A New Remote Guided Method for Supervised Web-Based Cognitive Testing to Ensure
High Quality Data

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ABSTRACT

Background. The global COVID-19 pandemic has triggered a fundamental reexamination of how human psychological research can be conducted both safely and robustly in a new era of digital working and physical distancing. Online web-based testing has risen to the fore as a promising solution for rapid mass collection of cognitive data without requiring human contact. However, a long-standing debate exists over the data quality and validity of web-based studies. Here, we examine the opportunities and challenges afforded by the societal shift toward web-based testing, highlight an urgent need to establish a standard data quality assurance framework for online studies, and develop and validate a new *supervised* online testing methodology, *remote guided testing (RGT)*.

Methods. A total of 85 healthy young adults were tested on 10 cognitive tasks assessing executive functioning (flexibility, memory and inhibition) and learning. Tasks were administered either face-to-face in the laboratory (N=41) or online using remote guided testing (N=44), delivered using identical web-based platforms (CANTAB, Inquisit and i-ABC). Data quality was assessed using detailed trial-level measures (missed trials, outlying and excluded responses, response times), as well as overall task performance measures.

Results. The results indicated that, across all measures of data quality and performance, RGT data was statistically-equivalent to data collected in person in the lab. Moreover, RGT participants out-performed the lab group on measured verbal intelligence, which could reflect test environment differences, including possible effects of mask-wearing on communication.

Conclusions. These data suggest that the RGT methodology could help to ameliorate concerns regarding online data quality and - particularly for studies involving high-risk or rare cohorts - offer an alternative for collecting high-quality human cognitive data without requiring in-person physical attendance. (275 words)

1 INTRODUCTION

In 2020, the global COVID-19 pandemic brought human lab-based psychological research to an abrupt halt as social distancing measures to prevent disease transmission forced the mass closure of laboratory facilities and prevented all but essential human contact, disrupting academic research at a profound level [1,2]. During this period of suspension, the research community has inexorably moved toward remote protocols to replace face-to-face activities. There has been an exponential rise in the use of online platforms such as video conferencing (Zoom [3], Skype) and online learning [3-4] for day-to-day academic activities, and use of social media platforms has surged not just as a means for interacting and connecting with others, but also for participant recruitment and outreach [5]. Concomitantly, interest in online experimental alternatives to in-person cognitive testing has grown significantly [1] and there is increasing focus on methodological developments that will allow the field to adapt in a changed world where reduced social contact is the new norm [1,6-7]. However, amidst this push toward new online research technologies, it is imperative that core issues of data quality and validity are not overlooked, and simple assumptions of equivalence between lab-based and online tests (e.g. on the basis that the use of similar tasks and platforms is sufficient [8-10]) should not be made. Failure to address these issues could lead to a proliferation of poorly regulated online research studies that exacerbate the current reproducibility crisis and raise new ethical dilemmas [11]. Here, we examine the opportunities and challenges afforded by the shift toward web-based testing, highlight an urgent need to establish a standard data quality assurance framework for online studies, and propose a new supervised online testing methodology, *remote guided testing (RGT)*, which could help to mitigate some of these challenges and offer an alternative for collecting high-quality human cognitive data within social distancing constraints.

1.1 The Rise of Web-Based Cognitive Testing: Opportunities and Challenges

Cognitive tests are valuable psychological tools that have been used for decades to interrogate mechanisms underpinning mental executive processes such as learning, decision making, inhibition and working memory [12]. Historically, tests of executive processes have typically involved pen-and-paper administration by an experimenter in lab-based settings [13-14]. The experimenter is able to confirm the participant's identity and deter dishonesty, as well as provide immediate assistance toward queries or technical problems. Further, the standardised testing environment and equipment help to ensure replicability and reproducibility of lab-based protocols [15-18]. However, this traditional in-person approach is associated with a high time cost and increased susceptibility to human error [12,13]. Further, since lab-based testing requires participants to be physically present in the laboratory, sampling may not be population-representative [19-21]. For instance, Henrich et al [19] and Nielsen et al [20] reported that samples used in lab-based settings consisted predominantly of Western, Educated, Industrialized, Rich and Democratic populations. This finding was further supported by Arnett (2008). In an analysis of six major APA journals, Arnett [21-22] found that a significant number of studies reported in these journals relied predominantly on American students. This suggests that current understanding of normal psychological and cognitive processes may in fact be heavily biased toward a particular privileged Western demographic.

In the current digital age, the mass availability of personal computers and web capability has afforded new avenues for conducting cognitive testing using more cost-effective, automated and open approaches [12,23,24]. Accordingly, there is growing momentum in the use of these online platforms to study cognitive function [12,25-27]. Computerized online testing platforms such as Gorilla [25], Inquisit [27], and CANTAB [26] can offer several attendant advantages, including (1) simple and precise control of

experimental parameters; (2) automatic calculation of key performance indices; (3) access to normative databases; (4) accessibility to a wider population of users (with use of crowdsourcing tools); (5) centralised and secure data storage on professional servers; (6) relatively low administrative cost per head [13,15,23,28]. In particular, since web-based online testing removes the physical constraint of test location, this permits a much wider (and more representative) demographic reach and increases ease of participant recruitment [15,29]. Further, social media platforms, recruitment portals (e.g. Amazon's Mechanical Turk (MTurk), Prolific Academic) and online advertisements have opened up new avenues for recruitment that enable high thorough-put data collection from thousands of participants, which would not be feasible in traditional lab-based settings [24,30-33].

Although web-based testing promises to revolutionise cognitive testing at scale, a longstanding debate exists regarding its data quality, comparability, replicability and validity as compared to traditional lab-based data collection methods [34,35]. Significant concerns have been raised in regard to experimental rigour [17,18], particularly pertaining to the lack of control over (and therefore of higher variability of) hardware specifications and the test environment [17,18,36]. For instance, a study by Bauer et al [17] reported that a high proportion of online studies suffer from a lack of environmental control and participant distraction. Further, the majority of online-based studies do not monitor or report measures of participants' environment, their equipment specification or web capability. These data, when reported, typically reveal large variations in the equipment and computer specifications used by participants [15,36]. In a landmark study on computing specifications in online and lab-based studies, Bridges et al [36] compared a range of web-based experimental platforms such as Gorilla and jsPsych, when used in conjunction with different operating systems such as Windows, MacOS and Ubuntu. In data collected from over 110,000 trials, the authors reported that compared to other operating systems, MacOS yielded the worst performance

across all web experimental platforms, particularly for visual stimuli. These results also suggest that online studies may not achieve a similar level of precision as compared to lab-based studies, owing to this variability. Further, since the data are contributed anonymously and without supervision, online data collection is vulnerable to abuse by dishonest participants with low or questionable motivation [17].

In fact, several comparative studies report only a moderate correlation when comparing web-based cognitive performance with its paper and pencil alternative across different cognitive tasks and populations [13,15,37]. For instance, Backx et al [15] assessed the comparability of cognitive data obtained from the CANTAB platform, when collected using either unsupervised web-based administration and lab-based administration. Using intraclass and bivariate correlations, they reported that many key performance indices (errors, correct trials and response sensitivity) were highly comparable across the two settings, with intraclass correlation coefficients ranging from $\rho=0.23-0.67$. However, participant reaction times were significantly and consistently slower for web-based assessments, and none of the 5 reaction time measures that were assessed met the full criterion for comparability across settings (namely reliability, equivalence and agreement). Further, in the online setting over 90% of participants reported being distracted across five different cognitive tasks, as compared to none in lab settings, and two online participant datasets were excluded due to a high number of errors on the Spatial Working Memory (SWM) task. These statistics suggest that a poor test environment and miscomprehension of task instructions could have affected participant performance in online settings. Therefore, with current unsupervised web-based testing protocols, there appears to be a tradeoff between data quantity (diversity and ease of collection) and data quality [18,36,38]. However, it is still unclear exactly *how*, and to what *extent*, data quality is compromised with web-based cognitive testing methods. With current efforts to move toward greater standardization of best practices in online task administration,

data quality indices and reporting benchmarks (e.g. [39]), this study addresses a timely need to develop data quality assurance frameworks for web-based cognitive testing.

1.2 Toward a Data Quality Assurance Framework for Web-Based Cognitive Testing

To assess data quality, it is first important to establish the indices and benchmarks by which data quality will be measured. On these points, there is currently no clear consensus. General statistics pertaining to participant non-completion, data attrition, and technical issues are typically reported and it is common to exclude data from participants who encounter technical difficulties, display dishonesty, or fail to complete the assigned tasks [38,40-42]. However, a more sensitive test of data quality pertains to the “usable fraction” of data that remains after task-specific exclusion criteria for data cleaning have been applied. One common index used for data exclusion is reaction time, since responses that are too fast (or alternatively too slow) are likely to reflect participant inattentiveness or task disengagement. Depending on the type of stimuli presented and the complexity of task demands, participant response latencies in cognitive tasks mostly vary between 400 ms to 2000 ms [43]. However, for web-based tasks, there is an additional (technical) source of variability to the measured response times. In order to collect response latencies from many (e.g. hundreds) of individual trials, a software program is typically required on the participant’s computer (i.e. client-side) to present the stimuli and collect response latencies locally. This reduces the temporal variation introduced by communication across networks and server response times if each individual response has to be sent over the network connection back to the server in order to be recorded. Several client-side technologies have been used to create such programs, with perhaps the most popular being JavaScript, Java and Flash [43]. However, most of these programs introduce a small but variable delay in the recorded response times. This delay is influenced not just by the program itself, but also by the computer’s operating system,

browser, hardware quality and any background programs that may be running. For example, when Schubert et al [43] measured standard automated response times (i.e. robot detection of a simple visual stimulus) natively using DMDX software and a keyboard, the mean response time was 68.24 (SD = 3.18). These mean latencies rose to 84.58 ms (SD = 6.25 ms) when E-prime software was used in the same configuration, and as high as 98.18 ms (SD = 4.17 ms) for Superlab, although interestingly response latencies were highly comparable for the Web version of Inquisit (mean = 66.21 ms, SD = 2.74 ms). When comparing human response times on a Stroop task, Schubert et al [43] reported that DMDX-recorded responses were significantly faster (mean = 551.98 ms, SD = 201.38 ms) than their custom-built Flash-based web software ScriptingRT (mean = 631.63 ms, SD = 243.42 ms), although the measured Stroop effect (difference in response latency between incongruent and congruent trials) was similar. Therefore, web-collected response latency data should be treated with particular care as the measured timings may be impacted by both psychological (e.g. participant distraction, inattentiveness) and technical factors, although the latter issue is ameliorated to some extent by newer and better online experimental platforms.

To control for data quality, some web-based studies implement a hard cut-off to exclude trials with response latencies that exceed a particular threshold. For instance, when analyzing data from a complex psycholinguistic task, Kim et al [44] excluded outlier responses that were faster than 300 ms as well as responses that were slower than 5000 ms. However, these excluded trials represented a mere 0.75% of their data (for both lab-based and web-based cohorts) which could either suggest superb data quality, or that their latency criteria were too lax for the particular task. Using similar reaction time-based exclusion criteria, Eisenberg et al [30] excluded participants whose median response latencies were shorter than 200 ms across a wide range of cognitive tasks. They also implemented three further quality checks: (1) <25% omitted (missed) responses; (2) >60% task accuracy; and

(3) no single response given >95% of the time. However, although rates for participant non-completion and multiple task failure were reported (see Table 1), the authors did not report how many trials and datasets failed their other response latency, omission and distribution quality checks. Further, it should be noted that for some tasks (Stop Signal, Probabilistic Selection and Two-Step Decision tasks), the authors reported that the datasets had between 10-30% missing values that were identified through additional quality control (manipulation) checks. Adding this figure to the reported 21% of data exclusions, this suggests that the actual fraction of “usable data” could be as low as 50% on some web-based tasks.

Table 1 provides examples of other data exclusion statistics that have been reported for analogous lab-based and web-based cognitive studies. These statistics typically focus on participant completion/drop-out rates rather than trial-level data quality indices. Of particular note are the studies by Hicks et al [45] and Ruiz et al [46] who administered matched sets of working memory and declarative memory tasks in lab-based and online conditions. Their data show a clear and consistent trend toward a higher rate of data exclusion and non-completion for web-based testing, with typically 15-20% more online participants excluded for non-completion (drop-out) and technical issues. Participant drop-out issues appear to be particularly exacerbated for online cognitive training studies, with one study reporting that 32% (80/249) of initially recruited healthy older adult participants eventually withdrew from their 12-week cognitive flexibility web-based training study [47]. However, this brief scan of the literature also highlights that – with the exception of a few studies (e.g. [15]) – very little is reported about what occurs *during* online experimental testing or about the computing and web capabilities of participants, and few benchmarks exist for identifying and removing poor quality web-based data (beyond crude RT thresholds and major task failures). There is a clear need to develop standardized data quality indices that web-based studies should collect and report, and the recommended benchmark(s) to be met for these indices.

LAB-BASED		WEB-BASED	
Citation & Task(s)	Data Excluded	Citation & Task(s)	Data Excluded
Kim et al., (2019) (<i>Lab</i>) [44] Psycho-linguistic task	5/42 (11.9%) excluded for high error rates and being outside demographic RT outlier removal = 0.75% of total data	Kim et al., (2019) (<i>Online</i>) [44] Psycho-linguistic task	3/39 (7.7%) excluded for high error rates and being outside demographic RT outlier removal = 0.75% of total data
Von Gunten et al., (2020) (<i>Lab</i>) [48] Inhibition tasks (Antisaccade, Go/No go, Stop Signal)	37/463 excluded (7.99%)	Eisenberg et al., (2019) (<i>Online, using Amazon Turk</i>) [30] Inhibition tasks (Go/No go, Stop Signal)	102/662 (15.4%) excluded for non-completion of task battery 38/560 (6.8%) further excluded for failing four or more tasks
Backx et al., (2020) (<i>Lab</i>) [15] #CANTAB tasks	No exclusions No distractions reported	Backx et al., (2020) (<i>Online</i>) [15] #CANTAB tasks	2/18 (11.1%) excluded, high SWM errors Distractions: 16/18 participants for PAL, ERT, OTS, PRM-I; 17 participants for SWM, RVP, PRM-D
Hicks et al., (2016) (<i>Expt 1 & 3, Lab</i>) [45] Working memory tasks	E1: 0/58 (0%) excluded, although 10% of participants reported cheating E3: 10/112 (8.9%) excluded due to excessive missing data	Hicks et al., (2016) (<i>Expt 2 & 4, Online</i>) [45] Working memory tasks	E2: 12/100 (12%) excluded for failure to complete test battery within 24 hours E4: 28/112 (25%) excluded due to non-completion of task battery
Ruiz et al., (2019) (<i>Lab</i>) [46] *Working memory, non/declarative memory tasks	(a) OSpan, 0% excluded (b) MLAT5, 0% excluded (c) CVMT, 1/50 (2%) excluded	Ruiz et al., (2019) (<i>Online</i>) [46] *Working memory, non/declarative memory tasks	(a) OSpan, 7/50 (14%) excluded (b) MLAT5, 8/15 (16%) excluded (c) CVMT, 10/50 (20%) excluded
Baniqued et al., (2013) [49] Cognitive video training	27/219 (12.3%) participants excluded or withdrew	Buitenweg et al., (2017) [47] Cognitive flexibility training	91/249 (36.5%) participants excluded for not meeting criteria (N=11) or withdrew from study (N=80)

Table 1. Examples of data exclusion statistics reported for lab-based and web-based

cognitive studies. #CANTAB Tasks: SWM = Spatial Working Memory; PAL = Paired Associates Learning; ERT = Emotion Recognition Task; OTS = One Touch Stockings of Cambridge; PRM = Pattern Recognition Memory; RVP = Rapid Visual Processing. *Memory Tasks: OSpan = Automated Operation Span Task; MLAT = Modern Language Aptitude Test; CVMT = Continuous Visual Memory Task.

1.3 A New Supervised Online Method: Remote Guided Testing (RGT)

In the preceding sections, we discussed the promise of web-based cognitive testing (in particular its scalability and reach) as well as current challenges for data quality assurance. In part, questions over experimental rigour and data quality have arisen due to the unsupervised nature of web-based testing [17,18,36]. Without supervision, experimenters have no control over (or insight into) the test environment, no way to monitor participant performance, deter dishonesty, or influence participant motivational and attentional states during task performance. Further, even genuinely motivated participants may struggle with tasks that have complex instructions and misunderstand what is required of them, leading to wasted effort and unusable data. Finally, without a human experimenter on hand to troubleshoot problems, participants who experience technical issues with web platforms may become frustrated and stressed, leading to poorer motivation and performance. To bridge this gap, we propose here a new method of supervised online data collection, Remote Guided Testing (RGT). This hybrid method is intended to marry the convenience and reach of online web-based testing with the enhanced rigour and quality control of in-person lab-based data collection. The addition of a supervisory component (and with it, greater environmental control) is meant to mitigate data quality degradation and attrition due to psychological as well as technical factors.

The RGT method simulates lab-based experimental testing via a video conferencing platform. Similar to in-person testing, the participant arranges to meet the experimenter online at a specific date and time, and the experimenter guides the participant virtually through each step of the experimental process. This includes obtaining informed consent, providing technical support for software installation, troubleshooting problems, monitoring performance and providing feedback where appropriate, and debriefing. The experimenter

also helps the participant to optimise their test environment (including lighting, sound and minimising distractions), and collects detailed data about the hardware, software and web capabilities of the participant. The remote tester can further schedule comfort breaks (for toilet trips, food or drink, rest, exercise), so that the comfort break does not adversely affect test delivery or data collection. This method is novel in its holistic approach as it provides a fully supervised and interactive online test experience, which to our knowledge has not been done or reported before for web-based cognitive testing.

To provide a deeper evaluation of the RGT method on data quality, here we measure and report three trial-level data quality indicators across a range of web-based cognitive tasks: (1) *Missed responses*, (2) *Data exclusions (at both trial and participant levels)*, and (3) *Reaction times*. To ensure close comparability and to isolate the effect of test modality, participants completed identical web-based versions of each cognitive task either in-person in a psychology lab, or at home via RGT. In both conditions, participants received expert supervision whilst they completed a range of cognitive tasks assessing executive function (cognitive flexibility, inhibition, working memory) and learning. While most of these tasks rely on measures of accuracy, we specifically included tasks with reaction time-dependent outcome measures, such as the Stroop task [50] and the Stop Signal task [51,52]. Given that there are well-quantified effects of web-based testing in terms of slower participant reaction times on cognitive tasks [15,43], it was of particular interest to us to assess if (and the extent to which) these differences could be ameliorated through greater supervisory and environmental control. Finally, to increase the generalisability of our findings, three different web-based experimental platforms were tested, including CANTAB, Inquisit and i-ABC (see Methods 2.4 for details). We hypothesised that the inclusion of supervision via the RGT method would yield high fidelity cognitive data that matched lab-collected cognitive data in all measured indices of data quality and task performance (including reaction times).

2 METHODS

2.1 Participants

A total of 85 healthy Singaporean young adults participated in the study and contributed data (Face-to-face [F2F] N=41; Remote guided testing [RGT] N= 44). A further 4 RGT and 5 F2F participants had initially expressed interest, but subsequently withdrew from the study. Data from these participants were not included in any analyses. All participants were native English speakers and reported no history of clinically diagnosed mental illness or developmental difficulties and had normal or corrected hearing and vision. Recruitment was carried out by posting online advertisements in social media outlets and through the University's recruitment channel. The demographic information for both groups is detailed in Table 2. There was no significant difference in age between groups ($t(83) = -1.29, P=.20$), and their gender, ethnicity, education and income distributions were also similar.

Modality (Group)			
Demographic Variable	F2F (N = 41)	RGT (N = 44)	Total (N = 85)
Age (Years)			
Mean (SD)	21.54 (2.26)	22.14 (2.05)	21.85 (2.16)
Range	18.11 – 29.22	18.51 – 26.83	18.11 – 29.22
Gender, N (%)			
Female	29 (70.7%)	33 (75%)	62 (72.9%)
Male	12 (29.3%)	11 (25%)	23 (27.1%)
Ethnicity, N (%)			
Chinese	34 (82.9%)	36 (81.8%)	70 (82.4%)

Malay	4 (9.8%)	6 (13.6%)	10 (11.8%)
Indian	2 (4.9%)	2 (4.5%)	4 (4.7%)
Not reported	1 (2.4%)	0 (0%)	1 (1.2%)
Income by Dwelling, N (%)			
Lower	13 (31.7%)	16 (36.4%)	29 (36.3%)
Higher	24 (58.5%)	27 (61.4%)	51 (63.7%)
Not reported	4 (9.8%)	1 (2.3%)	5 (5.9%)
Highest Education Level, N (%)			
Secondary School	27 (65.9%)	23 (52.3%)	50 (58.8%)
Bachelor's Degree	12 (29.3%)	16 (36.4%)	28 (32.9%)
Not reported	2 (4.9%)	5 (11.4%)	7 (8.2%)
Handedness, N (%)			
Right-handed	38 (92.7%)	42 (95.5%)	80 (94.1%)
Left-handed	2 (4.9%)	2 (4.5%)	4 (4.7%)
Not reported	1 (2.4%)	0 (0%)	1 (1.2%)

Table 2. Summary of participant demographics by testing modality. F2F = Face-to-Face; RGT = Remote Guided Testing.

All 85 participants attended and completed their scheduled testing session(s). None of them withdrew mid-way through their session(s). All 44 participants in the RGT group completed all 10 computerised tasks on web-based platforms. However, only 22 F2F participants completed all the computerised tasks on web-based platforms (17 females, 5 males; aged 21.06 years old on average [range = 18.11 to 26.68 years, SD = 2.09 years]). The remaining 19 F2F participants were tested prior to COVID-19 lockdown restrictions and

therefore only completed the 3 i-ABC tasks, Vocabulary and Digit Span tasks in a similar format to the other participants. The other Inquisit tasks (Trails, Stop Signal, Stroop) had either been completed on paper or using a different (offline) platform, and the CANTAB tasks were not administered. As these task-related differences could have generated performance differences, for consistency, only the data from the i-ABC tasks, Vocab and Digit Span were analysed for these 19 F2F participants.

2.2 *Equipment*

For the Face-to-face group, experimental testing was conducted in a psychology lab using a standard testing laptop which was a HP ProBook 430 G2/G3 with Intel Core i7 2/2.4GHz, 8 GB RAM, 500 GB HDD (+256 GB SSD) with a 13.3” display running Windows 10 OS, paired with a wired mouse. For the RGT group, sessions were completed at home using participants’ personal laptop or desktop that had to meet the following minimum requirements:

1. For Windows users, a Windows 7 or Windows 10 operating system (OS). For Mac users, OS Version 10.11.6 (El Capitan) or above (10.12, 10.13, etc.);
2. At least 8 GB RAM;
3. Webcam and microphone or mobile phone;
4. Administrator rights to download and install software;
5. A reliable internet connection (latency speed not exceeding 50ms);
6. Google Chrome, Safari or Mozilla Firefox web browsers installed;

To assess the actual quality of their computing hardware and web capability, all RGT participants completed an Equipment Questionnaire (Appendix A).

2.3 *Procedure*

To ensure standardised methodology and task delivery for participants in F2F and RGT groups, a Standard Operating Procedure (SOP, see Appendix D) was followed.

Prevailing COVID-19 precautions such as mask-wearing, temperature taking and checking of travel/quarantine history were also applied. The study protocol was approved by the NTU Ethics Institutional Review Board (IRB-2020-02-001). In brief, F2F participants completed one single in-person testing session lasting 3.5 hours whereas RGT participants completed two separate online video-conferencing sessions which were conducted via a secure Microsoft Teams or Zoom meeting. Both online sessions were video recorded. During the first 30-minute install and set-up session, participants were guided by the experimenter to download, install and test all necessary software. The testing environment was assessed to provide recommendations for minimising noise and disruption (see Testing Environment Checklist, Appendix B), and computing and input devices were recorded (Appendix A). During the second 3.5 hour session, RGT participants performed all computerised tests under the supervision of the experimenter, who remained online throughout the session (with video off/muted where appropriate). Five different task orders were generated to ensure that no two tasks from the same cognitive domain were administered consecutively. Participants were reimbursed with either \$20 in e-vouchers or cash (for F2F only) or completed the experiment for course credit. The respective procedures are summarised in Figure 1.

Figure 1. Overview of remote guided and face-to-face testing processes

2.4 Tasks

In total, participants completed 10 online experimental tasks assessing aspects of executive functioning (cognitive flexibility, working memory, inhibitory control), learning and verbal intelligence. These tasks were delivered using three different experimental web platforms: i-ABC [53], Inquisit (Millisecond) and CANTAB (Cambridge Cognition); or delivered verbally by the experimenter, as summarised in Table 3. Both groups also completed a short online demographics questionnaire.

Domain	Task	Delivery Platform			
		iABC	CANTAB	Inquisit	Verbal
Cognitive Flexibility	Wisconsin Card Sort Test (WCST)	✓			
	Probabilistic Reversal (PR)	✓			
	Trail Making Task (Trails)			✓	
Working Memory	Intra/Extra-Dimensional Set Shift (IED)		✓		
	Spatial Working Memory (SWM)		✓		
	Backwards Digit Span (BDS)				✓
Inhibition	Stroop Task (Stroop)			✓	
	Stop Signal Task (SST)			✓	
Learning	Structure Learning (SL)	✓			
Verbal IQ	WAIS Vocabulary (Vocab)				✓

Table 3. Summary of experimental tasks administered and respective delivery platforms

2.4.1 i-ABC Platform

Three experimental tasks were administered on the i-ABC platform [53]. The Wisconsin Card Sort Test (WCST; [54-55]) and the Probabilistic Learning & Reversal Task (PR; [56]) were measures of cognitive flexibility, whilst the structure learning (SL) task [53,57] assessed statistical learning. The i-ABC website enabled the administration of the three tasks on a platform that simulated playing a “space themed” video game and participants earned points for completing the tasks.

Wisconsin Card Sort Test (WCST). The WCST is a measure of cognitive flexibility that examines rule acquisition and set shifting [54-55]. The task involved a set of 64 cards which consisted of feature combinations of 4 colours, 4 shapes and 4 numbers (Appendix C1). Participants were shown a set of 4 cards and were instructed to sort (match) a test card to one of these four cards as accurately as possible within 5 seconds. To do so, the participant would have to figure out a matching rule according to a single feature (ie. colour, shape, number), by trial and error. After each selection, participants received feedback on whether

their response was correct or incorrect (Appendix C2). If the participant's match was incorrect, he or she would need to try a different matching rule. After 10 trials, the matching rule changed, and the participant was required to find the new rule and adjust their response accordingly. The total number of trials was 60 and the task lasted approximately 5 minutes.

Probabilistic Learning and Reversal (PR) Task. In the PR task, participants were presented with two different coloured visual icons and instructed to select one of them within 5 seconds. The stimuli used in this test were pairs of blue and yellow coloured rockets which might appear in any two out of four locations (boxes) on the screen (Appendix C3). The instructions reminded participants to choose the pattern that was most frequently correct and notified them that the rule which defined the correct pattern might change throughout this task though this would not happen often. In the first discrimination phase, the participant selected one of the two icons and was provided feedback about whether their response was correct or incorrect (Appendix C3). Response feedback was probabilistically determined (80-20) with one icon yielding positive feedback 80% of the time (and negative feedback 20%), whereas the other only yielded positive feedback 20% of the time (and negative feedback 80%). In the second reversal phase, these probabilities were reversed. Each phase consisted of 40 trials, giving a total of 80 trials. The task duration was approximately five minutes.

Structure Learning (SL) Task. This task involved making predictions based on previously learned patterns in the series of visual stimuli. The probabilistic sequences were determined by Markov models. The SL task was produced by Cambridge University's Adaptive Brain Lab. Here, participants would see a sequence of visual symbols [57] before they were required to predict which symbol should come next in the sequence. The symbols consisted of four sets: A, B, C or D (Appendix C4). These symbols were selected from Ndjuká syllabary and were highly distinct from one another [57]. Each symbol was presented in black on a grey background. The default stimuli size was 225 pixels and the stimulus size

was re-scaled following the screen size of each participant to ensure a consistent screen-to-stimulus size ratio across all participants.

The task had multiple levels. Level-0 was simply the probabilistic presentation of symbols i.e. out of the 4 symbols, one appeared with a high probability, one with a low probability and the other two rarely appeared. For example, the probabilities of occurrence for the four symbols A, B, C, and D were 0.18, 0.72, 0.05, and 0.05, respectively.

Presentation of a given symbol was independent of the stimuli that preceded it. At Level-1 the target stimulus depends on the stimulus immediately preceding it. For example, given a preceding symbol, only two targets could appear, one with a high probability (e.g. 80%) and the other with a lower probability (e.g. 20%). For example, when symbol A was presented, only symbols B or C were allowed to follow, and B had a higher probability of occurrence than C.

There were three task phases: a mandatory practice phase, followed by an optional practice phase and lastly the test phase. The mandatory practice phase had to be completed before a test phase could proceed and was only presented once per participant. If the participant chose to repeat this phase, the optional practice phase was launched; if not, participants continued to the test phase. Each practice phase had one block consisting of 5 trials, presenting symbols from set D in a random order. The test phase consisted of 7 blocks of 60 trials each, presenting symbols from sets A, B or C (randomly assigned by participant).

During the task presentation, each trial varied in length between 9-13 symbols. During each trial, every symbol was shown for 100ms, followed by a white dot fixation point appearing mid-screen for 400ms. The trial concluded with a response screen showing four symbols in a 2 x 2 grid. Participants indicated which of these might appear next in the sequence by clicking on one of the four symbols, after which they moved on to the next trial. If there was no selection made, the response screen would time-out after 2000ms and the next

trial would begin (Appendix C5). To prevent participants from learning the spatial location of the target response stimuli, the positions of the symbols were randomised. At the end of each block, participants received feedback on their performance. The task duration was approximately 50 minutes.

2.4.2 Inquisit 5 Web Platform

Computerised versions of the Stroop colour-word task, Stop Signal Task and the Trail Making task were hosted and administered on the Inquisit 5 web player by Millisecond software [58]. The software was downloaded before the session and when each task link was opened, participants were prompted to key in their unique ID before launching into full screen mode. The display dimensions of the task stimuli were standardised and automatically adjusted by the software according to the computer physical screen display size.

Stroop Task. The Stroop colour-word task is a well-known measure of cognitive inhibition [50]. In each trial, the participant is presented with a colour word (e.g. “RED” printed in green colour) shown in the centre of the display screen. They are required to respond by indicating the physical colour of the text while ignoring the semantic meaning of the word (Appendix C6). Four colours were used (red, green, blue, yellow) and these were mapped to four corresponding response keys on the keyboard (d,f,j,k for each colour respectively). This response button mapping was displayed at the top of the screen for all 180 trials to aid participants and reduce their memory load. Participants were instructed to respond as quickly and accurately as possible, with their response being timed. Once a response was made, the next trial followed. If an incorrect response was made, a red cross flashed on the screen. Before proceeding with the first trial, the participant was reminded to place their index and middle fingers on the ‘d’, ‘f’, ‘j’, ‘k’ keys. On congruent trials ($n = 144$), the print colour and the word meaning matched (e.g. “RED” printed in red). On

incongruent trials ($n = 36$), the print colour and word meaning were mismatched (e.g. “RED” printed in green). For each trial, the reaction time (RT) in milliseconds was recorded from the start of the word stimulus presentation to the participant’s response.

Stop Signal Task (SST). The Stop Signal Task is a measure of response inhibition and impulse control [51,52]. Prior to beginning the task, participants were shown an instructions screen and completed practice trials. In each trial, participants saw an arrow in the middle of the screen that either pointed to the right or left (Appendix C7). Participants had to press the left response key “d” if the arrow pointed to the left and the right response key “k” if the arrow pointed to the right, responding as quickly as possible. On certain trials, an auditory signal (a brief tone) was played after the presentation of the arrow. On these “stop” trials, participants were required from refrain from executing their response. The time delay between the presentation of the arrow and the signal tone was adjusted adaptively based on the participant’s performance, starting at 250 ms and decreasing or increasing in steps of 50 ms. The delay was increased if the previous stop trial was successful (up to 1150 ms) or decreased if the previous stop trials was not successful (down to 50ms). Each trial lasted for 2000 ms and participants could respond at any point during this period. There were four blocks in total: one practice block with 32 trials (8 stop signal trials, 24 no signal trials) and three test blocks of 64 trials each (16 stop signal trials, 48 no signal trials). The duration of this task was approximately 12 minutes.

Trails Task. The Trail Making task [59] is a neuropsychological test of visual search speed and motor tracking ability. It is also implicated in cognitive flexibility and in the ability to maintain sets [60]. The Trail Making task consists of two sub-tests: Trails A and Trails B. In the Trails A task, the participant was presented with a visual display containing 25 numbered circles positioned in a random order. They were instructed to use their computer mouse to draw a continuous line connecting the circles in sequential order (e.g. 1-2-3...) as

quickly as possible (see Appendix C8). Participants were told to hold down the mouse button while drawing. If the mouse was accidentally released from the participant's grip, a yellow circle would appear, highlighting where they last stopped. In the Trails B task, the stimuli consisted of a mixture of numbers and letters. Participants had to connect the circles in an alternating order between numbers and letters (i.e. 1→A→2→B). A total of 13 circles containing numbers 1-13 and 12 circles containing letters A-L were presented (Appendix C9). In addition, there were 15 empty distractor circles. The participant's completion reaction time for each task was recorded.

2.4.3 CANTAB Platform

The IED task and SWM task were both administered as part of the Cambridge Neuropsychological Test Automated Battery (CANTAB; [61-63]).

Intra-Extra Dimensional Set Shift task (IED). The IED task is a test of rule acquisition and reversal. It requires visual discrimination, attentional set formation and maintenance, shifting and flexibility of attention [61]. Participants advance through nine sequential task stages. On each trial, participants are presented with a pair of stimuli and they are required to select the correct stimulus based on an underlying rule which must be figured out and learned by trial and error. In the first two stages, the stimuli consist of simple white lines only (Appendix C10). From stage 3 onward, the stimuli increase in complexity and consist of purple shapes and white lines which are overlaid (Appendix C11). Participants respond by clicking on one of the two stimuli and then receive feedback about whether their selection was correct. After six consecutive correct responses, the rule and/or the stimuli change, though this transition is not made known to the participant. The new rule is either based on the same feature of the stimuli i.e. white lines that guided the selection rule in the prior stage

(intra-dimensional shift) or on the other stimulus feature i.e. purple shape (extra-dimensional shift). The test duration is approximately 7 minutes.

Spatial Working Memory (SWM) Task. The SWM task measures memory retention and manipulation of visuospatial information [62]. The task begins with a set of coloured squares (boxes) shown on the screen. The participant is required to search the boxes for a yellow ‘token’ (which then fills up an empty column on the right-hand side of the screen). Once found, a second yellow token is then hidden behind one of the remaining boxes, although all the original boxes remain available on screen. Therefore, participants have to remember which boxes have previously been successfully searched and narrow their search by a process of elimination. There are 5 stages with increasing levels of difficulty (3, 4, 6, 8 and 12 boxes/tokens respectively). An example is shown in Appendix C12. The colour and position of the boxes used are changed from trial to trial to discourage the use of stereotyped search strategies. The test duration is approximately 4 minutes.

2.4.4 Verbal Delivery

WASI-II Vocabulary Test. To assess verbal intelligence, the Vocabulary subtest of the Wechsler Abbreviated Scale of Intelligence - Second edition (WASI-II; [64]) was administered. Participants were asked to provide a verbal definition of an English word such as “haste”. A total of 22 word items were presented with increasing complexity. The experimenter prompted or sought clarification from the participant if their answer was unclear or very brief. Each participant was video or voice recorded for scoring and review purposes. The test usually took between 5 to 10 minutes to complete.

Backward Digit Span (BDS) Test. The BDS subtest from the Wechsler Adult Intelligence Scale- Fourth Edition (WAIS-IV; [65]) is a test of verbal working memory. Participants were told to listen to an audio clip which presented a sequence of digits of

increasing length (2 to 9 digits). Each clip was only played once. After listening to each audio clip, participants had to recall aloud each sequence in reverse order. Each trial consisted of two sequences of the same length. If participants gave a correct response to at least one of the two sequences for a specific digit length, the experimenter would proceed to the next length. When the participants gave incorrect responses to both items of equal length, the test would end. A total of 16 trials were presented. This test required about 5 to 10 minutes to complete.

2.5 *Data Quality Indicators*

2.5.1 Missed Trials

For tasks which involved a response within a specified time limit, the number of missed trials was calculated. If a participant did not enter a response within the specified time limit for a trial, this was considered a missed trial. As some tasks (e.g. Stroop) required a response before proceeding, this index was not available for these tasks.

2.5.2 Data Exclusion

Participant data could be excluded either at the trial level or at the task level (i.e. all participant data removed for that task).

Trial-Level Exclusions (Outliers). At the trial level, single trials were excluded if the reaction time (RT) on that trial was outlying (either too fast or too slow). Taking reference from previous research using similar tasks [30,44], response times faster than 300ms are generally deemed to indicate participant inattentiveness and/or a failure to fully process the stimulus on that trial. Conversely, response times which are greater than 2.5 SD of the response time distribution are also generally considered to be outliers indicating failures of attention. To ensure that the basis for identifying slow outlier response times was consistent

and provided a fair basis of comparison of data quality, the F2F reaction time distribution was used to set a fixed threshold for both groups. Specifically, slow outliers were defined as reaction times >2.5 standard deviations above the mean of the face-to-face distribution for each task. Any trials with reaction times slower than this threshold (for both F2F and RGT participants) were considered to be outliers and removed.

As an exception for the Stop Signal task, and with reference to Verbruggen et al [52], we additionally removed the first trials for each of the three blocks as participants were not expected to have fully engaged with the task at this early stage. Additionally, reaction times under 300 ms were not removed for the Stop Signal task as participants were required to provide a speeded response and failures of inhibition were of core interest. As the CANTAB web platform did not provide trial-level data, no trials were excluded for the IED or SWM tasks.

Task Level Exclusions. At the task level, participant data was excluded for either technical reasons or performance reasons. Data were excluded for *technical* reasons if the participant experienced difficulties with the experimental platform, equipment or testing environment during that task. Task-level *performance* exclusions occurred if the participant's total number of missed and excluded trials was $>25\%$ of all trials for that task (see above criteria for trial-level exclusions).

2.5.3 Reaction Times

The final index of data quality was the mean reaction time (by participant) of the remaining included trials. This was used as a data quality indicator because previous studies have indicated that mean reaction times may be more variable/longer during web-based delivery of experimental tasks [15,43]. As the CANTAB web platform did not provide trial-

level data, this RT index was not available for the IED or SWM tasks.

2.6 *Task Performance Indices*

2.6.1 i-ABC Platform

WCST. In this task, participants were required to shift between different rules for matching cards according to the feedback they received. Performance was assessed by analysing the number of trials the participant took to correctly identify a new rule after it had changed. Two key indices were computed: perseverative and non-perseverative errors. If participants persisted with the previous rule after a change in rule, the number of errors in this pattern were considered as perseverative errors. Any error which was not a perseverative error was considered as a non-perseverative error.

Probabilistic Learning and Reversal (PR) Task. Two indices were used to assess performance on the PR task: (a) Perseveration. In the reversal phase, the rule was reversed and the number of trials that the participant required to update their response in accordance with the new rule after reversal was computed as the perseveration index. (b) Switching Probability. This was the total number of times that the participant changed their response when negative feedback was displayed.

Structure Learning (SL) Task. In this task, participants were required to predict the next symbol to appear in a sequence of symbols shown. Even though the order of the symbols appeared stochastic, this was based on a Markov model which controlled the transitional probabilities between symbols. Structure learning is highly probabilistic in nature and hence responses cannot be analysed solely on the basis of accuracy. Following previous studies, responses were analysed in a probabilistic manner [57]. The absolute Euclidean distance (AbDist) between the distribution of participant responses and the distribution of presented targets was estimated across the 60 trials for each block as shown in Eq(1).

$$AbDist(context) = \sum |Pr(target|context) - Pp(target|context)|$$

Eq(1)

AbDist was computed for each context as the sum over all targets in the symbol set of $|Pr() - Pp()|$, where $Pr()$ denotes the probability distribution of participant responses to each target symbol, and $Pp()$ denotes the probability distribution of the presented symbols. The minimum overlap between the two distributions was then quantified by calculating a Performance Index (PI) for each context, as follows:

$$PI(context) = \sum \min(Pr(target|context), Pp(target|context))$$

Eq(2)

Hence, $PI(context) = 1 - AbDist(context)/2$.

This measure was then averaged across contexts and weighted by the corresponding stationary context probabilities as follows:

$$PI = \sum PI(context) \cdot P(context)$$

Eq(3)

Finally, the Performance Index was normalised by subtracting the expected Performance Index for random guessing (i.e. equal probability for each target). This normalised PI was computed for each experimental block, and the mean PI across all blocks was used as the first outcome measure. The second outcome measure, PI change, was defined as the difference in performance between the first two blocks (blocks 1 and 2) and the last two blocks (blocks 6 and 7) of the experiment.

2.6.2 Inquisit 5 Web Platform

Stroop task. The reaction times along with the accuracy for both congruent and incongruent trials were measured. For analysis of interference effect, the reaction times of only the correct responses were considered. Two interference indices were calculated based

on the difference in reaction time and accuracy respectively between the congruent and incongruent stimuli.

Stop Signal Task (SST). Performance on this task is dependent on the relative finishing time of two processes [52]: a go process, triggered by the presentation of the primary-task stimulus, and a stop process, triggered by the presentation of the stop signal. If the stop process finishes before the go process, participants successfully inhibit their response. If the go process finishes before the stop process, response inhibition fails, and participants respond when they should not. The latency of the stop process, or Stop Signal Reaction Time (SSRT), was estimated using the integration method following Verbruggen et al [52]. Specifically, the integration method involves “integrating” the reaction time (RT) distribution and identifying the n th RT, where n is the total number of response times in the RT distribution of go trials multiplied by the participant’s probability of responding on a stop-signal trial (i.e. $p(\text{respond}|\text{signal})$). The SSRT is then calculated by subtracting the mean Stop Signal Delay (SSD) from this identified RT value in the n th RT position. This version of the integration method is thought to produce the most reliable and least biased non-parametric SSRT estimates.

Trails Task. Two reaction times were recorded for the Trails A and Trails B tasks respectively. The Trails A reaction time was the total time taken by the participant to complete connecting all numbered circles in the correct sequential order. Similarly, the Trails B reaction time was the time taken by the participant to complete connecting circles, alternating between letters and numbers in the correct order. To estimation performance, the ratio of the Trails B to Trails A reaction time was computed.

2.6.3 CANTAB Platform

Intra-Extra Dimensional Set Shift task (IED). The IED is a nine-stage task, and the rule for the correct response was modified at the start of each stage. Specifically,

intradimensional rule shifts (IDs) assessed participants' ability to generalize a rule to new stimuli whereas extradimensional shifts (EDs) assessed cognitive flexibility as the ability to shift attention to a previously irrelevant dimension [66]. The two key performance indices in this task were the number of errors made to complete the stage where there was an ED shift (Stage 8), and the total number of errors made in the stages prior to the ED shift.

Spatial Working Memory (SWM) Task. The two key measures for this task related to errors and strategy. SWM Between Errors were computed as the number of times that the participant incorrectly revisited a box, calculated across 4, 6, 8 and 12 token trials. SWM Strategy which was the number of unique boxes from which a participant started a new search in the 6 and 8 box trials. More efficient searches are carried out by searching boxes in a fixed order [62].

2.6.4 Verbal Delivery

WASI-II Vocabulary Test. In the 22 word-item list, each item was scored as either zero, one or two depending on the detail and accuracy of the answer given. The raw score out of 59 was taken as the performance index, with 0 being the lowest and 59 being the highest score possible. This raw score was then transformed into standardised T-scores by participant age.

BDS Test. The score given for a correct response was 1 and for an incorrect response was 0. Out of the 2 sequences per length, the participant had to obtain a minimum score of 1 to proceed to the next sequence. The raw score out of 16 was taken as the performance index, with 0 being the lowest and 16 being the highest score possible.

3 RESULTS

3.1 Technology Profile of Remote Guided Participants

Participants who underwent remote guided testing (RGT) completed the experimental tasks at home using their own personal computer and internet connection. Although all participants used equipment that met certain minimum standards as stated in the eligibility criteria (see Methods Section 2.2), we wished to determine the actual range and quality of technology that was being used. As shown in Figures 2 & 3 and detailed in Table 4, in terms of hardware specifications, the lab equipment was a close match to the most common specifications reported by the RGT group (e.g. Windows OS, Intel Core i7 processor, 13-inch screen, 1920 x 1080 resolution, ~8 GB RAM). In terms of web capability, most RGT participants had better internet download/upload speeds than the F2F group (mean of 77.9/70.4 Mb/s versus 44.6/48.1 Mb/s), but slightly longer internet latencies (mean of 10.6 ms as compared to 5 ms).

Figure 2. Hardware specifications for remote guided participants (total $N=44$), including computer (a) brand; (b) operating system; (c) screen size (in inches) (d) screen resolution (in pixels); (e) processor and (f) RAM (in GB).

Figure 3. Web capability for remote guided participants (total $N=44$), including (a) internet download/upload speed (higher=better); and (b) internet latency (shorter=better).

		RGT N/Mean (%/SD)	F2F Standard
Hardware Specifications	Brand	Acer = 14 (13.6%) Apple = 6 (31.8%) Asus = 9 (20.5%) Dell = 3 (6.8%) HP = 7 (15.9%) Lenovo = 5 (11.4%)	HP Probook
	Operating System	Windows = 30 (68.2%) Mac OS = 14 (31.8%)	Windows 10
	Processor	Intel Core i3 = 2 (4.5%) Intel Core i5 = 21 (47.7%) Intel Core i6 = 1 (2.3%) Intel Core i7 = 17 (38.6%) Intel Core i8 = 1 (2.3%) Intel Core i9 = 1 (2.3%) Other = 1 (2.3%)	Intel Core i7 2/2.4GHz
	RAM (GB)	9.73 (4.35)	8.0
	Total Hard Disk Space (GB)	417 (229)	500 HDD (+256 SSD)
	Free Hard Disk Space (GB)	270 (223)	108
	Screen Size (Inches)	13.8 (1.74)	13.3

	Screen Resolution	1280 x 800 = 1 (2.3%) 1366 x 768 = 6 (13.6%) 1440 x 900 = 2 (4.6%) 1920 x 1080 = 19 (43.2%) 1920 x 1280 = 1 (2.3%) 2560 x 1600 = 10 (22.7%) 3200 x 1800 = 3 (6.8%) Unspecified = 2 (4.6%)	1920 x 1080
	Input devices	<u>Mouse</u> Wireless = 27 (61.2%) Wired = 15 (34.1%) Integrated = 2 (4.6%) <u>Keyboard</u> Wired = 2 (4.6%) Integrated = 42 (95.5%) <u>Webcam</u> Integrated = 43 (97.7%) Separate = 1 (2.3%) <u>Microphone</u> Integrated = 35 (79.6%) Separate = 9 (20.5%)	Wired mouse Integrated keyboard, webcam and microphone
Web Capability	Download Speed (Mb/s)	77.9 (88.6)	44.6
	Upload Speed (Mb/s)	70.4 (96.1)	48.1
	Internet Latency (ms)	10.6 (12.3)	5
	Web browser	Google Chrome = 38 (86.4%) Mozilla Firefox = 5 (2.3%) Safari = 1 (11.4%)	Google Chrome

Table 4. Summary of hardware and web capability specifications for remote guided participants, compared to the standard testing equipment used for the face-to-face group.

3.2 *Data Quality*

3.2.1 Missed Trials

The percentages of trials missed for each experimental task and group are shown in Table 5. To assess whether there was a difference in the number of missed trials across tasks as a function of testing modality, the data were analysed using a General Linear Model (GLM) with missed trials on each Task (4 levels) as dependent (within-subjects) variables and Modality (2 levels) as a predictor (between-subjects) variable. Participants' Age and Vocabulary standardised scores were entered as co-variables in the model. Since Mauchly's test indicated that the assumption of sphericity had been violated ($\chi^2(5)=176, P<.01$), degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity ($\epsilon=0.53$). The results indicated no significant main effect of Modality ($F(1,56)=.61, P=.44; \eta^2p=.01$) and no significant interaction between Modality and Task ($F(1.59, 89.3)=.44, P=.60; \eta^2p=.01$). Tukey HSD post-hoc tests indicated that F2F and RGT participants did not differ on missed trials for any individual task ($P>.99$ for all pairwise comparisons). There were also no significant effects of Age ($F(1,56)=.52, P=.47; \eta^2p=.01$) and Vocabulary ($F(1,56)=.01, P=.91; \eta^2p=.00$).

3.2.2 Data Exclusion

Trial-level exclusions. Table 5 provides a full breakdown of data exclusions by experimental task and group. To determine whether there was a difference in the overall percentage of excluded trials across tasks as a function of testing modality, the data was analysed using a General Linear Model (GLM) with excluded trials on each Task (5 levels) as dependent (within-subjects) variables and Modality (2 levels) as a predictor (between-subjects) variable. Participants' Age and Vocabulary standardised scores were entered as co-

variates in the model. Since Mauchly's test indicated that the assumption of sphericity had been violated ($\chi^2(9)=17.1, P<.05$), degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity ($\epsilon=0.88$). The results indicated no significant main effect of Modality ($F(1,56)=2.1, P=.15; \eta^2p=.04$) and no significant interaction between Modality and Task ($F(3.55, 198.5)=.37, P=.81; \eta^2p=.01$). Tukey HSD post-hoc tests indicated that F2F and RGT participants did not differ on excluded trials for any individual task ($P>.40$ for all pairwise comparisons). There were also no significant effects of Age ($F(1,56)=1.97, P=.17; \eta^2p=.03$) and Vocabulary ($F(1,56)=1.74, P=.19; \eta^2p=.03$).

Task-level exclusions. As shown in Table 5, a total of 12 participant task-level datasets (F2F=2, RGT=10) were not included in the analysis. Of these, 6 datasets were removed for technical reasons and 6 were removed for performance reasons. Technical exclusions ($n=6$) only occurred for the RGT group, due to technical issues encountered during task administration: One participant's computer OS version (Mac, OS X Yosemite, Ver 10.10.5.) was too old to launch the Inquisit webplayer and the participant was therefore unable to attempt all 3 Inquisit tasks; one participant did not have a computer mouse and attempted the Trails task using a trackpad (which alters tracking motion and speed); task responses were not recorded by the i-ABC server for the Probabilistic Reversal task for one participant, and finally one participant experienced loud background noise disruption whilst completing the Structure Learning task. No datasets in the F2F group were excluded for technical reasons. For performance-related exclusions, recall that task-level data was excluded if the participant's total number of missed and outlying trials was $>25\%$ of all trials for that task. Following these criteria, 2 participant task-level datasets were removed in the F2F group, and 4 participant task-level datasets were removed in the RGT group (total of 6 datasets removed for performance reasons).

3.2.3 Reaction Times

Finally, we assessed whether the mean reaction times of included trials differed as a function of testing modality (see Table 5 for group means). The data were analysed using a General Linear Model (GLM) with reaction times on each Task (6 levels) as dependent (within-subjects) variables and Modality (2 levels) as a predictor (between-subjects) variable. Participants' Age and Vocabulary standardised scores were entered as co-variates in the model. Since Mauchly's test indicated that the assumption of sphericity had been violated ($\chi^2(14)=176, P<.01$), degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity ($\epsilon=0.37$). The results indicated no significant main effect of Modality ($F(1,55)=.15, P=.70; \eta^2p=.00$) and no significant interaction between Modality and Task ($F(1.86, 102.3)=.21, P=.24; \eta^2p=.03$). Tukey HSD post-hoc tests indicated that F2F and RGT participants did not differ on reaction time for any individual task ($P>.80$ for all pairwise comparisons). There were also no significant effects of Age ($F(1,55)=.00, P=.98; \eta^2p=.00$) and Vocabulary ($F(1,55)=.14, P=.71; \eta^2p=.00$).

DATA QUALITY									
Delivery Platform	Task	(1) Missed Trials (mean, %)		(2) Data Exclusion				(3) Reaction Time (mean, seconds)	
				<u>Trial level</u> (mean, %)		<u>Task level</u> (tech/perf, N)			
		F2F	RGT	F2F	RGT	F2F	RGT	F2F	RGT
i-ABC	Wisconsin Card Sort Test (WCST)	0.73 (1.3)	1.02 (1.9)	3.50 (3.2)	4.92 (5.4)	0 / 0	0 / 0	1.33 (0.18)	1.39 (0.22)
	Probabilistic Learning & Reversal (PR)	0.30 (0.6)	0.74 (1.5)	3.06 (3.1)	5.80 (5.9)	0 / 1	1 / 1	0.90 (0.16)	1.01 (0.21)
	Structure Learning (SL)	3.41 (2.6)	3.27 (2.6)	0.99 (0.7)	1.72 (3.5)	0 / 0	1 / 1	1.07 (0.15)	1.04 (0.16)
Inquisit	Colour-Word Stroop	N.A.	N.A.	3.38 (4.5)	3.28 (4.7)	0 / 0	1 / 1	0.84 (0.13)	0.87 (0.14)
	Stop Signal Task (SST)	0.98 (1.8)	1.59 (3.3)	1.41 (2.4)	1.14 (2.7)	0 / 1	1 / 1	0.47 (0.08)	0.42 (0.09)
	Trails A and B	0 (0)	0 (0)	0 (0)	0 (0)	0 / 0	2 / 0	40.9 (10.7)	40.4 (10.2)
CANTAB	Intra-Extra Dimensional Set Shift (IED)	N.A.	N.A.	N.A.	N.A.	0 / 0	0 / 0	N.A.	N.A.
	Spatial Working Memory	N.A.	N.A.	N.A.	N.A.	0 / 0	0 / 0	N.A.	N.A.
Verbal	Backwards Digit Span, WASI Vocabulary	Nil							

Table 5. Summary of data quality indices for all tasks. Standard deviations are shown in brackets. F2F = Face-to-Face; RGT = Remote Guided Testing.

TASK PERFORMANCE				
Delivery Platform	Task and Performance Index	Scores by Group		GLM Modality Effects
		F2F	RGT	
i-ABC	Wisconsin Card Sort Test (WCST)			Modality F(1,72)=.00, P=.96 Modality*Task F(1.20, 86.2)=.02, P=.73
	• Non-perseverative errors	10.1 (5.5)	10.2 (6.8)	
	• Perseverative errors	9.3 (2.6)	10.0 (4.1)	
	Probabilistic Learning & Reversal (PR)			
	• Perseveration	3.1 (1.7)	3.7 (2.8)	
	• Switching Probability	6.6 (2.5)	6.7 (2.6)	
	Structure Learning (SL)			
	• PI mean	0.15 (0.22)	0.06 (0.18)	
	• PI change	0.18 (0.30)	0.16 (0.31)	
Inquisit	Colour-Word Stroop			Modality F(1,58)=.74, P=.39 Modality*Index F(1.80, 104.3)=1.65, P=.20
	• Interference (RT)	0.23 (0.10)	0.22 (0.11)	
	• Interference (Accuracy)	-0.08 (0.07)	-0.10 (0.09)	
	Stop Signal Task (SST)			
	• Stop signal reaction time	0.24 (0.19)	0.28 (0.27)	
	Trails A and B			
	• Trails B/A time ratio	1.26 (0.43)	1.17 (0.31)	
CANTAB	Intra-Extra Dimensional Set Shift (IED)			Modality F(1,59)=.02, P=.88 Modality*Task F(1,59)=.03, P=.86
	• ED shift errors	5.6 (7.2)	4.7 (5.2)	
	• Pre-ED shift errors	7.3 (2.6)	9.6 (7.7)	
	Spatial Working Memory			
	• Between errors	25.3 (16.7)	32.3 (21.3)	
	• Strategy	13.3 (4.6)	14.4 (4.1)	
Verbal delivery	WASI Vocabulary (std score)	50.1 (7.2)	56.0 (7.6)	Modality F(1,82)=16.6, P<.001
	Backwards Digit Span (total score)	8.7 (3.1)	9.7 (3.2)	Modality*Task F(1,82)=7.57, P=.007

Table 6. Summary of task performance indices. Standard deviations are shown in brackets. GLM Modality main and interaction effects for each platform are shown in the final column.

3.3 Task Performance

The task performance indices were grouped and analysed by delivery platform. Unlike the previous data quality measures of missed/excluded trials which were computed manually using simple and uniform criteria, these performance indices varied greatly in complexity and granularity (e.g. spanning estimations of strategy, accuracy/error, and timing). Most of the performance indices were also automatically calculated by the delivery software using built-in criteria and assumptions. Accordingly, we analysed task performance separately by delivery platform to allow us to detect any testing modality differences that emerged on some platforms and their tasks, but not others. Table 6 and Figure 4 show a full breakdown of participant performance by delivery platform, task and test modality.

Figure 4. Plot of performance indices for (a) i-ABC; (b) Inquisit; (c) CANTAB and (d) Verbally delivered tasks. Face-to-face participants are shown in dark grey bars, remote guided participants are shown in light grey bars. Errors bars indicate the standard error of the mean. Significant group differences in performance were only observed for WASI Vocabulary ($***P<.001$), where remote guided participants scored more highly on the task.

i-ABC. To assess task performance across the three i-ABC tasks (Wisconsin Card Sort, Probabilistic Reversal and Structure Learning), the data were analysed using a General Linear Model (GLM) with Task (3 levels) and Index (2 levels) as dependent (within-subjects) variables and testing Modality (2 levels) as a predictor (between-subjects) variable. Participants' Age and Vocabulary standardised scores were entered as co-variates in the model. Since Mauchly's test indicated that the assumption of sphericity had been violated (Task: $\chi^2(2)=78.7$, $P<.001$), degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity ($\epsilon=0.60$). The results indicated no significant main effect of Modality ($F(1,72)=.00$, $P=.96$; $\eta^2p=.00$) and no significant interaction between Modality and Task ($F(1.20, 86.2)=.02$, $P=.92$; $\eta^2p=.00$). Tukey HSD post-hoc tests indicated that F2F and RGT participants did not differ on performance for any individual task or index ($P>.99$ for all pairwise comparisons). There was a significant effect of Age ($F(1,72)=9.81$, $P=.003$; $\eta^2p=.12$) but no significant effect of Vocabulary ($F(1,72)=.02$, $P=.90$; $\eta^2p=.00$).

Inquisit. To assess task performance across the three Inquisit tasks (Stroop, Stop Signal and Trails), the data was analysed using a GLM with Index (4 levels) as dependent (within-subjects) variables and testing Modality (2 levels) as a predictor (between-subjects) variable. Participants' Age and Vocabulary standardised scores were entered as co-variates in the model. Since Mauchly's test indicated that the assumption of sphericity had been violated (Task: $\chi^2(5)=65.9$, $P<.001$), degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity ($\epsilon=0.60$). The results indicated no significant main effect of Modality ($F(1,58)=.74$, $P=.39$; $\eta^2p=.01$) and no significant interaction between Modality and Index ($F(1.80, 104.3)=1.65$, $P=.20$; $\eta^2p=.03$). Tukey HSD post-hoc tests indicated that F2F and RGT participants did not differ on performance for any individual task or index ($P>.77$ for all pairwise comparisons). There were no significant effects of Age ($F(1,58)=1.35$, $P=.25$; $\eta^2p=.02$) or Vocabulary ($F(1,58)=.11$, $P=.74$; $\eta^2p=.00$).

CANTAB. Performance on the two CANTAB tasks (Intra-Extra Dimensional Shift and Spatial Working Memory) was analysed using a GLM taking Task (2 levels) and Index (2 levels) as dependent (within-subjects) variables and testing Modality (2 levels) as a predictor (between-subjects) variable. Participants' Age and Vocabulary standardised scores were entered as co-variables in the model. The results indicated no significant main effect of Modality ($F(1,59)=.02, P=.88; \eta^2p=.00$) and no significant interaction between Modality and Task ($F(1,59)=.03, P=.86; \eta^2p=.00$). Tukey HSD post-hoc tests indicated that F2F and RGT participants did not differ on performance for any individual task or index ($P>.51$ for all pairwise comparisons). There was no significant effect of Age ($F(1,59)=.32, P=.57; \eta^2p=.01$) or Vocabulary ($F(1,59)=1.92, P=.17; \eta^2p=.03$).

Verbal delivery. Finally, participants' performance on the verbally delivered tasks (WASI Vocabulary and Backwards Digit Span) was assessed using a GLM with Task (2 levels) as dependent (within-subjects) variables and testing Modality (2 levels) as a predictor (between-subjects) variable. Only participant Age was entered as a co-variate in the model. Unlike all the previous tests, we observed a strong and significant main effect of Modality ($F(1,82)=16.6, P<.001; \eta^2p=.17$) as well as a significant interaction between Modality and Task ($F(1,82)=7.57, P=.007; \eta^2p=.08$). Tukey HSD post-hoc tests of the interaction indicated that F2F and RGT participants differed significantly on Vocabulary performance ($P<.0001, RGT>F2F$) but not on Digit Span ($P=.83$). There was no significant effect of Age ($F(1,82)=.96, P=.33; \eta^2p=.01$).

In summary, we observed no significant difference in task performance between F2F and RGT participants for any delivery platform or experimental task, with the notable exception of WASI vocabulary, where remotely tested participants scored significantly *higher* than participants tested in-person on the task.

3.4 *Verbal Intelligence Analysis*

To understand the source of this apparent difference in verbal intelligence, first, we assessed whether participants' background could explain their differences in vocabulary performance. Accordingly, the categorical factors of Gender (2 levels, M/F), Ethnicity (3 levels, Chinese/Malay/Indian), Education (2 levels, Secondary/Bachelors), home Dwelling (6 levels) and testing Modality (2 levels, F2F/RGT), and the continuous variable of Age were entered as predictors in a General Regression Model (GRM) analysis, taking Vocabulary score as the dependent variable. Overall, the model was significant ($F(11,62)=2.89$, $P<.01$; adjusted $R^2=0.22$), however the only significant predictor of Vocabulary was testing Modality ($B=-0.47$ [$SE=.11$], $t=-4.15$, $P<.001$). None of the other factors (Age, Gender, Ethnicity, Education or Dwelling) significantly predicted Vocabulary scores ($P>.25$ for all). Therefore, group differences in verbal intelligence could not be explained by differences in participant background characteristics.

Next, we conducted further analyses on participants' item-level responses. Recall that participants were either scored 0 (for an incorrect or null response), 1 (for a partial response) or 2 points (for a full response) on each word item. Accordingly, we assessed whether superior performance in the RGT group was due to (1) knowledge of more words (i.e. reaching a higher word item number) or (2) more complete description of words (i.e. attaining a full score of 2 for a higher proportion of words). Unpaired t-tests were conducted for each contrast. The results revealed that RGT participants reached a significantly higher item number than F2F participants on average (means (SDs): F2F = 24.0 (1.3), RGT = 25.3 (1.9); $t(83) = -3.79$, $P<.001$). However, RGT participants also attained a full score on a higher proportion of items than F2F participants (means (SDs): F2F = 0.53 (0.23), RGT = 0.63 (0.19); $t(83) = -2.18$, $P<.05$). Therefore, the item-level analysis supported both effects.

4 DISCUSSION

The COVID-19 pandemic has fundamentally changed the landscape of human psychological research and left in its wake a need for thoughtful re-calibration of the balance between new remote ways of working and traditional lab-based research approaches. Never before has there been greater urgency and impetus to shift toward web-based data collection methods. Yet data quality and assurance frameworks for online protocols – particularly for web-based cognitive measurements - are still lacking and current published web-based studies vary greatly in their data quality monitoring and transparency. As a result, we still know surprisingly little about how web-based datasets differ from data collected in person and significant questions remain regarding experimental rigour, reliability and validity [17,18,36]. To help to identify exactly how sources of unwanted participant variability may arise during online data collection and to mitigate these effects, here we propose a new *supervised* online testing methodology, Remote Guided Testing (RGT). This hybrid method may offer a close alternative to traditional lab-based methods for collecting high-quality human cognitive data, without requiring physical contact in the post-COVID “new normal” where many people now work from home.

Further, while used here in a research context - given our findings - there is no reason that the RGT method could not be used *clinically* for neuropsychological assessments, particularly in situations where face-to-face meeting would be difficult or impossible. For example, people in wheelchairs or care homes may find it easier to be tested in their home environment, particularly during winter when daylight hours are short and there can be significant weather deterrents to travel (ice or snow). Therefore, there is wide potential applicability for the RGT method to be used in tandem with traditional face-to-face methods across both clinical and non-clinical settings.

4.1 *RGT Data Quality*

Three data quality indices were examined in cognitive test data collected using either RGT or standard lab-based face-to-face (F2F) methods: (1) missed trials, (2) data exclusion (both at the individual trial and participant level) and (3) reaction times. The results showed that more participant datasets were excluded for technical reasons in the RGT dataset (N=6 across all tasks for RGT compared to none for F2F). These exclusions were due to hardware or software incompatibility issues, or in one case, to environmental disruption. However, RGT and F2F datasets did not differ on any of the other data quality indices of missed and excluded trials, or on reaction time. The latter result is of particular note since previous web-based studies that have examined reaction-time indices (e.g. [15,43]) have noted significant and consistent lags in participant response time latencies when *unsupervised* web-based methods are employed. This result suggests that experimenter supervision, even if only as a virtual presence, may be crucial for maintaining participant focus and attention on cognitive tasks, particularly when a speeded response is required. In addition, the supervising experimenter was also able to quickly troubleshoot several common software and setup problems that RGT participants experienced, which, if left unresolved could have led to a far higher number of technical issues and data degradation.

It well-established that the ‘experimenter effect’ [67] has a significant influence on participants’ motivation, mental state, performance, task engagement and credibility during experimental studies [67,68]. It should also be noted that, since F2F testing was also supervised, experimenter effects were likely to have been similar across groups, and in this case, apparently beneficial for task compliance. However, there are scenarios in which supervision may have an adverse effect on participants’ cognitive and behavioral performance as a result of the social desirability effect and increased cognitive load [14,69,70]. For instance, Richman et al [69] reported a reduction of the pressure to impress

(social desirability effect) with the use of online-based settings. Therefore, the proposed RGT method may not be optimal for experimental paradigms that are sensitive to social desirability effects.

4.2 *RGT Task Performance*

No significant differences in task performance were observed across all measures of executive function (cognitive flexibility, working memory, inhibition) and learning, which were administered using three different experimental platforms (CANTAB, Inquisit and i-ABC). However, we did observe a large and unpredicted difference in verbal intelligence (vocabulary) when measured in remote and face-to-face settings. Surprisingly, participants in the RGT group scored significantly higher than their F2F counterparts and this effect could not be accounted for by differences in background characteristics (age, gender, ethnicity, SES). Detailed analyses of the item-level responses of the participants suggested that RGT participants produced correct definitions for a significantly higher number of words, and also produced more fully-elaborated responses to individual test items than F2F participants. One possible explanation for this effect could be that, throughout their experimental session in the lab, both F2F participants and experimenter were required to wear a facial mask and to maintain a physical distance of at least 1m (in compliance with prevailing COVID-19 guidance). This could have influenced participants' general willingness to communicate with the experimenter, which is consistent with data from a previous large-scale randomised control study indicating that mask-wearing by physicians during consultations had a negative effect on doctor-patient communication, perceived empathy and relational continuity [71]. Therefore, in clinical settings, remote testing methods which do not require the wearing of personal protective equipment such as masks may in fact be beneficial to reduce the communication barrier between experimenter and participant, and consequently yield

improved performance on tasks that require verbal expressivity.

4.3 Toward a Data Quality Assurance Framework for Web-Based Cognitive Studies

Given the current societal momentum, it seems likely that the next few years will see a rapid rise in the number of cognitive studies that are conducted using web-based protocols. There exists, therefore, an urgent need to develop standard protocols, data quality assurance indices and benchmarks for the conduct and reporting of web-based cognitive studies. Here, we take a step in this direction by making the standard operating protocol (SOP) for our remote guided method freely available (see Appendix D). We further collect and report detailed information about participants' technological capability and home environment, and include the relevant survey instruments that were developed for this purpose (see Appendices A & B). We define and report a detailed set of data quality indices, which include measures of trial-level variability (e.g. missed responses, outlying responses, reaction times) as well as participant variability. We further distinguish between technical and performance related issues and exclusions and provide in-depth descriptions of each. This level and form of reporting may be helpful in moving the field of web-based cognitive testing toward greater transparency, reliability and replicability [17,18,36], and also provide common metrics on which the data quality of different datasets may be compared.

4.4 Limitations and Considerations for Selecting Test Methodology

Our results suggest that the RGT method can yield high-quality cognitive data that is comparable to data collected in-person in the lab. However, this gain in data quality comes at the cost of additional manpower and time required for remote human supervision. In fact, as compared to lab-based testing, the RGT method requires one additional set-up session (lasting 30 minutes) and therefore presents a greater time demand for both experimenter and

participant. This level of time investment may not be feasible or desirable for large-scale studies that aim to test thousands of participants over a short period of time, although the inclusion of clear instructions for online tests and brief online tutoring (e.g. using video clips) may increase the comprehensibility of instructions if the requisite research personnel are not available. As illustrated in Figure 5, one practical consideration when deciding on an appropriate test methodology is the trade-off between data quality and available time or resource. Purely unsupervised web-based testing has the attendant advantages of reaching large sample sizes with a broad demographic at a relative low cost per head [15,24,29,31-33]. However, this also comes at the risk of compromises in data quality, comparability, replicability and validity [34,35]. Therefore, the decision to adopt unsupervised web-based testing methods must be informed by the specific tasks to be used and their proven cross-setting reliability [15].

Figure 5. Summary of considerations for suitability of unsupervised, supervised web testing and in-person methodologies for cognitive testing

A further important consideration is the necessity and feasibility of in-person attendance at a physical location. Certain experimental protocols (e.g. neuroimaging, invasive procedures) require in-person attendance due to the need for specific equipment or

professional expertise. In these cases, in-person lab-based testing is the only option for data collection. However, in situations where physical attendance is not necessary or indeed, impossible (e.g. during recent periods of COVID-19 lockdown restrictions), RGT may be a viable alternative. The decision to adopt a supervised online method like RGT will be further weighted by considerations of group size and composition – for example in clinical studies that involve high-risk or rare cohorts where the maximization of individual data quality would be important. Similarly, longitudinal studies that have used in-person lab based cognitive tests at previous timepoints may view cross-setting comparability as a priority, and may therefore opt for supervised online methods that yield similar results to lab-based tests. Further, studies that include reaction time dependent tasks (e.g. Stroop, Stop Signal) may wish to use supervised online methods to ameliorate known reaction latency issues [43]. Finally, both supervised and unsupervised web-based methods require good internet connectivity and digital infrastructure for participants and research labs involved. The excellent web capability of RGT participants in the current study reflects the fact that Singapore has one of the highest levels of internet penetration in the world, estimated recently at 87% [72]. Therefore, while web-based testing would be highly feasible in countries like Singapore, this may present a significantly greater challenge in countries with less well-developed digital infrastructure.

4.5 *Conclusions*

The global COVID-19 pandemic has accelerated a move toward web-based cognitive testing, yet long-standing questions remain over the data quality and validity of web-based studies, compounding an urgent need to develop and implement data quality assurance frameworks for current and future online studies. Here, we propose a new supervised online testing methodology, remote guided testing, and present data quality benchmarks for this new

method. Across all measures of data quality and performance, the RGT method yielded data that was statistically-equivalent to data collected in person in the lab. We conclude that the RGT methodology is robust and offers a viable alternative for collecting high-quality human cognitive data in both lab-based research and clinical contexts without requiring in-person physical attendance.

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