Cognitive Test Scores Vary Based on Choice of Personal Digital Device

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Abstract

Mobile- and web-based psychological research are a valuable addition to the set of tools available for scientific study, reducing logistical barriers for research participation and allowing the recruitment of larger and more diverse participant groups. However, this comes at the cost of reduced control over the technology used by participants, which can introduce new sources of variability into study results. In this study, we examined differences in measured performance on timed and untimed cognitive tests between users of common digital devices in 59,587 (Study 1) and 3,818 (Study 2) visitors to TestMyBrain.org, a web-based cognitive testing platform. Controlling for age, sex, and cognitive performance on an untimed vocabulary test, users of mobile devices, particularly Android smartphones, showed significantly slower performance on tests of reaction time than users of laptop and desktop computers, suggesting that differences in device latency effect measured reaction times. Users of devices that differ in user interface (e.g. screen size, mouse vs. touchscreen) also show significant differences ($p < 0.001$) in measured performance on tests requiring fast reactions or fine motor movements. By quantifying the contribution of device differences to measured cognitive performance in an online setting, we hope to improve the accuracy of mobile- and web-based cognitive assessments, allowing the strengths of these methods to be effectively used.

Introduction

Mobile- and web-based studies are a valuable addition to the set of tools available for psychological research. Digital cognitive assessments allow researchers to recruit participants on a broader scale than would be possible in an individual lab by reducing logistical barriers such as travel to and from a research lab, leading to greater sample sizes with no need for additional recruitment efforts (Kraut et al., 2004; Germine et al., 2012). Research using personal digital devices for administering study measures has also proven to produce more diverse participant groups than are used in most conventional psychological research (Gosling & Mason, 2015). Computer-based measures can also provide types of data that traditional metrics do not, such as the time it takes participants to respond to individual survey questions (Joinson et al., 2007). By allowing researchers to draw on a larger, more diverse, and more representative sample of the general population and obtain more precise data, online research using digital devices could lead to increased scientific rigor in the fields of psychology and cognitive science. In addition, making studies broadly available online and through participants' own devices makes it easier for participants to learn about and engage with research in psychology, opening up channels of communication between researchers and the general public. Research participation can have significant educational benefits for those learning about psychology; citizen science through online research could make these benefits available to all (De Liaño, León, & Pascual-Ezama, 2012).

However, these benefits of research using personal digital devices come at the cost of control over the setting in which participants complete the study session (Reips, 2000; Nosek, Banaji, & Greenwald, 2002). This loss of control is particularly significant in relation to the specific technology used by study participants (Woods et al., 2015). While a lab-based study

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allows researchers to provide any necessary digital devices (and thus ensure that they remain consistent between all participants), participants in online research can use a wide variety of devices, including desktop and laptop computers, smartphones, tablets, and e-readers (De Bruijne & Wijnant, 2013). These devices can differ widely in hardware, software, and user interface, introducing uncontrolled and undetected variation into the experimental procedure (Woods et al., 2015; Germine et al., 2019), which may impact results.

One potential source of device variation that could affect data in psychological research, and particularly research involving reaction time, is device latency (Pavlovych & Gutwin, 2012). The latency of a device refers to the time necessary for a user's input (such as a mouse click or a touch on a touchscreen) to be registered by the computer. While device latencies for most commonly used technologies are short enough to be unnoticeable for most users, they can have a significant impact on time-dependent cognitive tests, such as tests of reaction time. The average simple reaction time has been shown to be in the range of 200-300 ms, with time increasing with age (Jain et al. 2015; Wilkinson & Allison, 1989; Woods et al., 2015). Therefore, variation in device latency, which usually ranges from 50-200 ms for touchscreen devices to 15-35 ms for modern desktop computers, has the potential to distort measured reaction times, causing true inter-individual differences in performance to be drowned out by increasing variation irrelevant to neurocognitive ability (Henze, Funk, & Shirazi, 2016; Pavlovych & Gutwin, 2012). For example, some studies of the difference in reaction time between schizophrenic and non-schizophrenic subjects show differences of approximately 100 ms, small enough to be affected by the differences in measurement caused by device latency (Ngan & Liddle, 2000). Thus, without a way to control for variations in device latency, one cannot adapt reaction time research

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to an online format without running the risk of conflating device variation with actual variation in participant performance.

Measures of reaction time are a key instrument for research in psychological science. Despite its simplicity, reaction time provides a robust measure of cognitive function; performance on tests of simple reaction time (the time between the presentation of a cue stimulus and the completion of a response) and related tasks are correlated with a broad range of general intelligence measures, including less time-dependent measures based on arithmetic and vocabulary knowledge (Luciano et al., 2003). In addition, cognitive processing speed as measured by reaction time may explain the relationship between general intelligence and life outcomes; a study of 898 adults followed from ages 56 to 70 showed that the established relationship between general intelligence and all-causes mortality is no longer significant after controlling for reaction time (Deary & Der, 2005). As a measure of brain function, reaction time is associated with cognitive impairment across disorders, including schizophrenia, Parkinson's disease, and traumatic brain injury (Ngan & Liddle, 2000; Evarts, Teräväinen, & Calne, 1981; Hetherington, Stuss, & Finlayson, 1996). Older adults and people with cognitive impairments frequently show reaction times that are not only slower than the population average, but also more variable from trial to trial (Hultsch, Macdonald, & Dixon, 2002; Gorus et al., 2008). Typical reaction times on a test of simple reaction time are approximately 200-300 ms, so the 50-200 ms of delay contributed by device latency could be greater than the true variation between individuals (Jain et al., 2015; Wilkinson & Allison, 1989; Ngan & Liddle, 2000).

Because tests of reaction time and other timed tasks that take place on the scale of milliseconds are such vital tools in psychological research, it is crucial that, in taking advantage of the many benefits of digital cognitive assessment, we do not lose the ability to measure

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cognition accurately. In this study we use a large, diverse online sample to characterize the extent to which variations between digital devices used by participants affects their scores on reaction time-based tests. Based on our understanding of device latency, we predict that users of different digital devices will show differences in observed performance on cognitive tests based on reaction time. We expect that some of these differences will be associated with cognitive and demographic factors that vary with device ownership - for example, tablet users tend to be older than users of other devices. However, we expect that device-related differences will persist after controlling for demographic and cognitive differences measured by device-robust tasks (e.g. untimed tasks with simple stimuli). Because true reaction times scale with the cognitive complexity of the task, while device latencies do not, we expect that device-related differences will be the largest (as a proportion of overall variability) in tasks with short reaction times. In contrast, we expect smaller relative contributions of device variability on more complex tests that produce longer reaction times. Finally, we suggest methods to reduce potential device-related confounds.

Study 1: Differences in Reaction Time by Device

In Study 1, we analyzed existing data on cognitive test performance and device characteristics from a large sample of visitors to TestMyBrain.org. We looked at each of the five most frequently used classes of devices on timed and untimed cognitive tests.

Methods

Participants

Study 1 was based on large samples of data collected across a range of tasks from 2013 - 2019 through the TestMyBrain.org platform. Our participants consisted of 59,587 volunteers who visited TestMyBrain.org, a citizen science website that allows people to participate in cognitive

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research studies in exchange for individualized feedback on their performance after each study. Data from TestMyBrain.org has been shown to be of similar high quality to data gathered in a lab setting (Germine et al., 2012) and replicate findings from traditional lab or clinical settings (Hartshorne & Germine, 2015; Halberda et al., 2012; Germine & Hooker, 2011). Before starting a task, participants read a study information sheet and gave informed consent. After completing the task, participants received feedback on their results relative to other individuals who had completed the same test. Consent and study procedures were reviewed by the Harvard Committee on the Use of Human Subjects.

Participants ranged in age from 18 to 80 years old, with a mean age of 35.92 years ($SD = 15.23$). The sample contained similar numbers of male and female participants (48.56% male, 51.24% female, 0.20% non-binary/genderqueer). While the TestMyBrain platform is open to participants in all parts of the world, we limited our sample to participants who reported speaking English as a native language since one of our measures assessed English vocabulary knowledge. Further information on the demographic characteristics of the sample can be found in Table 1.

This study included data from all participants who completed one or more of the following tests on TestMyBrain using a device that could be identified from user agent data: simple reaction time, digit symbol matching, or vocabulary (described below). Of 59,587 participants who completed any of these tests on an identifiable device, 30,751 completed simple reaction time, 17,507 completed digit symbol matching, and 21,524 completed vocabulary. See Table 1 in supplement for makeup of each test's data set by device.

Table 1. Study 1 Participant Characteristics and Analysis Sample Sizes

Variable [range]	Analysis N	<i>n</i> (%)	<i>M</i> (<i>SD</i>)
Age [18-80]	59,587		35.92 (15.23)
Gender	59,119		
Male		28,709 (48.56)	
Female		30,291 (51.24)	
Non-binary/Genderqueer		179 (0.20)	
Education*	46,701		
Primary school		10 (0.02)	
Middle school		482 (1.03)	
High school		6,024 (12.90)	
Some college		13,291 (28.46)	
Technical training/associate's degree		347 (0.74)	
Bachelor's degree		13,969 (29.91)	
Graduate school		12,578 (26.93)	

*Self-reported highest level of education completed

Measures

Simple Reaction Time. This simple reaction time test requires participants to respond to a green square cue after a waiting period indicated by a red square cue. They are asked to respond by pressing the space bar or touching their touchscreen as quickly as they can. The time between the two cues varies between 700 and 1500 milliseconds, with delays sampled based on an exponential random distribution from this range. There is also a consistent 700 ms delay between a participant's response in one trial and the presentation of the wait cue in the next trial. This task is a measure of basic psychomotor response speed and has been used in previous studies (McLean et al., 2019, Passell et al., 2019). Notably, this task produces relatively short reaction times; the median reaction time in our sample was 303.86 ms ($SD = 68.94$ ms).

Digit Symbol Matching. The digit symbol matching task requires participants to use a key presented on screen to indicate which of three numbers (1, 2, or 3) corresponds to a symbol shown on screen. Symbols are simple black and white icons and each number is paired with three symbols in the key. This task was adapted from the classic Wechsler digit symbol coding

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task (Drozdzick et al., 2012) and adapted for web/ mobile administration. This task is a measure of processing speed and short-term memory (Joy, Kaplan, & Fein, 2004) and has been used in previous studies as a measure of processing speed across the lifespan (Hartshorne & Germine, 2015; Mclean et al., 2019). This task produces longer reaction times than the simple reaction time task; the median reaction time on this test in our sample was 1360.03 ms (SD = 354.68).

Vocabulary. We used a 20-item test of English vocabulary, with words increasing in difficulty over the course of the test. In this test, the participant sees a word and has to select which of five words is closest in meaning to the target word. This test was included as a measure of cognitive ability that is not based on differences in reaction time, and thus would be expected to be relatively unaffected by device differences. This test has been used in previous studies as a measure of crystallized cognitive ability across the lifespan (Hartshorne & Germine, 2015; Mclean et al., 2019; Passell et al., 2019). Vocabulary has been shown to correlate significantly, however, with performance on tests of processing speed and with overall cognitive performance (Luciano et al., 2004; Crawford, 1989).

Data Analysis

All data analysis was performed in R (R Core Team, 2012). In addition to base R functions, we used the *effsize* R package to compute effect sizes and the *uaparserjs* R package to parse user agent information in order to identify digital devices (Torchiano, 2019; Rudis et al., 2016). We examined differences in performance by device group using linear regression, with effect sizes reported in terms of Cohen's *d*. Analyses were conducted with and without age and sex as covariates. Cognitive test data used in linear regressions reported in results are scaled to have a mean of 0 and a standard deviation of 1, and results of linear regression are reported in standard deviation units.

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To maintain data quality, we excluded participants whose performance indicated that they were not completing the task as intended. In reaction time tasks, we excluded individual trials with impossibly short response times and instead imputed the participant-level mean reaction time for those trials. The threshold for trial-level exclusions was set at 200 ms for simple reaction time and 600 ms on digit symbol matching. For simple reaction time, this threshold was determined based on established physiological limitations. For digit symbol matching, the threshold was based on examination of reaction times where accuracy reliably falls to chance-level. We also imputed the participant-level mean on all trials in which the participant did not make a response within the time limit (2 seconds for simple reaction time; 10 seconds for digit symbol matching). If a participant had more than 10% of their reaction times outside of this range on simple reaction time (200 - 2000ms) or digit symbol matching (600 - 10,000ms), their data on the test in question was excluded from analysis. 3,329 participants (10.83%) had their simple reaction time data removed, while 350 participants (2.00%) had their digit symbol matching data removed. These exclusions were mostly due to fast responding (96.4% of excluded simple reaction time trials were below the minimum RT cutoff, while 98.1% of excluded digit symbol matching trials were below the minimum RT cutoff). In addition, participants who chose the same response (e.g. repeatedly selecting 3) 90% of the time or more in digit symbol matching had their data from this test excluded; of the participants who were not excluded for outlying reaction times, only 2 additional participants (0.0001%) had their data excluded based on this criterion.

Results

Effect of Demographic Differences in Device Use

The participant groups that completed tests on each device differed from one another in demographic characteristics as well as cognitive test performance (see Table 2). A one-way

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ANOVA showed significant differences in the ages of users of different devices ($F(4, 5,9582) = 499.3, p < 0.001, R^2 = 0.03$); users of iPhone and Android devices were younger, on average, than users of laptop or desktop devices, while users of iPad tablets had a higher average age than all other groups. The full age distribution of each device group can be seen in Appendix 2.

Device groups also differed by gender, with users of mobile devices being more likely to be female than users of laptop or desktop devices. A chi-square test of independence showed that these differences were significant ($\chi^2(8) = 995.43, p < 0.001$). Also significant were differences in educational background between users of different devices ($\chi^2(24) = 1294.1, p < 0.001$), with users of Macintosh devices having completed the most years of education on average and users of Android devices having completed the fewest.

Age, sex, and educational background are known to predict performance on both timed and untimed cognitive tests. Previous research has shown that reaction time typically becomes slower over the course of the adult lifespan (Tun & Lachman, 2009). This is consistent with what we found in our data, which showed a significant positive correlation between age and latency in simple reaction time ($r = 0.23, 95\% \text{ CI } [0.22, 0.24], p < 0.001$). There is also evidence of sex differences in reaction time, with males showing faster reaction time on average (Dominika et al., 2012); this pattern was also demonstrated in our simple reaction data ($t = -23.16, p < 0.001$). Thus, differences in observed performance between users of different devices could reflect differences in the demographic characteristics of people who choose each device, as well as the effects of the devices themselves. For this reason, we looked at the association between device type and cognitive test performance before and after controlling for age and sex.

Table 2. Demographic Differences in Device Use*

Device**	N	Mean age (SD)	Percent female	Mean years of education (SD)
Android	6,593	33.23 (13.17)	55.01	14.72 (2.18)
iPhone	4,678	31.99 (11.96)	61.39	15.01 (2.15)
iPad	3,456	45.60 (15.85)	62.41	15.52 (2.21)
Macintosh	10,779	35.40 (15.40)	56.61	15.86 (1.96)
Windows	34,081	36.17 (15.45)	45.58	15.32 (2.14)

* Demographic statistics were computed based only on participants who successfully completed all tests and whose data was not removed for quality control.

** Android devices include both mobile phones and tablets; Windows devices include tablet, laptop, and desktop computers

Differences in Performance by Device

Based on linear regression (Windows used as comparison group, reaction time and vocabulary errors standardized), device type was associated with cognitive performance across all tests (simple reaction time: $R^2 = 0.16$, $p < 0.001$; digit symbol matching: $R^2 = 0.018$, $p < 0.001$; vocabulary: $R^2 = 0.03$, $p < 0.001$); variance explained by device type was greatest by an order of magnitude for simple reaction time. Users of mobile devices showed slower reaction times and more vocabulary errors than users of laptop and desktop devices on most tests (see Table 3). These differences persisted after controlling for age and sex; this effect is greatest on simple reaction time, with effect sizes that ranged from one standard deviation difference for Android vs. Windows (poorer performance for Android; $\beta = 1.03$, $p < 0.001$), more modest effect sizes for iPad and iPhone vs Windows (iPad: $\beta = 0.45$, $p < 0.001$; iPhone: $\beta = 0.34$, $p < 0.001$), and a small difference for Macintosh desktop/laptop vs Windows but in the opposite direction ($\beta = -0.15$, $p < 0.001$). Effect sizes were smaller but still significant for digit symbol matching (Android: $\beta = 0.31$, $p < 0.001$; iPad: $\beta = -0.035$, $p = 0.21$; iPhone: $\beta = 0.16$, $p < 0.001$; Macintosh: $\beta = -0.15$, $p < 0.001$) and vocabulary (Android: $\beta = 0.27$, $p < 0.001$; iPad: $\beta = -0.03$, $p = 0.37$; iPhone: $\beta = 0.03$, $p = 0.05$; Macintosh: $\beta = -0.29$, $p < 0.001$) (see Table 3 for effect size). Controlling for age and sex, Android users still showed the greatest differences on tests of reaction time, being significantly slower than the Windows comparison group. The fact that we

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saw differences for both timed and untimed tests suggests that some of these differences may be due to differences in the makeup of the participant groups that use each device, rather than a consequence of differences in the devices alone. The full distribution of age- and sex- controlled test performance for each device group can be seen in Figure 1.

Table 3. Performance by Device Across Tasks

Mean (SD) Performance for Frequently Used Device Groups			
Device*	Simple RT (ms)	DSM** RT (ms)	Vocabulary errors
Android	374.53 (75.13)	1494.44 (333.16)	7.27 (4.18)
iPhone	326.05 (56.34)	1418.30 (290.67)	6.55 (3.87)
iPad	346.94 (66.84)	1522.89 (335.70)	4.46 (3.55)
Macintosh	293.65 (48.97)	1342.29 (302.33)	4.44 (3.54)
Windows	304.44 (64.07)	1407.71 (377.70)	5.71 (4.26)
Effect Size (95% CI) of Device Differences on Performance (Cohen's d, Windows device as comparison group)			
Android	1.05 (1.01, 1.08)	0.23 (0.18, 0.28)	0.37 (0.31, 0.43)
iPhone	0.34 (0.31, 0.38)	0.03 (-0.03, 0.09)	0.20 (0.13, 0.27)
iPad	0.66 (0.61, 0.71)	0.28 (0.22, 0.34)	-0.29 (-0.36, -0.23)
Macintosh	-0.18 (-0.21, -0.14)	-0.18 (-0.22, -0.14)	-0.31 (-0.34, -0.27)
Effect Size (95% CI) of Device Differences on Age- and Sex-Residualized Performance (Cohen's d, Windows device as comparison group)			
Android	1.08 (1.04, 1.11)	0.33 (0.28, 0.38)	0.30 (0.24, 0.36)
iPhone	0.36 (0.32, 0.40)	0.17 (0.11, 0.23)	0.07 (0.00, 0.14)
iPad	0.48 (0.43, 0.53)	-0.03 (-0.10, 0.03)	-0.03 (-0.09, 0.04)
Macintosh	-0.18 (-0.22, -0.15)	-0.16 (-0.20, -0.12)	-0.34 (-0.37, -0.31)

* Android devices include both mobile phones and tablets; Windows devices include tablet, laptop, and desktop computers. For all measures, lower values indicate better performance.

** Digit symbol matching test

Figure 1. Distribution of Test Performance by Device

In addition to overall reaction time, we examined variance in within-participant variability between device groups. We conducted this analysis to determine if the consistency of

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reaction time measurement varies among commonly used device types. If some device groups show greater within-person variability than others, this could be an indication of imprecision in reaction time measurements from those devices. Variability for each participant was calculated as the standard deviation of their reaction times across trials in the Simple RT and Digit Symbol Matching tasks (see Table 2 in supplemental materials). Controlling for age and sex in a linear model (variability scores standardized to have a mean of 0 and standard deviation of 1; Windows devices as a reference group), we found differences in variability by device type on simple reaction time (Android: $\beta = -0.17$, $p < 0.001$; iPad: $\beta = -0.24$, $p < 0.001$; iPhone: $\beta = -0.14$, $p < 0.001$; Macintosh: $\beta = -0.12$, $p < 0.001$) and digit symbol matching (Android: $\beta = 0.015$, $p = 0.53$; iPad: $\beta = -0.25$, $p < 0.001$; iPhone: $\beta = 0.018$, $p = 0.53$; Macintosh: $\beta = -0.15$, $p < 0.001$). These effects were consistent with greater within-person variability among Windows users than users of other devices. These differences could be due to differences in the precision of measurement or to inconsistent responses caused by differences in input method; mobile devices almost universally use touchscreens as opposed to mouse or keyboard input, which could affect response patterns. For more detailed information on differences in variability by device, see Table 2 in supplemental materials.

Study 2: Differences in Reaction Time by Device, Controlling for General Cognitive Ability

Study 1 indicated that there were differences in cognitive test performance between users of different devices. However, we also found differences in cognitive test performance on a test of vocabulary knowledge, where contributions of software/hardware characteristics should be minimal. Thus, it is possible that differences in reaction time measurement by device are related to differences in cognitive ability that vary with device ownership. In the next study, we recruited a group of participants to complete a larger set of timed tests and an untimed test of

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vocabulary knowledge, allowing us to examine how device differences differentially affect performance within the same participant, after controlling for device-insensitive differences in general cognitive ability (as measured by vocabulary). We also collected additional device information to be able to better distinguish between Android and Windows tablets and smartphones.

Methods

Participants

Participants consisted of 3,818 volunteers who visited TestMyBrain.org over a period of 6 months in 2018. Participants ranged in age from 18 to 80 years old, with a mean age of 35.44 years ($SD = 15.96$). The sample contained similar numbers of male and female participants (46.10% male, 51.70% female, 2.20% non-binary/genderqueer). While the TestMyBrain platform is open to participants in all parts of the world, we limited our sample to participants who reported speaking English as a native language. Further information on the demographic characteristics of the sample can be found in Table 4.

Table 4. Study 2 Participant Characteristics and Analysis Sample Sizes

Variable [range]	Analysis N	<i>n</i> (%)	<i>M</i> (<i>SD</i>)
Age [18-80]	3,818		35.44 (15.96)
Gender	3,818		
Male		1,760 (46.10)	
Female		1,974 (51.70)	
Non-binary/Genderqueer		84 (2.20)	
Education	2,875		
Primary school		8 (0.28)	
Middle school		71 (2.51)	
High school		441 (15.61)	
Some college		711 (25.17)	
Technical training/associate's degree		206 (7.29)	
Bachelor's degree		782 (27.68)	
Graduate school		656 (23.22)	

Measures

For Study 2, participants completed a battery of tests including simple reaction time, digit symbol matching, and vocabulary. In addition, to look at potential effects of screen size on cognitive test performance, we included a digital trail-making task in a subset of later participants ($N= 1,997$, parts A and B) (Reitan, 1958). The trail-making task, commonly used in neuropsychological assessment, requires participants to connect a series of points in a predetermined order as quickly as possible. In part A, the points are numbered and must be connected in numerical order (i.e. connecting point 1 to point 2, point 2 to point 3, etc.). In part B, some points are numbered while others are given letter labels, and participants must alternate numbered and letter-labeled points while maintaining numerical and alphabetical order (i.e. connecting point 1 to point A, point A to point 2, point 2 to point B, etc.). This task measures processing speed (parts A and B) and cognitive flexibility (part B). This test is scored based on the speed with which items are connected; the median time to connect two points in part A was 661.5 ms ($SD = 264.35$ ms), while in part B it was 1008 ms ($SD = 462.97$ ms).

Data Analysis

All data analysis was performed in R, using the same packages used in Study 1 (R Core Team, 2012; Torchiano, 2019; Rudis et al., 2016). We examined differences in performance by device group using linear regression, with effect sizes reported in terms of Cohen's d . Cognitive test data used in linear regressions reported in results are scaled to have a mean of 0 and a standard deviation of 1, and results of linear regression are reported in standard deviation units. Age and sex were included as covariates in all models. We also included vocabulary performance as a covariate to control for general cognitive ability, as this test is unlikely to be directly affected by device differences. Outlying data was removed according to the same quality

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control criteria used in Study 1. 413 participants (11.74%) had their simple reaction time data removed, while 93 participants (2.78%) had their digit symbol matching data removed.

In this study, we also collected information on screen size and input type (mouse/keyboard or touchscreen) for all devices used by participants. Based on these data, we found that 13.68% of Windows devices were touchscreen-based tablets; the remainder were laptop or desktop computers.

Power

Data collection continued until we had at least 100 participants using each of the 5 most common device types (iPhone, Android phone or tablet, iPad, Macintosh laptop or desktop computer, or Windows laptop or desktop computer) on each test. Using a linear model to identify differences in performance between device groups, this sample size would provide 80% power to identify an effect size of $f^2 = 0.13$ ($\alpha = 0.05$). Because some devices were more frequently used by participants, final group sizes ranged from 136 iPad users to 927 Windows users. Thus, our *a priori* power estimate should be considered a conservative estimation of the effect sizes detectable based on these data.

Results

Performance on Timed Tests After Controlling for Vocabulary

Consistent with findings from Study 1, after controlling for age, sex, and vocabulary, we found significant differences in measured performance between device groups (using Windows as a comparison group) on simple reaction time (Android: $\beta = 1.00$, $p < 0.001$; iPad: $\beta = 0.59$, $p < 0.001$; iPhone: $\beta = 0.29$, $p < 0.001$; Macintosh: $\beta = -0.01$, $p = 0.84$), digit symbol matching (Android: $\beta = 0.17$, $p < 0.001$; iPad: $\beta = -0.11$, $p = 0.11$; iPhone: $\beta = 0.09$, $p = 0.05$; Macintosh: $\beta = -0.01$, $p = 0.71$), trails A (Android: $\beta = 0.53$, $p < 0.001$; iPad: $\beta = -0.60$, $p < 0.001$; iPhone: $\beta =$

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0.42, $p < 0.001$; Macintosh: $\beta = -0.001$, $p = 0.98$), and trails B (Android: $\beta = 0.68$, $p < 0.001$; iPad: $\beta = -0.12$, $p = 0.28$; iPhone: $\beta = 0.60$, $p < 0.001$; Macintosh: $\beta = -0.06$, $p = 0.30$). In general, users of mobile devices showed slower responses than users of laptop and desktop computers. This indicates that differences in performance between device groups are unlikely to be due solely to differences in general cognitive ability between users of different devices, suggesting that differences in device characteristics are contributing to differences in measured performance. As in Study 1, the effects for simple reaction time were greater than those for digit symbol matching. Both trails A and trails B showed moderate effects for use of mobile phones compared to the Windows group (see Table 6).

Table 5. Age-, Sex-, and Vocabulary-Controlled Differences in Performance by Device (mean standard residual)

Mean Age-, Sex-, and Vocabulary-Controlled Standard Residualized Performance for Frequently Used Device Groups				
Device*	Simple RT	DSM RT	Trails A	Trails B
Android	0.82 (1.16)	0.16 (1.01)	0.46 (1.63)	0.56 (1.41)
iPhone	0.04 (0.79)	0.06 (0.94)	0.34 (1.40)	0.48 (1.10)
iPad	0.37 (1.02)	-0.15 (1.09)	-0.82 (0.83)	-0.21 (1.13)
Macintosh	-0.25 (0.76)	-0.05 (0.96)	-0.08 (0.72)	-0.18 (0.76)
Windows	-0.25 (0.92)	-0.04 (1.02)	-0.08 (0.75)	-0.12 (0.87)
Effect Size of Device Differences on Age-, Sex-, and Vocabulary-Controlled Residualized Performance (Cohen's d, Windows device as comparison group)				
Device*	Simple RT	DSM RT	Trails A	Trails B
Android	1.07 (0.96, 1.19)	0.19 (0.09, 0.30)	0.54 (0.38, 0.70)	0.68 (0.52, 0.85)
iPhone	0.33 (0.22, 0.44)	0.09 (-0.007, 0.20)	0.45 (0.29, 0.62)	0.66 (0.49, 0.83)
iPad	0.67 (0.51, 0.83)	-0.11 (-0.28, -0.04)	-0.74 (-0.97, -0.50)	-0.10 (-0.33, 0.13)
Macintosh	-0.004 (-0.10, -0.09)	-0.02 (-0.11, 0.08)	0.005 (-0.11, 0.12)	-0.06 (-0.18, 0.05)

* Android devices include both mobile phones and tablets; Windows devices include tablet, laptop, and desktop computers

We also found differences between device groups in within-participant standard deviation of reaction time after controlling for age, sex and vocabulary (see Table 3 in supplemental materials). A linear regression using Windows as the comparison group showed significant differences for mobile phones on simple reaction time (Android: $\beta = -0.12$, $p = 0.030$; iPad: $\beta = -$

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0.13, $p = 0.11$; iPhone: $\beta = -0.17$, $p = 0.002$; Macintosh: $\beta = -0.08$, $p = 0.11$) and trails B (Android: $\beta = 0.49$, $p < 0.001$; iPad: $\beta = -0.15$, $p = 0.90$; iPhone: $\beta = 0.54$, $p < 0.001$; Macintosh: $\beta = -0.04$, $p = 0.51$), for all devices other than iPad on trails A (Android: $\beta = 0.65$, $p < 0.001$; iPad: $\beta = 0.13$, $p = 0.25$; iPhone: $\beta = 0.62$, $p < 0.001$; Macintosh: $\beta = -0.12$, $p = 0.04$), and for iPad and Macintosh on digit symbol matching (Android: $\beta = -0.01$, $p = 0.77$; iPad: $\beta = -0.36$, $p < 0.001$; iPhone: $\beta = -0.05$, $p = 0.36$; Macintosh: $\beta = -0.09$, $p = 0.03$). Mobile device users had lower variability than laptop and desktop users on simple reaction time and digit symbol matching, but higher variability in reaction time on trails A (see Table 3 in supplemental materials). Unlike the pattern of differences seen in overall reaction time, the greatest device effects on variability were seen in trails A and B; effects of device group on simple reaction time variability were negligible.

Effects of Screen Size and Input Type on Test Performance

While device latency is one factor that varies between digital devices that can directly impact measured performance, other differences between digital devices may contribute to differences in observed performance. As well as the hardware and software that contribute to differences in latency, digital devices differ in screen size, user interface, and precision with which one can select items on the screen. To examine the effects of these mechanisms, in further analysis, rather than classifying devices into categories based on hardware and OS, we examined differences in participant performance based on two device characteristics: screen size and input type. To determine the effects of screen size, we compared age-, sex-, and vocabulary-controlled performance of iPhone and iPad users; these devices use the same operating system and are both touchscreen-operated, but vary in size. To examine the effects of input type, we compared Macintosh laptop and desktop computers, which primarily use mouse and keyboard input, and

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iPad tablets, which primarily use touchscreen input; both devices are developed by the same company and have relatively large screens. By classifying devices based on specific characteristics, we can determine which differences between devices contribute most to differences in observed participant performance by observing whether one classification criterion shows greater effects for a particular test.

The effect of screen size on test performance was greatest on the trail-making tasks, with iPhone users showing slower performance than iPad users. This is consistent with our expectations based on the nature of these tests. Because these tasks require participants to connect targets without accidentally crossing over non-target points, clustering the points on a small screen makes it easier to unintentionally hit an incorrect point due to lack of precision, making the test more difficult. The small screen could also make it difficult to correctly identify the points to be connected. Effects on performance on other tests, both timed and untimed, were small or negligible.

Table 6. Relationship Between Device Characteristics and Performance (age-, sex-, and vocabulary-controlled standard residuals)

Test	Cohen's d (95% CI) (iPad vs. iPhone)	<i>p</i>	Cohen's d (95% CI) (iPad vs. Mac OS)	<i>p</i>
Simple reaction time	0.38 (0.21, 0.56)	<0.001	0.76 (0.59, 0.93)	< 0.001
Digit symbol matching	-0.22 (-0.39, -0.05)	0.02	-0.09 (-0.26, 0.06)	0.27
Trails A	-0.77 (-1.05, -0.50)	<0.001	-0.76 (-1.01, -0.52)	< 0.001
Trails B	-0.62 (-0.90, -0.36)	<0.001	-0.11 (-0.66, 0.44)	0.77
Vocabulary (age- and sex-controlled)	0.004 (-0.17, 0.18)	0.96	-0.38 (-0.21, -0.54)	<0.001

The effect of input type on simple reaction time performance was moderate, with users of mouse-operated devices showing faster performance than users of touchscreen devices. There was also a moderate effect on performance on trails A, with touchscreen users showing faster performance, though this effect was smaller than the effect of screen size on the same test. No other tests showed significant effects of input type. Input type is closely related to device latency;

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touchscreens typically have latency between 50 and 200 ms, while mouse input has a measured latency of approximately 20 ms (Henze, Funk, & Shirazi, 2016; Pavlovych & Gutwin, 2012). Thus, the greater effect of input type (relative to screen size) on performance in simple reaction time suggests that the slower performance seen in users of smartphones is likely due to latency, rather than to screen size or other characteristics of the device.

Discussion

In this manuscript, we looked at differences in cognitive test performance by device type, with a focus on the measurement of reaction times across different devices. We found three potential sources of variability in cognitive test performance related to device type. First, device ownership was related to differences in demographic characteristics associated with differences in reaction time. Second, device type was associated with differences in performance on an untimed measure (vocabulary), suggesting that cognitive differences between groups exist beyond what can be explained by age and sex. Finally, after controlling for demographic characteristics and general cognitive ability, differences in device group were associated with differences in reaction time that were associated with operating system, input type (touch vs. mouse), and screen size. In general, measures that elicit shorter reaction times were most affected by factors that influence response time latency (operating system, mouse) whereas measures with larger, more complex stimuli and responses (Trails A/B) were most affected by screen size. Our results suggest that differences in cognitive test performance between device groups is due to both effects of the devices themselves and differences in the traits of the users who choose each device, beyond what can be explained by age and sex.

To determine possible mechanisms contributing to these differences between device groups, we examined the effects of screen size and device input type on measured test

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performance. We found that the use of touchscreens had a stronger association with tests of reaction time, while screen size had a stronger association with tests that require fine motor input and clear perception of the full screen. Android touchscreen devices showed particularly strong associations with reaction time compared to iOS touchscreens. These differences were significant with moderate to large effect sizes even after controlling for cognitive performance (as measured by vocabulary) as well as demographic variables.

The present study does have some important limitations. Although we controlled for demographic factors and performance on an untimed measure of cognitive ability, it is possible that there are other factors that differ between users of different devices. In addition, because digital devices are constantly changing with the introduction of new hardware and software, the specific differences in measured reaction time associated with each device may not be directly applicable to future versions of these devices. However, the methods used here to determine the effects of device variability from the devices most commonly used in our sample could be applied to other devices used for cognitive testing.

Despite the widespread use of online cognitive testing tools in psychology research, this is the first study to directly examine the new sources of variability that mobile- and web-based research introduce in large samples of participants using a bring-your-own-device model (Germine et al., 2019). Previous research has examined the effects of device latency in cognitive testing and found significant device effects on the measurement of reaction times (Damian, 2010; Pronk et al., 2019). Our study expands on these findings by measuring the contribution of device variability to the measurement of reaction time in a naturalistic setting that draws on the full range of commercially available digital devices. Our online testing platform enabled us to recruit a large and demographically diverse sample of participants, which allowed us to examine the

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contribution of demographic factors to device group differences. The use of data from participants completing tests on their own devices, in a naturalistic setting, allowed us to go beyond existing measures of device variability, which typically focus on one aspect of a digital device, such as user interface or latency. While device differences introduce new sources of variability into cognitive testing, this variability can be measured and quantified, unlike many sources of variability in in-person testing such as measurement error and tester bias. If the variability introduced by these new tools is measured and appropriately mitigated, it could ultimately lead to greater precision in cognition research.

Mitigating the Effects of Device Variability

Users of smartphones typically showed the slowest reaction times on time-based tasks, indicating that these devices may produce artificially longer reaction times. Mobile phones can also cause problems on some tasks due to the small size of their screens and the difficulty of precise input. Thus, if it is important for the purposes of a study that reaction times be measured with minimal latency, one could choose not to make the test compatible with mobile phones and touchscreen devices and require participants to use a laptop or desktop computer. However, since many people access the internet regularly through their phones, this may result in lower participation. Furthermore, some study designs, such as ecological momentary assessment, require that participants be able to complete assessments on portable devices. There is a trade-off between accuracy of reaction time-based assessments and the flexibility with which these assessments can be performed.

When participants are using a wide variety of digital devices, tests based on reaction time measurement may be less precise than tests based on other outcome measures, such as accuracy or biases in response. Although not all domains of cognitive function can be measured in this

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way, such measures avoid many of the sources of unquantified variation introduced by device variability. When reaction times are necessary, one way to reduce the effects of device latency on measures of participant performance is to choose tasks that produce longer response times. The efficacy of this approach can be seen by comparing the effects of device differences on performance in simple reaction time and performance in digit symbol matching. There are significant relationships for both tasks, but the effect size of input type is moderate to large for simple reaction time and relatively small for digit symbol matching. While both the digit symbol matching task and the simple reaction time task measure processing speed and are scored based on measured reaction time, digit symbol matching produces longer reaction times due to the additional cognitive challenge of matching each number to the appropriate image. Because the scale on which responses occur is greater, the proportion of variability attributable to the person - and presumably differences in processing speed rather than device effects -- is correspondingly greater. Therefore, by choosing tasks that produce longer true response times, the proportion of observed variation that is due to device latency can be reduced, even if the latency itself remains the same.

Another way to mitigate the effects of device latency is to measure reaction times in ways that keep latency as consistent as possible, allowing reaction times to be more easily accounted for. For example, in tasks with multiple trials, one could measure reaction time as the time between when a response was registered for the previous trial and when a response is registered for the current trial. Since device latency is typically consistent within a single device over a short period of time, one can assume that the effect of device latency will be consistent from trial to trial. Thus, the time between registered responses is the same as the time between actual responses, even if all measurements are delayed by a consistent length of time reflecting device

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latency. Using this method of measurement, only the measured time between the start of the task and the first response will be altered by device latency; if one removes the first trial from analysis, the remaining measurements would be unaffected by latency. However, when tasks are presented this way, the time used to redirect attention from one trial to the next is included in the measured reaction time, which may not be desirable for all tasks. This approach also does not reduce the impact of user interface (separate from its relationship to latency) and screen size on performance.

While the previous solutions can minimize the effects of differences in device latency, different approaches are needed to avoid bias introduced by differences in user interface and screen size. In order to scale across devices of different sizes, stimuli must be simple enough to be easily viewable on small screens at the level of detail necessary to complete the task. Stimuli that are visually distinct and memorable on a laptop or desktop device may be difficult to differentiate on a mobile phone screen. The means by which a participant provides a response - pressing a key, clicking on a button, moving a cursor - must also be considered to ensure that differences between devices do not change the difficulty of the task. For example, if response buttons are placed close together (as in the trail-making tasks used in this study), it may be difficult to reliably select only the correct one when using a small touchscreen. The use of simple, scalable stimuli could help mitigate these effects in future research.

Each of these approaches can reduce the impact of device-related variability on measured performance on cognitive tests. However, there is no single approach that is appropriate for all forms of online research; each solution imposes some limitations on the research methods that can be used and the circumstances under which research can be conducted. When conducting online research in cognition, researchers will need to consider whether device variability could

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have a significant impact on their results, and if so, which approach is most appropriate to mitigate it. Whatever approach is chosen, simply measuring device characteristics in web- and mobile-based assessment is vital in any research in which latency, screen size, user interface, or other device characteristics could affect performance; without this information, the research methods made available by new technologies cannot be used to their full potential.

Supplemental materials: All supplemental materials are available in the Open Science Foundation repository, https://osf.io/xf5v8/?view_only=8fedb487110e47198fc72f3d26bf5ccf

Open practices statement: The datasets generated and/or analyzed during the current study are available in the Open Science Foundation repository, https://osf.io/xf5v8/?view_only=8fedb487110e47198fc72f3d26bf5ccf. This research was not preregistered.

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