Journal of Experimental Psychology: General

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Online First Publication, September 24, 2020. http://dx.doi.org/10.1037/xge0000773

AMERICAN PSYCHOLOGICAL ASSOCIATION

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ISSN: 0096-3445

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The foundational tenet of brain training is that general cognitive functioning can be enhanced by completing computerized games, a notion that is both intuitive and appealing. Moreover, there is strong incentive to improve our cognitive abilities, so much so that it has driven a billion-dollar industry. However, whether brain training can really produce these desired outcomes continues to be debated. This is, in part, because the literature is replete with studies that use ill-defined criteria for establishing transferable improvements to cognition, often using single training and outcome measures with small samples. To overcome these limitations, we conducted a large-scale online study to examine whether practices and beliefs about brain training are associated with better cognition. We recruited a diverse sample of over 1000 participants, who had been using an assortment of brain training programs for up to 5 years. Cognition was assessed using multiple tests that measure attention, reasoning, working memory and planning. We found no association between any measure of cognitive functioning and whether participants were currently "brain training" or not, even for the most committed brain trainers. Duration of brain training also showed no relationship with any cognitive performance measure. This result was the same regardless of participant age, which brain training program they used, or whether they expected brain training to work. Our results pose a significant challenge for "brain training" programs that purport to improve general cognitive functioning among the general population.

Keywords: brain training, transfer, cognition, working memory, reasoning

Supplemental materials: http://dx.doi.org/10.1037/xge0000773.supp

The promise of brain training is appealing: completing online "games" targeting certain cognitive systems, such as attention and memory, will result in global improvements in cognitive functioning, and even IQ. There is also a strong incentive to improve our cognitive abilities; factors such as vocational success, levels of happiness, and even life expectancy are all linked to cognitive health (Calvin et al., 2017; Deary, Strand, Smith, & Fernandes, 2007; Gale, Batty, Tynelius, Deary, & Rasmussen, 2010; Kuncel & Hezlett, 2010). In recent years, the brain training industry has grown at a remarkable rate; it is estimated that there are nearly 70 million active users of various brain training programs, driving a billion-dollar industry (Simons et al., 2016). However, has the promise of brain training outweighed the science that supports it?

The literature on this topic remains conflicted and continues to be debated. Although a number of studies have provided evidence in support of the benefits of brain training, many of these effects were limited to *near transfer*—improvements that extend only to tasks similar to the tasks involved in the brain training itself. For instance, individuals who trained on the dual n-back, an example of a commonly employed working memory task, have been shown to improve not only on variants of the same task (Li et al., 2008), but on different memory tasks that recruit similar cognitive mechanisms (Dahlin, Nyberg, Bäckman, & Neely, 2008; Morrison & Chein, 2011; Tulbure & Siberescu, 2013). This pattern of results appeared to be the same for younger (Dahlin et al., 2008; Holmes, Gathercole, & Dunning, 2009; Rueda, Checa, & Cómbita, 2012)

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Bobby Stojanoski does not have any financial agreement or affiliation with any product or services discussed in the manuscript. Adrian M. Owen is the Chief Scientific Officer of Cambridge Brain Sciences, and Michael E. Battista, Conor J. Wild, and Emily S. Nichols provide consulting services for the company. Under the terms of the existing licensing agreement, Adrian M. Owen and his collaborators are free to use the cognitive tests at no cost for their scientific studies, and such research projects neither contribute to, nor are influenced by, the activities of the company. Consequently, there is no overlap between the current study and the activities of Cambridge Brain Sciences, nor was there any cost to the authors, funding bodies, or participants who were involved in the study. That is, Cambridge Brain Sciences received no financial support, or in-kind contributions from funding agencies, government bodies, or commercial sources for the study. The authors declare that there were no other potential conflicts of interest with respect to the authorship or the publication of this article.

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and older populations (Richmond, Morrison, Chein, & Olson, 2011; Rosi et al., 2018; Salminen, Kühn, Frensch, & Schubert, 2016), with healthy (Jaeggi et al., 2010; Klingberg, 2010; Tudor, 2017) or diseased brains (Beck, Hanson, Puffenberger, Benninger, & Benninger, 2010; Klingberg et al., 2005). However, even this rather limited brain training effect has been challenged, with several studies failing to replicate the original results (Redick et al., 2013; Thompson et al., 2013). To fully meet its promise, brain training must result in some degree of *far transfer*—improved performance on completely unrelated tasks, reflecting an enhancement of general cognitive abilities.

One of the first studies to suggest that brain training produces far transfer appeared to show that training on the dual n-back task increased fluid intelligence (Jaeggi, Buschkuehl, Jonides, & Perrig, 2008). Encouraged by these results, numerous studies followed, claiming that training on working memory tasks can improve language comprehension (Carretti, Borella, Zavagnin, & de Beni, 2013), reading abilities (Dahlin, 2011), math (Bergman-Nutley & Klingberg, 2014), and even delay aging-related cognitive decline (Basak, Boot, Voss, & Kramer, 2008), across the life span. Nevertheless, follow-up studies attempted, but often failed, to replicate these effects (Thompson et al., 2013), even when identical procedures were employed (Redick et al., 2013). Difficulties in establishing "far transfer" are not limited to working memory-based brain training. For instance, training on video games (Basak et al., 2008), inhibitory control tasks (Enge et al., 2014) and decision making tasks (Kable et al., 2017), have all failed to produce far transfer effects. Even when training has involved an assortment of tasks that tap multiple cognitive systems, participants improved only on the training tasks themselves (Owen et al., 2010).

The results of meta-analyses—intended to extract the most robust effects in the literature—have been equivocal, with some claiming that brain training improves global cognition (Au, Buschkuehl, Duncan, & Jaeggi, 2016; Au et al., 2015) and others concluding that it does not produce transferable gains (Melby-Lervåg & Hulme, 2016; Redick et al., 2013). However, meta-analyses have a number of limitations (Lyman & Kuderer, 2005); first, there is a publication bias; unpublished studies, which are more likely to report negative findings, are neglected. Second, and perhaps more importantly in the context of brain training, the conclusions of a meta-analysis are constrained by any poorly designed studies included in the analysis. Factors such as inconsistent experimental designs and control groups, training protocols that rely on different training tasks, inappropriate statistical analyses, poorly defined criteria for transfer, and small sample sizes (Shipstead, Redick, & Engle, 2012; Simons et al., 2016), all contribute to the disparity evident across studies and limit the efficacy of meta-analyses.

To assess the real-world benefits of brain training, a broader perspective is required that considers larger and more diverse samples and various different training programs, yet assesses changes in cognition with an identical set of multiple outcome measures for each participant (Makin, 2016; Simons et al., 2016). While this would be nearly impossible in a laboratory setting, the Internet provides an ideal platform to meet these criteria. To this end, we conducted a large-scale online study, recruiting more than 11,000 individuals from all over the world, over 1000 of whom claimed to have been active users of commercially available brain training programs for up to 5 years. General cognitive function in this convenience sample was evaluated using the 12 tasks that make up the Cambridge Brain Sciences (CBS) online assessment battery, which collectively measure many aspects of working memory, verbal ability, reasoning, decision-making and inhibitory control. The tests have been shown to be sensitive to subtle changes in cognition due to neurodegeneration (Owen et al., 1993, 1992), sleep deprivation (Wild, Nichols, Battista, Stojanoski, & Owen, 2018) and pharmacological intervention (Lange et al., 1992; Mehta et al., 2000), and their neural correlates have been well studied using functional neuroimaging in healthy adults (Owen et al., 1992).

We hypothesized that, if brain training produces generalizable improvements in higher-level cognition, then, on average, the 1009 participants with an active history of active brain training should outperform those who had no such history on some aspects of general cognitive function. Moreover, we expected to see a duration-dependent (Bamidis et al., 2015) relationship between the amount (duration) of brain training and performance on a variety of outcome measures; that is, the more an individual brain trains the larger the benefit to cognitive functioning.

Materials and Method

Participants and Procedure

Individuals interested in participating in the study were recruited via the Cambridge Brain Sciences online platform (www.cambridgebrainsciences.com). Before starting, all individuals consented to participate in the study, which was approved by the Health Sciences Research Ethics Board of the University of Western Ontario. Finally, in keeping with principles of transparency, we report how we determined our sample size, all data exclusions (if any), all manipulations, and all measures in the study (Simmons, Nelson, & Simonsohn, 2012).

The study proceeded in two phases. First, participants were asked to complete a questionnaire which, in addition to enquiring about demographic variables (e.g., age, handedness, gender, education etc.), contained four questions related to their practices and opinions about brain training: (a) "Are you of the opinion brain training works?" (response: "yes" or "no"); (b) "Do you participate in brain training programs?" (response: "yes" or "no"); (c) "Which brain training programs do you use?" (response: "Lumosity', "Peak," "BrainHQ," "Elevate," "NeuroNation," "Other (text input)"); and (d) "How long have you participated in brain training?" (response: duration in months). However, participants had no knowledge that they would be asked about brain training at enrolment. As this was not a randomized controlled trial, all data were self-reported. After completing the questionnaire, participants proceed to phase 2, where they completed the battery of 12 cognitive tests (presented in a randomized order for each participant) included in the CBS platform (Hampshire, Highfield, Parkin, & Owen, 2012); see online supplementary materials for a detail description of each task. Participants were allotted 4 hr to complete the 12 tests and were encouraged to take breaks when necessary. A total of 12,029 participants (from 145 countries, who as a group speak 76 different languages, represent various ethnic/racial groups, from varying levels of education socioeconomic backgrounds), registered for the study, completed all 12 tests plus the questionnaire, and were between the ages of 18 and 100. From that sample, outliers were removed based on performance on the 12 CBS tasks over two iterations: first those that were six (to remove obvious errors, $N = 33$) then four, standard deviations ($N = 159$) from the mean, leaving 11,837 participants. Participants were excluded if they did not indicate whether they did or did not brain train ($N = 78$), reporting the duration of brain training with a non-number ($N = 2850$), for reporting more than 96 months ($N = 9$), and a mismatch between whether they brain train and for how long (e.g., reporting they brain train with a duration of 0 months, or reporting not brain training with a duration of greater than 0 months; $N = 337$). A total of 8,563 individuals enrolled in the study and met all of the inclusion criteria.

Statistical Analyses

In addition to scores from the 12 individual CBS tests, three component cognitive domain scores were also included that reflect working memory, verbal, and reasoning abilities. These component scores were calculated by multiplying each participant's score on the 12 tasks with the Moore-Penrose pseudoinverse of a set of component weights (factor loadings) computed from an exploratory principal component analysis (PCA) by Hampshire et al., (2012), on an independent set of 75,000 participants who had completed all the CBS tests. The component cognitive domain scores were converted to z-scores before conducting further analyses, while performance on the individual tasks remained in their original format.

We examined two avenues by which brain training might be related to cognitive functioning. First, we investigated whether the amount of self-reported brain training had any impact on cognitive abilities across the 15 outcome measures (12 test scores plus 3 component variables). Specifically, we tested whether those who engage in brain training showed a cognitive advantage over those who do not, and whether there is a duration-dependent effect of brain training; that is, does more brain training translate to better cognitive functioning? Second, we investigated the hypothesis that prior expectations about the merits of brain training might be related to performance on different measures of cognition, and that these expectations might interact with amount of brain training to affect cognition.

We analyzed the data with a combination of ANOVAs, post hoc *t* tests, and effect sizes using both frequentist and Bayesian statistics to determine whether there was any relationship between self-reported amount of brain training, or prior expectations about the merits of brain training, with better cognition. We included both frequentist and Bayesian statistics (positive: BF_{10} 3–20; strong: BF_{10} 20–150; or very strong: $BF_{10} > 150$ support of the alternative hypothesis) because they provide complimentary perspectives—controlling for Type I and Type II errors, and determining the likelihood the result falls under the null hypothesis, respectively (Lakens, 2017). We used χ^2 and *t* tests to compare similarity between those who claim to participate in brain training ("brain trainers") and those who do not ("non-brain trainers") across the relevant demographic variables (age, gender, SES, and education). All analyses were conducted using a combination of MATLAB, SPSS, and the Bayesian statistics software package JASP (JASP Team, 2017). We used JASP's default settings, which generates a Bayes Factor that can be interpreted as the relative likelihood of one model versus another given the data and a certain prior expectation (Kass & Raftery, 1995; Wagenmakers, 2007).

We also ran multiple linear regressions (with a gamma distribution to account for skewed data) where we constructed models to predict performance on each of the 12 CBS tests, plus the three component cognitive domains scores, from self-reports about the amount of brain training, along with interactions with age, opinion of brain training, and brain training program. Gender, level of education, and SES were included as categorical covariates of no interest, with N-1 regressors (where N = number of categories for each variable). All results were corrected using a False Discovery Rate at 0.05 (Benjamini & Hochberg, 1995).

Results

A total of 8,563 participants were included in the final analysis after data cleaning. Of those, 1,009 (11.78%) reported actively participating in "brain training," many of whom had been training for over 3 years (mean training period: 8.54 months; range: 2 weeks to 60 months), while 7,554 reported not currently using any brain training program. The two samples were demographically well matched; we found no difference between those who participate in brain training and those who do not in terms of socioeconomic status (92% in both groups ranked "At or above poverty level"), and education (except for slightly more nonbrain trainers with doctorate/professional degrees), although active brain trainers were slightly older (by approximately 1 year) and had a slightly higher proportion of females relative to males. See Table 1 for more details.

Of the group of self-reported brain trainers, we found that 58.96% relied on only one of 5 training programs (Lumosity 32.61%; Peak 16.35%; Elevate 7.53%; Brain HQ 1.68%; and Neural Nation 0.79%), with a further 19.13% using some combination of those programs. The remaining 21.91% of brain trainers reported "Other," or "None," meaning they used a program not listed as one of the options.

We conducted a series of analyses to assess the relationship between self-reported brain training practices and cognitive function. First, we examined whether brain trainers outperformed nonbrain trainers on the three component cognitive domain measures. To test this, we ran a 2 (training vs. no training) × 3 (component cognitive variables: memory, reasoning, verbal) mixed effects ANOVA (accounting for both between and within participant factors), along with a Bayesian ANOVA. We found a significant, but weak main effect of cognitive domain ($F_{(2,\ 17{,}122)} = 3.35$; $p = .025$; $\eta^2_P < 0.001$; $BF_{10} = 0.008$), suggesting that participants scored differently on the three domain measures, an expected result when using various metrics to measure different aspects of cognition. More importantly, we did not find a significant main effect of training ($F_{(1,\ 8561)} = 1.63$; $p = .23$ $\eta^2_P < 0.001$; $BF_{10} = 0.049$), or a significant interaction between training and cognitive domain ($F_{(2,\ 17{,}122)} = 2.59$; $p = .053$; $\eta^2_P < 0.001$; $BF_{10} = 0.03$). These results indicate that there is no difference in performance between active brain trainers and nonbrain trainers on the three measures of higher-level cognition, aspects of cognition which brain training is designed to improve. We ran the same analysis after randomly selecting groups of 1009 nonbrain trainers that were perfectly matched with the group of brain trainers in terms of age, gender, education and socioeconomic status. Across 10 iter-

Table 1
Participant Demographics

Measure	Percentage or *M* (*SD*)			
	"Non– brain trainers"	"Brain trainers"	$\chi^2(df)$ or $t(df)$	*p*
N	7,554	1,009		
Age	40.12 (14.04)	42.5 (14.77)	4.65 (1264)	<.001
Gender				
Female	60.01%	67.29%	19.53 (1)	<.001
Male	38.15%	30.22%	23.58 (1)	<.001
Other	1.84%	2.49%	1.6 (1)	.21
SES				
At or above poverty line	92.3%	92.5%	0.04 (1)	.85
Education				
None	4.63%	5.43%	0.94 (1)	.34
High School	21.98%	24.1%	2.2 (1)	.14
Post-secondary	41.16%	41.43%	0.06 (1)	.8
Master's degree	21.49%	20.32%	0.53 (1)	.46
Doctorate/Professional	10.75%	8.72%	5.12 (1)	.024

Note. *t*-test used to compare age; χ^2 was used to compare gender, socioeconomic status (SES) and education.

ations, of randomly selecting a matched sample of nonbrain trainers, we found no main effect of brain training (mean $F_{(1,2016)} = 2{,}39$ [$SE = 0.59$]; mean $p = 0.19$ [$SE = 0.04$]; mean $\eta^2_P = 0.0004$ [$SE = 0.0002$]; mean $BF_{10} = 0.11$ [$SE = 0.03$]) and no significant interaction between brain training and cognitive domain (mean $F_{(2,4032)} = 1.86$ [$SE = 0.39$]; mean $p = 0.26$ [$SE = 0.07$]; mean $\eta^2_P = 0.0003$ [$SE = 9E\text{-}5$]; mean $BF_{10} = 0.34$ [$SE = 0.014$]).

We followed up this analysis by examining whether demographically matched brain trainers and nonbrain trainers (across 10 iterations of random samples) differed in performance on any of the individual tasks. The results of a 2 (training vs. no training) × 12 (cognitive tasks) mixed effects ANOVA (plus a Bayesian ANOVA) revealed no main effect of brain training (mean $F_{(1,\ 2011)} = 0.65$ [$SE = 0.21$]; mean $p = 0.56$ [$SE = 0.1$]; mean $\eta^2_P = 1.05E\text{-}5$ [$SE = 3.42E\text{-}6$]; mean $BF_{10} = 0.03$ [$SE = 0.012$]), and no interaction between brain training and cognitive task (mean $F_{(11,\ 22{,}121)} = 1.68$ [$SE = 0.22$]; mean $p = 0.18$ [$SE = 0.06$]; mean $\eta^2_P = 1.39E\text{-}4$ [$SE < 1E\text{-}5$]; mean $BF_{10} = 1.57e\text{-}5$ [$SE = 1.1E\text{-}5$]).

To test whether the benefits of brain training on cognition arise only after extensive training periods, we compared performance on the 12 CBS tasks plus the three component domain scores for the top 15% of individuals who have brain trained the longest ($N = 159$), each of whom have trained for at least 18 months, with a demographically matched group of nonbrain trainers. We found no evidence that these two groups differed; that is, we found no main effect of brain training (mean $F_{(1,\ 31{,}950)} = 0.53$ [$SE = 0.19$]; mean $p = 0.59$ [$SE = 0.09$]; mean $\eta^2_P = 5.78E\text{-}4$ [$SE = 2.01E\text{-}6$]; mean $BF_{10} = 0.023$ [$SE = 0.008$]), nor any significant interaction between brain training and any measure of cognitive functioning (mean $F_{(14,\ 31{,}950)} = 1.36$ [$SE = 0.32$]; mean $p = 0.36$ [$SE = 0.09$]; mean $\eta^2_P = 0.005$ [$SE = 5.89E\text{-}4$]; mean $BF_{10} = 8.09E\text{-}5$ [$SE = 6.1E\text{-}5$]).

To investigate whether self-identified brain trainers have poorer baseline cognitive abilities relative to nonbrain trainers, we compared those who reported completing less than one month of brain training (approximating baseline cognitive functioning) with nonbrain trainers (groups were demographically matched; ($N = 237$) on their component variable scores. We found no significant difference between the two groups ($F_{(1,\ 472)} = 0.67$; $p = .41$; $\eta^2_P < 5.4E\text{-}4$; $BF_{10} = 0.07$), nor did we find significant interaction between group and cognitive domain ($F_{(2,\ 6608)} = 1.32$; $p = .27$; $\eta^2_P = 0.002$; $BF_{10} = 0.06$). Relatedly, we also compared performance on the three cognitive domains between those who reported brain training for less than one month ($N = 237$) with those who reported brain training between one and six months ($N = 319$) to determine whether those with poorer cognitive functioning are more likely to demonstrating better cognitive functioning by training for longer. However, we did not find evidence for this; that is, we found no significant main effect of group ($F_{(1,\ 554)} = 0.02$; $p = .96$; $\eta^2_P < 0.0001$; $BF_{10} = 0.06$) or a significant interaction between group and cognitive domain ($F_{(1,\ 1108)} = 1.04$; $p = .35$; $\eta^2_P = 0.001$; $BF_{10} = 0.02$).

Despite not finding group level differences between brain trainers and nonbrain trainers, we next considered whether there is a duration-dependent effect of brain training—that is, the more one brain trains, the greater the benefit to cognition. A regression analysis, including only participants who reported some duration of brain training ($N = 1009$), revealed no relationship between amount of brain training and scores on the three component variables (Memory: $R^2 = 0.007$; $\beta = 0.007$; $t_{(1007)} = 1.46$; $p = 0.14$; Reasoning: $R^2 = -9.1E\text{-}04$; $\beta = -0.0014$; $t_{(1007)} = -0.3$; $p = 0.76$; Verbal: $R^2 = 0.001$; $\beta = 0.007$; $t_{(1007)} = 1.52$; $p = 0.13$; Figure 1).

Similarly, we found no relationship between self-reported length of time participants devoted to brain training and performance on each of the 12 CBS cognitive tasks (see online supplementary materials, Figure S1 and Table S1).

To ensure the lack of a relationship between amount of self-reported brain training and cognition is not biased by unrelated factors, we estimated the contribution of brain training on cognition, by modeling each of the 12 cognitive tasks, plus the three component domain scores, using multiple linear regression. In the model we included duration of brain training (in months) as a variable of interest, with gender, SES, and education as covariates of no interest. We found no relationship between the amount of

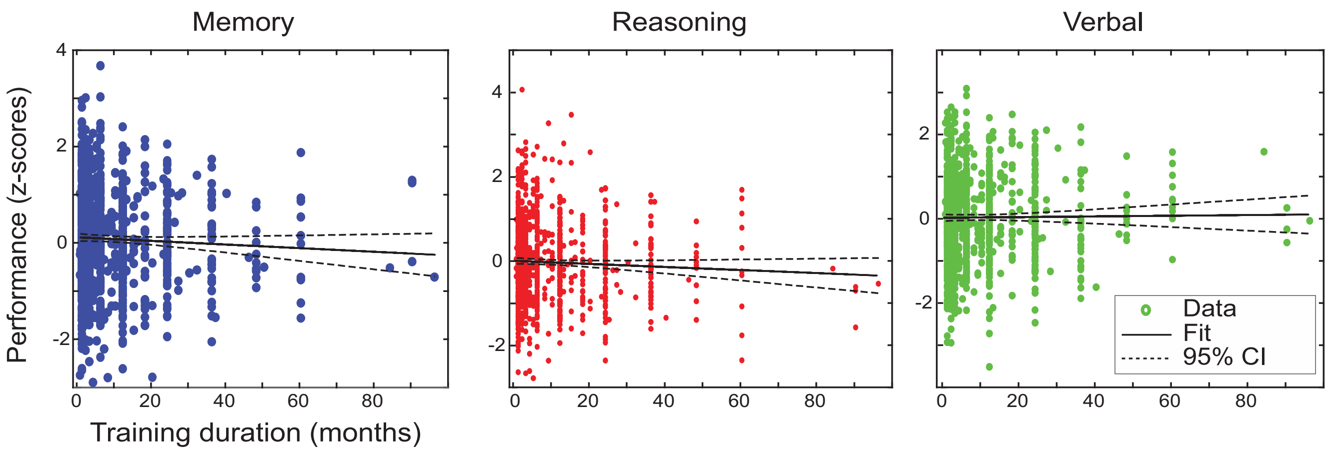

Figure 1. Scatter plot of overall performance (represented as a z-score) for memory (blue), reasoning (red) and verbal abilities (green) versus duration of brain training (months). Circles represent performance scores for each participant across the three component variables. The solid line is a linear regression fit ($R^2 < 0.003$) surrounded by a dashed line reflecting 95% confidence intervals. See the online article for the color version of this figure.

time an individual reported brain training and any measure of cognitive ability ($\Delta R^2 < 0.03$; $\beta < 0.3\text{E-}03$; $t_{(965)} < 2.32$; $p_{\text{FDR}} > 0.26$). The small effects indicate that brain training accounts for less than 1.5% of the variance across all of the measures of cognitive functioning.

Perhaps the benefits of brain training emerge only in certain contexts, or specific subpopulations. First, we investigated whether age interacts with amount of brain training reported by participants by modeling the 15 measures of cognitive functioning using a linear regression that included age, self-reported duration of brain training and their interaction as factors of interest. We found no interaction between age and brain training for any of the cognitive performance measures ($\Delta R^2 < 0.12$; $\beta < 1.6\text{E-}05$; $t_{(962)} < 1.01$; $p_{\text{FDR}} > 0.95$), suggesting that amount of self-reported brain training was not associated with cognitive abilities independent of the age of the participants. Similarly, we found no significant interaction between brain training and level of education ($t_{(972)} < 1.72$; $p_{\text{FDR}} > 0.75$) or socioeconomic status ($t_{(999)} < \pm\ 2.59$; $p_{\text{FDR}} > 0.06$). To ensure subtle effects of brain training in specific age groups were not obfuscated by weaker effects in other age groups, we ran a linear regression with self-reported duration of brain training as the factor of interest for the youngest 25% (250 individuals; age: 18–30) and oldest 25% (254 individuals; age:55–86) who may benefit the most from brain training (Dahlin, 2011; Holmes et al., 2009; Richmond et al., 2011; Salminen, Kühn, et al., 2016). Again, no significant relationship was observed between amount of brain training and cognitive functioning (across the 15 measures) for either the youngest ($\Delta R^2 < 0.01$; $\beta < 0.03$; $t_{(237)} < 2.31$; $p_{\text{FDR}} > 0.33$) or oldest participants ($\Delta R^2 < 0.006$; $\beta < 1.02\text{E-}02$; $t_{(237)} < \pm\ 1.44$; $p_{\text{FDR}} > 0.89$; Figure 2).

We also examined whether certain brain training programs are more likely than others to produce transferable benefits to cognition. It is possible that by grouping together all the training programs in our previous analyses we may have masked the benefits of those that are particularly effective. To test this, we ran separate multiple linear regressions for each of the three most commonly used programs (Lumosity: $N = 327$; Peak: $N = 165$; Elevate: $N = 76$) plus combinations of those training programs ($N = 193$). We observed no positive relationship between the amount of reported training and cognitive function on our 15 performance measures regardless of whether participants trained using Lumosity ($\Delta R^2 < 0.008$; $\beta < 0.093$; $t_{(313)} < \pm\ 1.49$; $p_{\text{FDR}} > 0.92$); Peak ($\Delta R^2 < 0.013$; $\beta < 0.002$; $t_{(151)} < 2.65$; $p_{\text{FDR}} < 0.13$); Elevate ($\Delta R^2 < 0.098$; $\beta < 0.07$; $t_{(64)} < 2.42$; $p_{\text{FDR}} > 0.27$); or a training regime that use a combination of those programs ($\Delta R^2 < 0.01$; $\beta < 0.001$; $t_{(174)} < \pm\ 1.1$; $p_{\text{FDR}} > 0.85$).

Finally, to determine whether perceived value of brain training has an effect on cognition, we conducted 2 (opinion: "yes" vs. "no" to the question "Are you of the opinion that brain training works?") × 3 (component factors: memory, reasoning, verbal) mixed effects and Bayesian ANOVAs. Despite no differences in the amount of self-reported brain training between the two groups (many individuals who do not consider brain training to work still brain train, and conversely, many who think brain training does work, do not themselves participate; $t_{(1945)} = 1.59$; $p = .11$), we found a main effect of prior expectations about brain training ($F_{(1,\ 11{,}706)} = 11.08$; $p < .001$; $\eta^2_P < 0.0001$; $\text{BF}_{10} = 5.67$). Specifically, those who were of the opinion that brain training does not work performed better than those who believed it did. The significant interaction between opinion and cognitive functioning ($F_{(2,\ 23{,}412)} = 7.32$; $p < .001$; $\eta^2_P = 0.0001$; $\text{BF}_{10} = 1.5$), suggests that those who think brain training works and those who do not differ in their cognitive abilities across cognitive domains, although the Bayes analysis indicates this is a small effect. Post hoc comparisons using Welch's and Bayesian *t* tests revealed those with a favorable opinion of brain training performed significantly lower on tests that measure verbal ability (favorable opinion (M $= -0.02$, *SEM* $= 0.01$); unfavorable opinion ($M = 0.09$, *SEM* $= 0.02$); $t_{(3019)} = -4.51$; $p < .0001$; Cohen's $d = -0.12$; $\text{BF}_{10} = 714.7$), only marginally lower on tests that measure reasoning (favorable opinion (M $= -0.01$, *SEM* $= 0.01$); unfavorable opinion ($M = 0.04$, *SEM* $= 0.02$); $t_{(3019)} = -2.01$; $p = .044$; Cohen's $d = -0.047$; $\text{BF}_{10} = 0.28$), but not on tests that tap memory. To ensure the results were not due to a selection bias, we

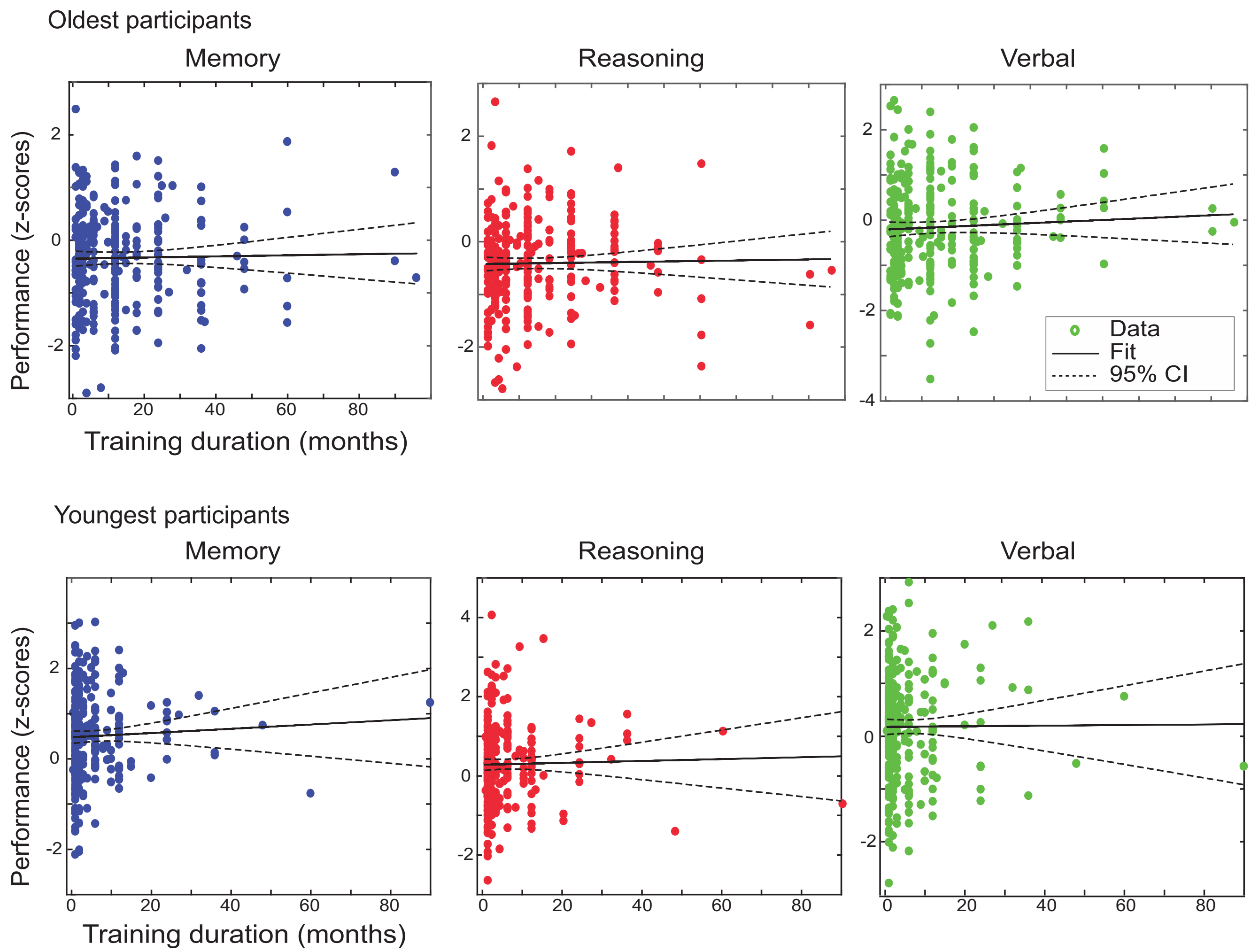

Figure 2. Scatter plot of overall performance (represented as a z-score) for memory (blue), reasoning (red) and verbal abilities (green) versus duration of brain training (months) for the A) oldest and B) youngest participants. Circles represent performance scores for each participant across the three component domains. The solid line is a linear regression fit, for older ($R2 < 0.005$) and younger ($R2 < 0.006$) surrounded by a dashed line reflecting 95% confidence intervals. See the online article for the color version of this figure.

compared brain trainers who had a positive prior expectation of the benefit of brain training with brain trainers who did not. Similar to the previous result, we found main effects of prior expectations ($F_{(1,\ 7328)} = 6.51$; $p = .01$; $\eta_P^2 < 0.0004$; $BF_{10} = 0.64$) and cognitive domain ($F_{(2,\ 14{,}656)} = 6.21$; $p = .002$; $\eta_P^2 < 0.0006$; $BF_{10} = 0.83$), as well as a significant interaction between prior expectations and cognitive domain ($F_{(2,\ 14{,}656)} = 3.95$; $p = .02$; $\eta_P^2 < 0.0004$; $BF_{10} = 0.09$). Post hoc comparisons using Welch's t tests indicated that brain trainers with positive opinions performed worse on measures of memory (favorable opinion ($M = 0.019$, $SEM = 0.013$); unfavorable opinion ($M = 0.103$, $SEM = 0.03$); $t_{(1694)} = -2.66$; $p < .008$; Cohen's $d = -0.083$; $BF_{10} = 1.3$) and verbal ability (favorable opinion ($M = -0.043$, $SEM = 0.013$); unfavorable opinion ($M = 0.103$, $SEM = 0.03$); $t_{(1690)} = -2.57$; $p < .014$; Cohen's $d = -0.08$; $BF_{10} = 0.8$). This result suggests that those with a favorable opinion of brain training have poorer memory and verbal abilities among active brain trainers. Next, we determined whether perceived value of brain training interacts with the amount of brain training to impact cognition, by running a linear regression with two additional predictors: responses to the question "Are you of the opinion that brain training works?," along with an interaction term with amount of brain training (with the same covariates of no interest described earlier). We found no interaction between opinion of brain training and the amount individuals train on cognitive functioning ($\Delta R^2 < 0.006$; $\beta < 0.02$; $t_{(956)} < 0.85$; $p_{FDR} = 0.94$). That is to say, there is no added benefit to expecting brain training to work on cognition, independent of the amount of reported brain training.

Discussion

Of all the recent debates in cognitive psychology and cognitive neuroscience, perhaps none is as contentious as the issue surrounding the efficacy of brain training. Excitement over initial findings suggesting that completing online "games" that target specific cognitive systems (primarily working memory) could improve global cognition functioning, and even increase IQ, were soon overshadowed by subsequent failures to replicate and extend those findings (Melby-Lervåg, Redick, & Hulme, 2016; A. B. Morrison & Chein, 2011; Owen et al., 2010; Redick et al., 2013; Thompson et al., 2013). A number of follow-up meta-analyses yielded equally inconsistent conclusions. In some ways, this is not surprising—the literature is replete with studies using different definitions of transfer based on different training tasks, limited numbers of training and assessment tests, discrepant analysis methods, and small sample sizes (Simons et al., 2016). The current study was designed to meet three essential criteria: (a) a large and diverse population sample, (b) various training programs that target different aspects of cognition, and (c) multiple outcome measures of cognition designed to assess the effectiveness of brain training as it is practiced in a real-world setting. The use of multiple training programs and outcome measures in such a large sample ensured that even subtle effects of brain training would be detected.

Nevertheless, using various analyses we consistently failed to find evidence that self-reported brain training benefitted any aspect of cognitive functioning. First, we found no association between the self-reported duration of brain training (ranging from 2 weeks to 5 years) and performance on any of the individual cognitive tests or the component domains of memory, reasoning, and verbal abilities. These domain scores, which served to approximate high-level cognitive functioning, are important because they are precisely the type of outcome measures that should be better, if brain training does indeed produce improvements in general cognitive function. Second, we considered the possibility that the benefits of brain training are constrained to specific subpopulations of our sample, for instance, younger or older adults (Richmond et al., 2011; Rosi et al., 2018; Salminen, Frensch, Strobach, & Schubert, 2016). Our results suggested this is not the case; neither age group showed any evidence of a relationship between cognitive performance and duration of training. Third, we examined whether certain brain training programs are associated with better cognitive functioning than others. Again, we found no evidence to support this hypothesis—cognitive performance was equivalent regardless of which of the three most common training programs (or any combination of the three) was used (i.e., Lumosity, Peak, or Elevate). Even when we selected the most committed (self-proclaimed) brain trainers, those who had reported brain training for at least 18 months, we still failed to find any cognitive benefit in this group.

By capitalizing on the unique opportunity afforded by the Internet to conduct a large-scale study of brain training as it is practiced in the real world we were able to mitigate many of the limitations of previous studies in this area. For instance, our results cannot be explained by a biased selection of training tasks. Participants in our sample reported using at least five different training programs, with nearly 20% of them training on multiple programs, each with different tasks, in order to improve many different aspects of cognition. Similarly, our results cannot be explained by inadequate training periods. Nearly 39% of the participants reported brain training for at least five months, with approximately 15% training for over a year and a half, far surpassing the training durations of 4–8 weeks that have frequently been reported in previous brain training studies (Melby-Lervåg et al., 2016; A. B. Morrison & Chein, 2011). Importantly, training occurred in naturalistic (or "real world") conditions, which do not suffer from biases that may affect performance in laboratory settings, such as the Hawthorne effect (McCambridge, Witton, & Elbourne, 2014).

It is worth considering whether any other factors could explain the pattern of results observed in this study. For instance, is it possible that our outcome measures were insensitive to performance changes due to brain training? This is unlikely. Tasks such as the Spatial Span and Digit Span tests used here have been commonly used as test tasks in previous brain training studies (Caeyenberghs, Metzler-Baddeley, Foley, & Jones, 2016; Jaeggi et al., 2008; Lilienthal, Tamez, Shelton, Myerson, & Hale, 2013; Stojanoski, Lyons, Pearce, & Owen, 2018), and both have been shown to change with practice (Ericsson, Chase, & Faloon, 1980; Ericsson & Chase, 1982). Clearly then, there are contexts under which performance on both spatial span and digit span can be improved. The other CBS tasks, including the Spatial Planning Task (Williams-Gray, Hampshire, Robbins, Owen, & Barker, 2007), the Token Search Task and the Paired Associates task (Wood et al., 2002), have also all been shown to be sensitive to subtle changes in cognitive functioning due to disease or pharmacological intervention (Lange et al., 1992; Mehta et al., 2000). Moreover, the component variable measures of memory, reasoning, and verbal processing reflect exactly those general cognitive abilities that brain training programs are designed to improve.

Is it possible that biases in the data obscured our ability to detect between brain trainers and nonbrain trainers; for instance, the data were too "noisy"? Although self-reported data can introduce biases, recent work suggests that online studies produce data that is comparable to data acquired in lab settings (G. E. Morrison, Simone, Ng, & Hardy, 2015; Ruano et al., 2016; Wesnes et al., 2017). Moreover, if the data were too noisy, we would expect to find no systematic effects in the data. However, we found significant age- and sleep-related changes to cognition from the same dataset (Wild et al., 2018) consistent with previous lab-based studies (Banks & Dinges, 2007; Ferreira, Owen, Mohan, Corbett, & Ballard, 2015; Hampshire et al., 2012; Krause et al., 2017; Lim & Dinges, 2010). A second question is whether selection biases can explain the findings. Perhaps, after brain training, those with poorer baseline cognitive abilities improved their cognitive functioning to a level that matched nonbrain trainers? If so, we should find worse performance on the different cognitive measures between those who recently started brain training and nonbrain trainers. However, this was not the case; we found no difference between these groups in their cognitive domain scores. We further investigated this hypothesis by comparing those who reported brain training for one month or less with those who reported training between one and six months; if recent adopters of brain training, do in fact, have worse cognitive functioning and brain training was responsible for increasing their cognitive abilities, that difference should have been evident between these two groups. Again, we found no difference in cognitive functioning between these two groups of active brain trainers.

It is also important to consider placebo effects in the context of this literature—expectations about the efficacy of brain training may drive improvements in cognition in some studies. For instance, Foroughi and colleagues found that participants who were recruited using methods intentionally designed to induce a placebo effect performed better on measures of fluid intelligence than participants who were recruited using nonsuggestive methods. This placebo effect emerged after only a 1-hr training period, although whether expectations derived from believing in the merits of brain training have longer lasting effects is not known. Our results suggest that this is not the case; we found that active brain trainers who expect brain training to have a positive effect on cognition did not show any evidence of better performance on any measure of cognitive functioning. In fact, those who held positively biased expectations about brain training produced significantly lower scores on verbal and reasoning ability compared to those who did not believe that brain training improves cognition, although the Bayes analysis suggests the evidence supporting this effect is small. The exact relationship between belief in brain training and poorer verbal and reasoning scores is unclear, and cannot be inferred directly from the current study; however, a possible explanation is that individuals with lower scores on these measures are more likely to believe that brain training works, and therefore, if they do engage in brain training, they are more likely to expect (erroneously) a boost to their cognitive functioning.

Conclusion

In summary, we were unable to identify a positive effect of brain training, and this large-scale online study suggests that brain training has no appreciable effect on cognitive functioning in the "real world," even after extensive training periods, for both older and younger adults, and independent of the training program used. The data also showed that even when there is an expectation that brain training works, this had no effect on cognition, even when those expectations interacted with training duration.

Finally, to expand on our findings, we encourage replication (and all future) studies examining the effects of brain training on cognitive functioning to preregister and include an estimate for the smallest effect size of interest (SESOI) for equivalence testing. By preregistering and including estimates for the SESOI, novel and existing hypotheses and analyses, including the ones used in this study, can be specifically outlined, and support for or against the null can be evaluated before the study is conducted.

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Received April 10, 2019
Revision received February 24, 2020
Accepted March 8, 2020 ■