbeaa313>
- Unsworth, N., Fukuda, K., Awh, E., & Vogel, E. K. (2014). Working memory and fluid intelligence: Capacity, attention control, and secondary memory retrieval. *Cognitive Psychology*, 71, 1–26. <https://doi.org/10.1016/j.cogpsych.2014.01.003>
- Unsworth, N., McMillan, B. D., Brewer, G. A., & Spillers, G. J. (2012). Everyday attention failures: An individual differences investigation. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, 38(6), 1765–1772. <https://doi.org/10.1037/a0028075>
- Wood, G., Hartley, G., Furley, P. A., & Wilson, M. R. (2016). Working Memory Capacity, Visual Attention and Hazard Perception in Driving. *Journal of Applied Research in Memory and Cognition*, 5(4), 454–462. <https://doi.org/10.1016/j.jarmac.2016.04.009>

TABLES

Table 1. Correlations between Full-length and Ultra-brief Tasks in Study 1

Variable	1	2	3	4	5	6	7	8
1. OSpan	61.1(8.7)							
2. SSpan	0.36	29.6(7.8)						
3. RSpan	0.32	0.50	27.9(8.2)					
4. amb-OSpan	0.40	0.21	0.18	14.3(1.1)				
5. amb-SSpan	0.15†	0.57	0.31	0.19	9.7(2)			
6. amb-Rspan	0.31	0.44	0.50	0.24	0.34	9.3(2)		
7. RAPM	0.28	0.45	0.44	0.19	0.30	0.33	15.3(4.5)	
8. Letters	0.25	0.30	0.34	0.27	0.20	0.47	0.43	15.9(4.1)

NOTES: all correlations in the table above are significant, $p < 0.05$, except † correlation between OSpan and amb-SSpan was marginal, $p = 0.086$. Values on the diagonal = Mean(SD).

Table 2. Generalizability and Decision Study Results

Variance Source	Study 2	Study 3
	Composite WMC	amb-RSpan
<i>G-Study Momentary</i>		
Person	0.871	0.488
Occasion*	0.008	0.007
Item‡	4.639	0.008
Person $\times$ Occasion	0.094	0.177
Person $\times$ Item	0.381	0.005
Occasion $\times$ Item	0.000	0.000
Error	1.409	0.914
m (# of items)	3	3
R_{WPM}	0.17	0.37
<i>G-Study Daily</i>		
Person	0.887	0.486
Occasion*	0.016	0.009
Item‡	4.642	0.008
Person $\times$ Occasion	0.057	0.064
Person $\times$ Item	0.377	0.001
Occasion $\times$ Item	0.000	0.000
Error	1.451	1.032
m (# of items)	12	15
R_{WPD}	0.32	0.48
R_{BP} for burst	0.96	0.97

NOTES: * = For Momentary models, Occasion = sessions; for Daily models, Occasion = day. R_{CM}/R_{CD} = Reliability of within-person change at momentary/daily level. ‡ = Study 2 Item = task; Study 3 Item = trial

FIGURE CAPTIONS

Figure 1. Smart Phone-adapted Complex Span Tasks. (A) Ultra-Brief Rotation Span task (“amb-RSpan”). (B) Ultra-Brief Operation Span task (“amb-OSpan”). (C) Ultra-Brief Symmetry Span task (“amb-SSpan”). Images presented in the figure are screen captures of each task as presented via the Mobile Monitoring of Cognitive Change (“M2C2”) mobile application used in Studies 2 and 3.

Figure 2. Convergent and Criterion Validity Measurement Models. (A) Model 1, one-factor model of WMC indicated by full-length in-lab and ultra-brief phone-based complex span tasks. (B) Model 2, hierarchical factor model of WMC indicated by two subordinate latent WMC factors representing full-length in-lab complex span tasks (lab-WMC) and ultra-brief phone-based complex span tasks (amb-WMC). WMC = Working Memory Capacity; Gf = fluid intelligence.

Figure 3. Incremental Correlations between amb-WMC, lab-WMC, and Gf. After one session, amb-WMC was significantly correlated with lab-WMC and Gf. After 7 sessions (< 2 days of the measurement burst/~21 mins of total testing) amb-WMC reached an asymptotic level of correlation with the lab-based tasks ($r > 0.6$ with lab-WMC, $r > 0.5$ with Gf).

Figure 4. Incremental Between-Person Reliability Estimates. (A) Between-person reliability for each ultra-brief complex span task and composite amb-WMC incremented by session in the measurement burst in Study 2. (B) Between-person reliability for the ultra-brief Rotation Span task incremented by session in the measurement burst in Study 3.