

**COGNITIVE ABILITY SCORE DIFFERENCES ON MOBILE AND
NONMOBILE DEVICES: THE ROLE OF WORKING MEMORY**

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TABLE OF CONTENTS

	Page
ABSTRACT.....	1
DEDICATION.....	3
ACKNOWLEDGEMENTS.....	4
CHAPTER	
I INTRODUCTION.....	5
II METHODS.....	11
Participants.....	11
Measures.....	11
Procedure.....	12
III RESULTS.....	14
Cognitive and noncognitive scores and device types.....	14
Working memory, construct scores, and device types.....	15
IV CONCLUSION.....	17
REFERENCES.....	20

ABSTRACT

Cognitive Ability Score Differences on Mobile and Nonmobile Devices: The Role of Working Memory

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In the last few decades there has been a dramatic shift in the way employment-related assessments are administered due to technological advancements. Mobile devices are increasingly used in employment-related assessments despite documented significant performance differences in scores on cognitive tests completed on mobile and nonmobile devices. These performance differences have been attributed to structural characteristic differences between mobile and nonmobile devices, which place differentiated information processing demands on test takers (Arthur, Keiser, & Doverspike, 2016). This relationship between the structural characteristic differences and information processing demands serves as the basis for Arthur et al.'s Structural Characteristics Information Processing (SCIP) model. The present study examines one component of this model, working memory, and the role it plays in the observed performance differences on mobile device cognitive assessments. Participants were recruited from the Texas A&M University Psychology Department Subject Pool ($n = 196$), and were randomly assigned to either a smartphone ($n = 100$) or desktop computer ($n = 96$) device condition to complete the specified cognitive and noncognitive assessments; they then completed a working memory test on a desktop computer. The relationship between participants' working

memory test scores and their cognitive and noncognitive test scores were examined to investigate whether the relationships differ as a function of the device type on which participants were tested. The results failed to show the expected device type differences for cognitive ability. However, as hypothesized, there was a stronger relationship between working memory and general mental ability (GMA) when the GMA test was completed on a smartphone compared to a desktop computer. Also as hypothesized, there was no significant difference between the smartphone and desktop device conditions on noncognitive test scores, nor in the working memory-noncognitive test score correlations for smartphones and desktop computers. The findings provide partial, initial support for Arthur et al.'s SCIP model, which can be utilized to explain the effects of internet-based testing devices on scores on employment-related assessments and tests.

DEDICATION

In dedication to my father, Gary Hagen, for his support and constant faith in me.

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CHAPTER I

INTRODUCTION

With continued advances in technology, there has been an increase in the use of unproctored internet-based tests (UIT) in employment-related testing and assessment for selection purposes (Arthur, Doverspike, Munoz, Taylor, & Carr, 2014). Unproctored internet-based tests allow an organization to remotely administer employment-related tests on any internet-capable device. As a result, organizations have benefited from this change in assessment delivery by reducing their cost of test administration, increasing their applicant pool, and having relative administrative ease (Tippins, Beaty, Drasgow, Gibson, Pearlman, Segall, & Shephard, 2006). UITs also provide some benefits to test takers by permitting them even more degrees of freedom in terms of how, when, and where they can take an assessment (Arthur, Keiser, & Doverspike, 2016).

However, a cause for concern in UIT administration is the ability to interpret scores because of the differentiated context through which an assessment is given (Tippins et al., 2006). Due to the increase in the ownership and use of smartphones, job applicants are no longer restricted to desktop and laptop computers to complete these high-stakes assessments which is further cause for concern for the ability to interpret scores due to the lack of standardization in test administration between mobile and nonmobile devices (Arthur et al., 2014; Tippins et al., 2006). This lack of standardization can render the validity of a test unknown between device types until the equivalency of the methods is empirically verified (Květon, Jelínek, Vobořil, & Klimusová, 2007).

As of April 2015, 64% of American adults owned a smartphone, which is up from 58% in early 2014 (Smith, 2015). This 8% rise in smartphone ownership over the course of a year, indicates that the use of smartphones to complete employment related-assessments will continue to increase. Scores derived from testing done on mobile devices, such as smartphones (compared to nonmobile devices, such as desktops) may not accurately represent test takers abilities, especially for cognitive assessments (i.e., general mental ability tests). As discussed in Arthur et al. (2016), this may be because testing done on mobile devices differentially utilize working memory, perceptual speed and visual acuity, psychomotor ability, and selective attention. For example, mobile device testing places a greater demand on working memory due to an increased number of screens to display an equivalent amount of information on a nonmobile device. Thus, individuals with higher working memory capacity should show smaller differences between mobile-test derived scores and nonmobile-test derived scores than those with low working memory capacity. Despite these concerns, the use of mobile devices in employment-related selection testing was the Society for Industrial Organizational Psychology's (SIOP) number one workplace trend for 2015 (SIOP, 2015).

As shown in Arthur et al. (2014), the relative percentage of those choosing to take high-stakes employment assessments on a mobile device is low (1.93%). However, with the growing ownership of smartphones, the percentage of test takers taking an assessment on a mobile device is likely to increase. Despite SIOP's recognition of the growth of smartphones in employment-related selection testing, there is a dearth of research and literature on the equivalence of assessments that are delivered via mobile and nonmobile devices (Arthur et al., 2014). Of the 19 papers identified by Arthur et al. (2016) of relevance to this topic only four were peer-reviewed articles, fourteen were conference presentations, and one was a masters thesis. Clearly, more

research is needed to determine if the growing use of mobile devices in high-stakes employment testing is appropriate.

Research has indicated that score differences between mobile and nonmobile devices vary as a function of the type of assessment being administered. For noncognitive measures (i.e., personality tests), there are no significant score differences reported between mobile and nonmobile devices (Arthur et al., 2016; Illingworth, Morelli, Scott, & Boyd, 2014). In comparison, for cognitive measures (i.e., general mental ability tests) there are significant score differences between mobile and nonmobile devices, with higher scores reported on nonmobile devices (Arthur et al., 2016). These score differences are posited to arise from differences in screen size, screen clutter, the input interface, and permissibility of where the device can be used (Arthur et al., 2016). The smaller screen size of mobile devices, greater scrolling requirements, and the ability to take assessments in distractible environments that characterize mobile devices translate into a differentiated demand on the four different information-processing variables identified by Arthur et al. (2016), specifically working memory, perceptual speed and visual acuity, psychomotor ability, and selective attention. On the basis of these structural and information-processing differences, Arthur et al. (2016) placed device types on a continuum, ranging from smartphones, phablets, tablets, laptops, to desktops, with smartphones engendering the highest degree of cognitive load and desktops requiring the least. These information-processing differences are cause for ethical and professional concern, and it can be argued that the use of internet-based testing violates multiple parts of Section 9 of APA's *Ethical Principles of Psychologists and Code of Conduct*. Specifically relevant to mobile device testing, it can be argued that the use of mobile and nonmobile devices to deliver the same assessment violates the standard of standardization (Pearlman, 2009).

In spite of the lack of research directly testing Arthur et al.'s (2016) structural characteristics information processing (SCIP) model, there is some evidence that indirectly supports it. In two studies that focused on mobile devices (Sanchez & Branagan, 2011; Sanchez & Goolsbee, 2010), there were significant score differences between assessments taken on mobile and nonmobile devices as a result of differences in scrolling and text size, which places a differentiated demand on working memory. Due to the smaller size of mobile devices, communication oftentimes runs on multiple screens requiring the user to scroll to read the entirety of the text (Sanchez & Branagan, 2011). In Sanchez and Branagan (2011), this scrolling was shown to negatively affect reasoning performance. However, when the orientation was switched from portrait to landscape those who were lower in working memory capacity significantly improved their reasoning performance, while those higher in working memory capacity were relatively unaffected. Sanchez and Goolsbee (2010) found that text size could affect how well information is remembered. When text size increased the amount of scrolling on a small screen device, information recall was negatively impacted because of the higher demand placed on working memory. Although these studies did not directly focus on employment tests, they suggest that there may be a negative impact on performance when assessments are delivered via a mobile device versus a nonmobile device due to the increased demand on working memory and cognitive load in general (Arthur et al., 2016). Additional information-processing variables associated with screen size are perceptual speed and visual acuity, which can be impaired if there are clutter-related issues that vary with screen size.

In regards to psychomotor ability, the interface of the device plays an important role in the ability of a person to manipulate the screen. As noted by Arthur et al. (2016), the use of finger swipes versus a keyboard/mouse can result in more difficulty interacting with a mobile device.

Due to the smaller screen size of mobile devices, people inevitably interact more with the device since more screens are needed to present an equivalent amount of information on a nonmobile device placing a higher demand on psychomotor ability.

Lastly internet-based testing devices vary in the amount of permissibility a test taker has to decide where to take an assessment. Test takers have more degrees of freedom (high permissibility) in choosing where to take an assessment when completing it on a mobile device, resulting in assessment being completed in more distracting environments. The ability of test takers to remain focused on goal-relevant stimuli (i.e., a test) varies when people are distracted by task-irrelevant stimuli (i.e., noise in a public space) (Lavie, 2005). In a study comparing proctored and unproctored test administration, of the 163 students in the unproctored condition, 89% took the assessment at home, 2% from the library, and 9% from the office. Of the unproctored group 61% were somewhat bothered by the noise, 31% were bothered, 4% were very bothered, and 2% were extremely bothered. In contrast, of the 252 in the proctored condition 90% were not bothered by the noise, 8% were somewhat bothered, 0% were bothered, 1% were very bothered, and 0% were extremely bothered (Shephard, Do, & Drasgow, 2003). Clearly, the relationship between environment and distractibility cannot be ignored. Taking an assessment on a mobile device can result in a greater demand placed on selective attention due to the higher degree of permissibility, and can cause test takers to become distracted with task-irrelevant stimuli.

While Arthur et al.'s (2016) SCIP model of the interaction between internet-based testing device type and score differences between cognitive and noncognitive measures logically makes sense, there has yet to be any empirical tests of the model. For the purposes of this study, the focus is

specifically on smartphones and desktop computers, which occupy the higher and lower ends of the device engendered construct-irrelevant cognitive load (Arthur et al., 2016).

The present study addresses one component of Arthur et al.'s (2016) model—working memory. Working memory is defined as “the use of short-term memory as a temporary store for information needed to accomplish a particular task” (Reed, 2013, p. 72). When information is displayed on a mobile device, it oftentimes will require more screens to display an equivalent amount of text on a nonmobile device. This requires the test taker to keep more information active in their short-term memory resulting in a higher cognitive load. In turn, this will translate into differentiated scores between mobile and nonmobile devices due to the greater demand on working memory in mobile device testing versus the demand on working memory in nonmobile device testing.

In summary, on the basis of the preceding review and aligned with the tenets of the SCIP model the following were hypothesized:

Hypothesis 1: For cognitively-loaded constructs, smartphone derived mean scores will be significantly lower than desktop computer derived mean scores.

Hypothesis 2: For noncognitive constructs, smartphone and desktop computer mean scores will not be significantly different.

Hypothesis 3: For cognitively-loaded constructs, smartphone scores will display a higher relationship with working memory than desktop computer scores.

Hypothesis 4: For noncognitive constructs, the relationship between working memory and device type will be weak, and nonsignificant.

CHAPTER II

METHODS

Participants

Participants were recruited from the Texas A&M University Psychology Department Subject Pool ($n = 196$). Participants received a total of 3 research credits to fulfill an introductory psychology course research requirement. No monetary compensation was provided. As a result of recruiting participants from a psychology department subject pool, the selection process was restricted and may not be representative of the general population. Participants were randomly assigned into the mobile ($n = 100$) and nonmobile ($n = 96$) conditions. Of the sample, 43.59% were male ($n = 86$) and 56.41% were female ($n = 110$) and the average age reported was 19.08 ($SD = 1.30$) with a minimum of age of 18 and a maximum age of 28.

Measures

Cognitive Ability. Cognitive ability was operationalized as scores on a general mental ability (GMA) test developed by Arthur (2014). Participants were allotted 10 minutes to complete the 60-item (30 verbal, 30 numeric), multiple-choice assessment. Scores were computed as the number of items answered correctly. A 7-10 day retest reliabilities of .76 and .70 have been reported for two alternate forms of the test (Naber, Arthur, Edwards, & Franco-Watkins, 2016).

Noncognitive constructs. Three dimensions of the five-factor model (FFM) of personality—agreeableness, conscientiousness, and emotional stability—were used to operationalize noncognitive constructs. Participants were administered a 30-item FFM International Personality

Item Pool (IPIP) measure with 10 items per dimension (Goldberg, 1999). Each participant utilized a five-point Likert scale (1 = very inaccurate, 5 = very accurate) to rate how descriptive an item is of them. Internal consistency reliability estimates of .82, .79, and .83 were obtained for agreeableness, conscientiousness, and emotional stability respectively.

Working memory. Working memory was measured using a computerized version of the N-back lag task (Shelton, Metzger, & Elliott, 2007). Participants were presented with a list of items (letters) at the rate of one item per second. After being presented with the list, the participants were asked to recall the last item in the list, the item presented 1-back, 2-back, or 3-back in the list. Participant scores were then calculated as the average number of items correctly recalled minus incorrect recalls. No test-retest reliability data are reported in the extant literature for Shelton et al.'s (2007) N-back lag task. However, in a convergent validation study by Geffen (2004) an average correlation of .51 between the subscales (0-, 1-, 2-, or 3-back trials) of the N-back lag task, indicates some degree of internal consistency between the trials. Similarly, a correlation of .35 between a short form of the Raven's Advanced Progressive Matrices and total N-back lag task scores was obtained by Naber et al. (2016).

Procedure

Devices at the extreme ends of the Arthur et al.'s continuum (desktop computers [nonmobile device] and smartphones [mobile devices]) were used as a between-subjects condition.

Participants were randomly assigned to these two conditions. The cognitive ability test, IPIP Likert-scale measure, and a FFM-SJT¹ were completed on the participants' assigned devices, and

¹ This is a situational judgment test based measure of the five-factor model dimensions of conscientiousness and agreeableness, which was administered as a part of a larger project.

all other measures were completed on the desktop computer. All participants completed the assessments in the proctored lab. Within each condition, the administration of measures was counterbalanced as follows: (1) cognitive ability measure, IPIP Likert-scale, FFM-SJT, N-back lag test, social desirability measure², demographics; and (2) N-back lag test, FFM-SJT, IPIP Likert-scale, cognitive ability test, social desirability measure, and demographics.

² This is a measure of social desirability responding, which was administered as a part of a larger project.

CHAPTER III

RESULTS

Cognitive and noncognitive scores and device type

Hypothesis 1 had posited that for cognitively-loaded constructs, smartphone mean scores would be lower than mean scores obtained on a desktop computer. As reflected in the results presented in Table 1, this hypothesis was not supported since the scores for the device types were very similar ($t(193) = 0.32, p > 0.05; d = 0.05$). Hypothesis 2 had posited that for noncognitive constructs, smartphone derived mean scores would not differ significantly from desktop derived mean scores. Contrary to what was hypothesized, the differences for agreeableness between device types were significant ($t(192) = -2.01, p < 0.05, d = -2.90$). In contrast, the differences for conscientiousness ($t(192) = -1.48, p > 0.05; d = -0.23$) and emotional stability scores ($t(192) = 1.12, p > 0.05; d = 0.16$) was not significant.

Table 1

Means, Standard Deviations, and Effect Sizes for Cognitive and Noncognitive Construct Scores Across Device Types

Variable	Device Type				
	Smartphone		Desktop		<i>d</i>
	<i>M</i>	<i>SD</i>	<i>M</i>	<i>SD</i>	
GMA	59.90	11.74	58.35	11.93	0.05
Agreeableness	37.60*	5.52	39.24*	5.87	-2.90*
Conscientiousness	35.11	5.10	36.27	5.79	-0.23
Emotional Stability	31.48	7.04	30.45	5.69	0.16

Note. * $p < 0.05$ (two-tailed); GMA means general mental ability

Working memory, construct scores, and device type

Hypothesis 3 posited that for cognitively-loaded constructs, smartphone scores would display a higher relationship with working memory than desktop computer scores. As the results in Table 2 indicate, the relationship between GMA and working memory for the smartphone condition was statistically significant ($r = 0.23, p < 0.05$), and more than twice as large as the relationship between GMA and working memory for the desktop condition which was not statistically significant, $r = 0.11, p > 0.05$. However, the difference between these two correlations was not statistically significant, $Z(193) = 0.57, p > 0.05$.

Hypothesis 4 posited that for noncognitive constructs, the relationship between working memory and device type would be weak and nonsignificant. As the results in Table 2 show, none of the relationships between the noncognitive constructs and working memory for both either device types were statistically significant. Furthermore, the differences between the correlations for each device type were not significant either.

Table 2

Correlations Between Construct Scores and Working Memory

Variables	Device Type		<i>Z</i>
	Smartphone	Desktop	
GMA/WM	.23*	.11	0.57
Agreeableness/WM	.09	.03	0.41
Conscientiousness/WM	-.03	-.14	0.76

Emotional Stability/WM	.12	-.04	1.10
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Note. * $p < 0.05$ (two-tailed); WM means working memory

CHAPTER IV

CONCLUSION

The findings of this study provide partial support for the hypotheses. Hypothesis 1 was not supported, and results showed that GMA scores did not differ significantly between the smartphone and desktop computer conditions. Contrary to Hypothesis 2, there was a significant effect for agreeableness and its relationship with device type contradicted the hypothesis that there would not be any significant differences in noncognitive scores between device types. However in line with Hypothesis 2, there were no significant effects for conscientiousness and emotional stability and their relationships with device type. Hypothesis 3 was partially supported and showed that when smartphones are used to assess GMA, there is a higher relationship with working memory than when GMA is assessed on desktop computers. However, this difference was not statistically significant. Additionally, Hypothesis 4 was supported; the results showed that when smartphones and desktop computers are used to measure noncognitive constructs, the relationship between working memory and device type is weak and nonsignificant.

A possible explanation for the inconsistency between the results showing that cognitive scores did not differ between smartphone and desktop device types and prior findings could be due to differences between the field (high-stakes) and lab (low-stakes) settings. Of the five studies examining differences in cognitive scores between device types identified by Arthur et al. (2016), only one study (i.e., Parker & Meade, 2015) did not obtain significant group mean differences on the cognitive assessments and similar to the present study, it was lab-based. The four other studies examining differences in cognitive scores between device types identified by

Arthur et al. (2016) used operational field data obtained from organizations delivering high-stakes selection assessments. In contrast to the field-based studies, the present lab study was low-stakes, which may point to motivational factors as another plausible explanation for the inconsistent finding. Participants in this study received the same amount of research credit regardless of their performance. In contrast, in the field a higher level of performance on an assessment translates into a higher chance of being selected for a job. In the future, a monetary incentive for top performers could be added to motivate participants to perform to the best of their ability to attempt to replicate the high-stakes nature of the field.

Another possible explanation for the observed cognitive score differences between devices seen in the field versus the lack of differences seen in the lab pertain to self-selection. Participants in this study were randomly assigned to conditions, whereas in the field applicants have the choice to take an assessment on any device type with Internet access. Research has documented demographic differences between smartphone and desktop computer applicants, such as a higher percentage of female, African-American, Hispanic, and younger applicants using smartphones at a higher rate (Arthur et al., 2014). Further research on differences between those who select to take assessments on smartphones versus those who chose to take assessments on desktop computers will need to be undertaken to determine if individuals who choose to take assessments on specified device types are inherently different resulting in the observed score differences in the field operational data.

The mixed support for Hypothesis 2 is an anomaly and at the present time is difficult to explain. Additionally, because of the relatively small sample size, some of the tests reported here (e.g., the test for differences between correlations) may be underpowered.

In conclusion, the results of this study provide partial, initial support for Arthur et al.'s SCIP model. To the extent that additional support is obtained for the SCIP model, it would provide a framework to understanding how the structural characteristic differences between internet-based testing device types translate into differential demands on the information processing variables of working memory, perceptual speed and visual acuity, psychomotor ability, and selected attention, and how these information processing demands result in score differences. The present study examined the role that working memory plays in the score difference observed between smartphones and desktop computers. Further research will be needed to empirically examine the role the other information processing variables (i.e., perceptual speed and visual acuity, psychomotor ability, and selective attention) identified by the SCIP model play in influencing device-type scores, and the relative importance of these information processing variables as well.

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