

Small Effects: The Indispensable Foundation for a Cumulative Psychological Science

Perspectives on Psychological Science
1–11

© The Author(s) 2021



Article reuse guidelines:

sagepub.com/journals-permissions

DOI: 10.1177/1745691620984483

www.psychologicalscience.org/PPS



Friedrich M. Götz^{1,2} , **Samuel D. Gosling^{3,4}** ,
and **Peter J. Rentfrow¹**

¹Department of Psychology, University of Cambridge; ²Department of Psychology, University of British Columbia; ³Department of Psychology, University of Texas at Austin; and ⁴Melbourne School of Psychological Sciences, University of Melbourne

Abstract

We draw on genetics research to argue that complex psychological phenomena are most likely determined by a multitude of causes and that any individual cause is likely to have only a small effect. Building on this, we highlight the dangers of a publication culture that continues to demand large effects. First, it rewards inflated effects that are unlikely to be real and encourages practices likely to yield such effects. Second, it overlooks the small effects that are most likely to be real, hindering attempts to identify and understand the actual determinants of complex psychological phenomena. We then explain the theoretical and practical relevance of small effects, which can have substantial consequences, especially when considered at scale and over time. Finally, we suggest ways in which scholars can harness these insights to advance research and practices in psychology (i.e., leveraging the power of big data, machine learning, and crowdsourcing science; promoting rigorous preregistration, including prespecifying the smallest effect size of interest; contextualizing effects; changing cultural norms to reward accurate and meaningful effects rather than exaggerated and unreliable effects). Only once small effects are accepted as the norm, rather than the exception, can a reliable and reproducible cumulative psychological science be built.

Keywords

small effects, research culture, questionable research practices, scientific community

From cognitive functioning, memory, and sleep to well-being, interpersonal perception, sexual attraction, and mental health, the more that is learned about complex psychological phenomena, the more probable it appears that none of them are determined by a single cause. Instead, it is likely that many factors of varying degrees of influence are likely to cause such processes (Ahadi & Diener, 1989; Funder & Ozer, 2019; Gladstone et al., 2019). Hence, with limited variance to explain, any individual cause should be expected to have only a small effect.

Our position draws on recent approaches in genetics. Researchers have recognized that complex human psychological phenomena such as personality (Smith-Woolley et al., 2019) or cognitive ability (Plomin, 1999) can be understood only through the complex interplay of multiple genes (Plomin et al., 1994). Consequently, in the early 2000s, geneticists abandoned reductionist one-gene-one-outcome approaches in favor of genome-wide

associations studies (GWAS; Boyle et al., 2017; Visscher et al., 2017) that identify hundreds or even thousands of genes associated with human phenotypes. This approach explicitly acknowledges that each individual gene is likely to have a very small effect that may account for only 1.0%, 0.1%, or even less variance (Okbay et al., 2016; Smith-Woolley et al., 2019). Indeed, given the results of this new generation of large-scale genetic studies, Chabris and colleagues (2015) even proposed small effects as the fourth law of behavioral genetics: “A typical human behavioral trait is associated with very many genetic variants, each of which accounts for a very small percentage of behavioral variability” (p. 304).

Corresponding Author:

Friedrich M. Götz, Department of Psychology, University of British Columbia

E-mail: friedrich.goetz@ubc.ca

Rather than relegating genetics to irrelevance, this recognition has ushered in a new era of research in the field of genetics and paved the way for important discoveries (Donnelly, 2008; Mackay et al., 2009). Specifically, in modern GWASs, tens of thousands—and sometimes millions (Lee et al., 2018; Liu et al., 2019)—of individuals with varying phenotypes for a particular disease or trait provide DNA samples. Across these extremely large samples of genetic variants, geneticists then track the frequency with which specific genes and the trait or disease in question co-occur, thereby identifying complex systems of dozens and hundreds of candidate genes, which together influence the risk of a specific disease or likelihood of a specific trait. In recent years, this approach has resulted in a broad range of significant advances, from uncovering the genetic architecture of the human plasma proteome, which may crucially inform future drug development (Sun et al., 2018); to identifying etiologic pathways for diseases such as cancer, diabetes, hypertension, inflammatory bowel disease, obesity, and multiple sclerosis (Altshuler et al., 2008; Anderson et al., 2011; Hindorff et al., 2009; Son et al., 2017); to mapping loci that influence adult height (Weedon et al., 2008). In the present article, we argue that the same basic logic—that complex phenomena are likely to have many causes—is also bound to be true for the causes of complex psychological phenomena and that similar progress can be made if the field adopts this insight.

Consider the case of personality as an illustration of the multidetermined nature of complex psychological phenomena. There is ample evidence that personality is affected by a multitude of diverse factors, ranging from proximal influences such as genetics (e.g., Bouchard, 2004; McCrae et al., 2000; Mõttus et al., 2017; Polderman et al., 2015; Turkheimer et al., 2014), childhood experiences (e.g., Eisenberg et al., 2014; Furnham & Cheng, 2018; Rothbart et al., 2000), family environments (e.g., Bleidorn et al., 2010; Hoffman, 1991; Sutin et al., 2017), and major life events (e.g., Bleidorn et al., 2016; Specht et al., 2011) to distal influences such as neighborhood characteristics (e.g., Götz, Yoshino, & Oshio, 2020; Jokela, 2020; Jokela et al., 2015), climate (e.g., Fischer et al., 2018; Van de Vliert & Van Lange, 2019; Wei et al., 2017), evolutionary pressures (e.g., Buss, 2009; Revelle, 1995), and culture (e.g., Church, 2010; Kitayama et al., 2010; Obschonka et al., 2018).

Similar cases can be made for virtually any complex psychological construct, which are all shaped, to varying degrees, by a broad range of proximal (e.g., Hufer et al., 2020; Hutteman et al., 2015; Krapohl et al., 2014; Krauss et al., 2020; Luhmann et al., 2012; Orth, 2018) and distal factors (e.g., Ofosu et al., 2019; Paluck, 2009; Talhelm et al., 2014; Tankard & Paluck, 2017; Uskul

et al., 2008). Against this backdrop, it is not merely unjustified to expect large effects for any individual determinant of complex psychological phenomena, it is also dangerous.

The Dangers of Demanding Large Effects

Social scientific disciplines often cultivate publication cultures that favor or even demand large effects (Fanelli et al., 2017). In an academic system in which decisions about hiring, promotion, tenure, and funding are largely determined by the quality and quantity of publication (Nosek et al., 2012), the pressure to publish large effects is dangerous for at least two reasons. One reason is that it rewards lucky or exaggerated effects that are unlikely to be real (Lindsay, 2020; Shrout & Rodgers, 2018) and encourages practices that are likely to yield these inflated effects (Munafò et al., 2017; Nosek et al., 2012), such as *p*-hacking (Nelson et al., 2018), optional stopping (Lakens, 2019), HARKing (Kerr, 1998), and other questionable research practices (Wicherts et al., 2016). In doing so, the publication culture will contribute to the lack of replicability plaguing the social sciences in general (Camerer et al., 2016, 2018) and psychology in particular (Open Science Collaboration, 2015). The second reason is that an emphasis on large effect sizes increases the chances of overlooking the small effects that are most likely to be real (Funder & Ozer, 2019), thereby hindering attempts to identify and understand the actual determinants of complex psychological phenomena.

The Importance and Consequence of Small Effects

Does this new focus on many causes (or genes in the case of genetics) and small effects mean the effects are unimportant? Not at all. Understanding complex psychological phenomena remains as important as it ever was. The new focus merely tells us, as researchers, that to complete this important task, we must focus on the interplay of many tiny causes working alone and in concert, with each individual cause playing a smaller individual role than we previously may have thought.¹ Thus, a nuanced consideration, rather than categorical dismissal, of small effects can yield important theoretical advances that would otherwise be missed (Murray et al., 2021; Prentice & Miller, 1992).

In addition, some small effects may also have direct real-world consequences (Funder & Ozer, 2019; Gelman & Carlin, 2014). This phenomenon is especially true for effects that accumulate over time and at scale (Abelson, 1985; Bond et al., 2012; Funder & Ozer, 2019;

Greenwald et al., 2015; Matz, Gladstone, & Stillwell, 2017). A particularly compelling example of this phenomenon is personality, for which effects accumulate over entire lifetimes (Nofle & Robins, 2007; Prentice & Miller, 1992) and across most major life domains, including occupational attainment, social success, personal relationships, financial security, and mortality (Ozer & Benet-Martínez, 2006; Roberts et al., 2007; Soto, 2019). Thus, even comparatively removed predictors such as climate (Fischer et al., 2018; Van de Vliert & Van Lange, 2019; Wei et al., 2017) or physical topography (Götz, Stieger, et al., 2020) that may have only a small effect on personality may ultimately be quite consequential.

Similar processes can be observed in other fields of psychology (e.g., consumer spending: Matz et al., 2016; Weston et al., 2018; social influence: Bond et al., 2012; Kramer et al., 2014; Ofori et al., 2019) and other disciplines such as medicine and education. For instance, the correlations between aspirin and prevention of heart attacks ($r = .03$; Rosenthal, 1990; Rosnow & Rosenthal, 2003; Steering Committee of the Physician's Health Study Research Group, 1988), calcium intake and bone mass in premenopausal women ($r = .08$; Meyer et al., 2001), ibuprofen intake and pain alleviation ($r = .14$; Funder & Ozer, 2019; Meyer et al., 2001), or cardiac patient education and exercise ($r = .09$; Rosenthal & DiMatteo, 2001) are small to minimal, according to Cohen's (1988) classic guidelines, but still highly consequential from a public-health perspective. The same is true for the relationships between educational interventions such as growth-mindset trainings (grade point average increase of $.05$ *SD*; Yeager et al., 2019; for a meta-analysis, $r = .08$, see Sisk et al., 2018) or universal free school breakfasts (math achievement increase of $.09$ *SD*; Frisvold, 2015) and academic performance. All of these effects can scale up to yield large impacts at national or global levels. For example, over the course of a year, the learning benefits of handing out free school breakfast may equate to approximately 1.6 months of schooling per child (Kraft, 2020), and in a group of 10,845 individuals taking aspirin, 85 heart attacks might be prevented (Funder & Ozer, 2019; Rosenthal, 1990).

Moving Forward: Toward a Cumulative Psychological Science Built on Small Effects

So far, we have argued for (a) the theoretical necessity of small effects, (b) the dangers of marginalizing them in favor of unrealistically large effects, and (c) the empirical relevance and practical significance of small effects. In this section, we discuss research implications and outline specific steps that reinforce and leverage

the potential of small effects to advance a robust and reproducible psychological science.

First, to combat the issue of inflated effect sizes, we reaffirm preregistration (Nosek et al., 2018; Wagenmakers et al., 2012) and registered reports (Chambers, 2019; Hardwicke & Ioannidis, 2018; Nosek & Lakens, 2014) as potent means to gain a more realistic understanding of actual effect sizes in psychological science. Note that to be useful for our purposes, preregistrations need to contain clear specifications of methods, study procedures, and statistical analyses, and researchers need to strictly adhere to their preregistrations and justify deviations wherever they occur. Then and only then will preregistrations and registered reports buffer against questionable research practices that likely yield inflated effect sizes (Lakens, 2019). Moreover, when preregistering, we strongly encourage researchers to specify the smallest effect size of interest (SEOI; Anvari & Lakens, 2019; Funder et al., 2014) that would still be considered meaningful and also use this estimate to inform power analyses. To be sure, just because all small effects could be relevant, this does not mean that all effects will be relevant, and it remains the task of the study investigators to make a compelling case for why their effects matter.

The most appropriate way of defining the SEOI depends on the study context and should thus be chosen on a case-by-case basis, but there are a number of existing approaches that might be useful starting points for researchers who are new to this exercise. For example, the concept of clinical significance posits that effects matter only if they make a difference that individuals notice (Kazdin, 1999). The thresholds for such minimally detectable differences can be extracted through so-called anchor-based methods (Anvari & Lakens, 2019), which can be implemented either as longitudinal within-persons designs (i.e., global transition method) or as cross-sectional between-persons designs (i.e., subjective comparison method). In the global transition method, within a suitable time frame, the same individuals are assessed twice on a psychological construct of interest and are asked to indicate whether they perceive a change. The mean change in scores from Time 1 to Time 2 among individuals who just about perceived a difference is then used as an estimate for the minimally detectable difference and hence serves as the SEOI (Button et al., 2015). The same principle is applied in the subjective comparison method, in which interaction partners are both assessed on a psychological construct and then asked to indicate how strong, if at all, a difference they perceive between themselves and their interaction partner regarding the construct of interest (Anvari & Lakens, 2019). In more applied and intervention-focused settings, cost-benefit

analyses can be helpful to assess when an effect is too small to claim practical importance (Bleidorn et al., 2019; Robertson et al., 2001), whereas the sheer existence and robustness of an effect can be enough when the primary goal is to develop psychological theory (Murray et al., 2021; Prentice & Miller, 1992).

Overall, the emphasis on preregistration is in line with a rising recognition that, in contrast to widespread underpowered studies in psychology, which likely report exaggerated effect sizes (Button et al., 2013; Schäfer & Schwarz, 2019; Szucs & Ioannidis, 2017), effect sizes obtained from well-powered preregistered studies (Funder & Ozer, 2019; Miller, 2019; Schäfer & Schwarz, 2019; Schooler, 2011; Szucs & Ioannidis, 2017) accurately capture highly reliable effects. As in the case of genetics (Bycroft et al., 2018), such studies of small yet robust effects in psychology require large-scale research designs (De Boeck & Jeon, 2018) and computationally powerful analytic methods (Chen & Wojcik, 2016; Kosinski et al., 2015). Fortunately, the advent of big data (Adjerid & Kelley, 2018; Harari et al., 2016), novel machine-learning methods (Bleidorn & Hopwood, 2019; Yarkoni & Westfall, 2017), and crowdsourcing science (Chartier et al., 2018; Moshontz et al., 2018; Uhlmann et al., 2019) now affords opportunities to identify such small yet meaningful effects. Furthermore, special efforts should be made to eliminate confounding variables and improve measurement precision to further increase the reliability and reproducibility of psychological effects (De Boeck & Jeon, 2018; Funder & Ozer, 2019).

To be clear, we do not assert that large effects are flawed or unreliable per se. Indeed, under certain circumstances, such as in tightly controlled lab studies that explicitly seek to isolate an effect, large effect sizes might be very accurate, albeit limited in their external validity. Moreover, just as with any distribution, the fact that the majority of real effects is likely to be small does not rule out the possibility that some real effects are large. Rather, we believe that in evaluating research output, the reliability and precision of an effect should take primacy over its size and that preregistered, well-powered, and rigorously analyzed studies likely offer the best way to achieve such an outcome.

Second, to facilitate a better understanding of the meaning and relevance of effects, we advocate for more contextualization in the way in which effects are reported. One promising strategy is benchmarking (Funder & Ozer, 2019; Kraft, 2020). That is, an effect should be evaluated in light of typical effects sizes from the immediately relevant, specialized literature (Bosco et al., 2015; Gignac & Szodorai, 2016; Richard et al., 2003) rather than generic one-size-fits-all thresholds such as those proposed by Cohen (1988). In conjunction

with rigorous preregistration as advocated above, benchmarking can create a mutually reinforcing and self-correcting cycle in which carefully preregistered studies lead to the publication of more realistic effect sizes and null findings. Such a system would simultaneously decrease publication bias and increase the accuracy of meta-analyses (Grand et al., 2018), which would help provide more precise calibrations of empirical benchmarks for specifying meaningful SEOs in future preregistrations. For practical applications and interventions, such as those commonly encountered in clinical and educational psychology, implementation costs (Duncan & Magnuson, 2007; Harris, 2009; Levin & Belfield, 2015), scalability (Kraft, 2020), and expected growth or change in the absence of an intervention (Hill et al., 2008) might be useful additional criteria to assess the relevance of an effect.

To illustrate, whereas individualized tutoring (.23 *SD*; Cook et al., 2015) produces substantially bigger improvements in academic achievement than universal free school breakfast (.09 *SD*; Frisvold, 2015) or a 1-hr online growth-mindset intervention (.05 *SD*; Yeager et al., 2019), the latter strategies are much cheaper and more feasible to implement at scale. More broadly, in contextualizing effects, evaluating relevance and specifying SEOs, researchers should also consider how consequential their outcomes are. Indeed, for some extremely important and consequential outcomes (e.g., suicide prevalence, adherence to social distancing during a pandemic), any effect can matter. Put differently, whereas identifying policy-relevant psychological forces that explain 1% of variation in people's propensity to shelter at home during the COVID-19 pandemic (Götz et al., 2021) would likely justify extensive research efforts and funding, accounting for 1% of variation in Stroop task performances may not. Crucially, it is conceivable that some of these extremely important outcomes are largely or even entirely determined by factors that each exert only a very small effect; in such contexts, declaring effects below a certain magnitude to be too small to matter may mean that researchers will never understand the phenomenon at hand, just as geneticists would have sentenced themselves to never understanding various important phenomena if they had held on to the position that some effects (e.g., explaining less than 1% of the variance) are in principle too small to be important.

Relatedly, contextualization should also refer to the way that effects are presented. Rather than casting effects in terms of standardized but abstract and difficult to interpret effect size metrics, researchers should strive to make the meaning of effects understood by highlighting how they translate into real-world outcomes. Promising examples include cases in which in addition to reporting β s, r s, or Cohen's d s, researchers explicitly

stated the corresponding changes in prevented heart attacks (Rosenthal, 1990; Rosnow & Rosenthal, 2003), money spent (Matz, Kosinski, et al., 2017), class percentile rank (Kraft, 2020), and vote gains during the 2016 UK Brexit referendum (Garretsen et al., 2018).

Note that this approach is more challenging if researchers report certain psychological outcomes that may not have a natural metric and are often assessed on more arbitrary metrics such as Likert scales (Blanton & Jaccard, 2006); however, even under such circumstances, a better understanding can be achieved if researchers undertake efforts to contextualize their effects. For example, to contextualize the effect of neighborhood poverty on subjective well-being (SWB), a core psychological construct without a natural metric, Ludwig and colleagues (2012) explained that a 1 *SD* decrease in neighborhood poverty (approximately 13 percentage points) corresponded to an increase in SWB that is equivalent to (a) two thirds of the gap in SWB between Black and White individuals in the United States or (b) the SWB gap between families that differ in their annual incomes by \$13,000.

We hope that together these steps enable researchers to gain a better understanding of when and how small effects matter. This being said, we do not wish to replace thoughtless adherence to universal effect size thresholds such as those proposed by Cohen (1988) with an equally thoughtless, universal claim that all effects matter. Rather, we contend that on a general level, most real effects in psychology will be small and that many of these small effects may be of theoretical and practical importance. However, this claim does not obviate the need for researchers to show that their effects—however big or small—matter. In other words, we encourage psychologists to think differently about their effects but no less hard.

Conclusion

We argue here that just as in the field of genetics, research on the causes of complex psychological phenomena needs to stop searching for implausibly large effects and invest more effort in identifying and contextualizing robust, albeit small, effects (Funder & Ozer, 2019; Miller, 2019). Such research will provide the foundation for future work that can seek to understand how exactly these many small influences combine to influence consequential outcomes. We call on researchers, reviewers, editors, institutions, societies, publishers, and funding bodies to cease expecting or demanding large effects. If we are to progress as a science, we must adjust our expectations and align our incentive structures to reward accurate and meaningful effects rather than exaggerated and unreliable effects (De Boeck & Jeon, 2018; Lindsay, 2020; Munafò et al., 2017; Spellman,

2015). It is only once psychological science accepts that small effects are to be expected—as the norm, rather than the exception—that we have any realistic hope of understanding causal processes in our field. Only then can we start building a cumulative psychological science—on the foundation of small effects.

Transparency

Action Editor: Laura A. King

Editor: Laura A. King

Declaration of Conflicting Interests


The author(s) declared that there were no conflicts of interest with respect to the authorship or the publication of this article.

Funding

This work was supported by Economic and Social Research Council PhD Scholarship and Cambridge Commonwealth, European and International Trust PhD Scholarship.

ORCID iDs

Friedrich M. Götz  <https://orcid.org/0000-0001-8900-6844>

Samuel D. Gosling  <https://orcid.org/0000-0001-8970-591X>

Acknowledgments

We thank Paige Harden for her thoughtful comments on an earlier draft of the article.

Note

1. Prentice and Miller (1992) noted that in some cases researchers may deliberately seek out small effects under the assumption that if even minimal manipulations can have effects (e.g., Sawaoka & Monin, 2018; Tajfel, 1970) or if small effects replicate across very different situations and stimuli (e.g., Klein et al., 2018; Lu et al., 2017), then the basic phenomena underlying these studies must be robust, strong, and wide-reaching.

References

- Abelson, R. P. (1985). A variance explanation paradox: When a little is a lot. *Psychological Bulletin*, *97*, 129–133. <https://doi.org/10.1037/0033-2909.97.1.129>
- Adjerid, I., & Kelley, K. (2018). Big data in psychology: A framework for research advancement. *American Psychologist*, *73*, 899–917. <https://doi.org/10.1037/amp0000190>
- Ahadi, S., & Diener, E. (1989). Multiple determinants and effect size. *Journal of Personality and Social Psychology*, *56*, 398–406. <https://doi.org/10.1037/0022-3514.56.3.398>
- Altshuler, D., Daly, M. J., & Lander, E. S. (2008). Genetic mapping in human disease. *Science*, *322*, 881–888. <https://doi.org/10.1126/science.1156409>
- Anderson, C. A., Boucher, G., Lees, C. W., Franke, A., D'Amato, M., Taylor, K. D., & Lagacé, C. (2011). Meta-analysis identifies 29 additional ulcerative colitis risk loci, increasing the number of confirmed associations to 47. *Nature Genetics*, *43*, 246–252. <https://doi.org/10.1038/ng.764>

- Anvari, F., & Lakens, D. (2019). *Using anchor-based methods to determine the smallest effect size of interest*. PsyArXiv. <https://doi.org/10.31234/osf.io/syp5a>
- Blanton, H., & Jaccard, J. (2006). Arbitrary metrics in psychology. *American Psychologist*, *61*, 27–41. <https://doi.org/10.1037/0003-066x.61.1.27>
- Bleidorn, W., Hill, P. L., Back, M. D., Denissen, J. J. A., Hennecke, M., Hopwood, C. J., Jokela, M., Kandler, C., Lucas, R. E., Luhmann, M., Orth, U., Wagner, J., Wrzus, C., Zimmermann, J., & Roberts, B. (2019). The policy relevance of personality traits. *American Psychologist*, *74*(9), 1056–1067. <https://doi.org/10.1037/amp0000503>
- Bleidorn, W., & Hopwood, C. J. (2019). Using machine learning to advance personality assessment and theory. *Personality and Social Psychology Review*, *23*, 190–203. <https://doi.org/10.1177/1088868318772990>
- Bleidorn, W., Hopwood, C. J., & Lucas, R. E. (2016). Life events and personality trait change. *Journal of Personality*, *86*, 83–96. <https://doi.org/10.1111/jopy.12286>
- Bleidorn, W., Kandler, C., Hülshager, U. R., Riemann, R., Angleitner, A., & Spinath, F. M. (2010). Nature and nurture of the interplay between personality traits and major life goals. *Journal of Personality and Social Psychology*, *99*, 366–379. <https://doi.org/10.1037/a0019982>
- Bond, R. M., Fariss, C. J., Jones, J. J., Kramer, A. D. I., Marlow, C., Settle, J. E., & Fowler, J. H. (2012). A 61-million-person experiment in social influence and political mobilization. *Nature*, *489*, 295–298. <https://doi.org/10.1038/nature11421>
- Bosco, F. A., Aguinis, H., Singh, K., Field, J. G., & Pierce, C. A. (2015). Correlational effect size benchmarks. *Journal of Applied Psychology*, *100*, 431–449. <https://doi.org/10.1037/a0038047>
- Bouchard, T. J. (2004). Genetic influence on human psychological traits. *Current Directions in Psychological Science*, *13*, 148–151. <https://doi.org/10.1111/j.0963-7214.2004.00295.x>
- Boyle, E. A., Li, Y. I., & Pritchard, J. K. (2017). An expanded view of complex traits: From polygenic to omnigenic. *Cell*, *169*, 1177–1186. <https://doi.org/10.1016/j.cell.2017.05.038>
- Buss, D. M. (2009). How can evolutionary psychology successfully explain personality and individual differences? *Perspectives on Psychological Science*, *4*, 359–366. <https://doi.org/10.1111/j.1745-6924.2009.01138.x>
- Button, K. S., Ioannidis, J. P. A., Mokrysz, C., Nosek, B. A., Flint, J., Robinson, E. S. J., & Munafò, M. R. (2013). Power failure: Why small sample size undermines the reliability of neuroscience. *Nature Reviews Neuroscience*, *14*, 365–376. <https://doi.org/10.1038/nrn3475>
- Button, K. S., Kounali, D., Thomas, L., Wiles, N. J., Peters, T. J., Welton, N. J., Ades, A. E., & Lewis, G. (2015). Minimal clinically important difference on the Beck Depression Inventory–II according to the patient's perspective. *Psychological Medicine*, *45*, 3269–3279. <https://doi.org/10.1017/S0033291715001270>
- Bycroft, C., Freeman, C., Petkova, D., Band, G., Elliott, L. T., Sharp, K., Motyer, A., Vukcevic, D., Delaneau, O., O'Connell, J., Cortes, A., Welsh, S., Young, A., Effingham, M., McVean, G., Leslie, S., Allen, N., Donnelly, P., & Marchini, J. (2018). The UK Biobank resource with deep phenotyping and genomic data. *Nature*, *562*, 203–209. <https://doi.org/10.1038/s41586-018-0579-z>
- Camerer, C. F., Dreber, A., Forsell, E., Ho, T.-H., Huber, J., Johannesson, M., Kirchler, M., Almenberg, J., Altmejd, A., Chan, T., Heikensten, E., Holzmeister, F., Imai, T., Isaksson, S., Nave, G., Pfeiffer, T., Razen, M., & Wu, H. (2016). Evaluating replicability of laboratory experiments in economics. *Science*, *351*, 1433–1436. <https://doi.org/10.1126/science.aaf0918>
- Camerer, C. F., Dreber, A., Holzmeister, F., Ho, T.-H., Huber, J., Johannesson, M., Kirchler, M., Nave, G., Nosek, B. A., Pfeiffer, T., Altmejd, A., Buttrick, N., Chan, T., Chen, Y., Forsell, E., Gampa, A., Heikensten, E., Hummer, L., Imai, T., . . . Wu, H. (2018). Evaluating the replicability of social science experiments in *Nature* and *Science* between 2010 and 2015. *Nature Human Behaviour*, *2*, 637–644. <https://doi.org/10.1038/s41562-018-0399-z>
- Chabris, C. F., Lee, J. J., Cesarini, D., Benjamin, D. J., & Laibson, D. I. (2015). The fourth law of behavior genetics. *Current Directions in Psychological Science*, *24*, 304–312. <https://doi.org/10.1177/0963721415580430>
- Chambers, C. (2019). What's next for registered reports? *Nature*, *573*, 187–189. <https://doi.org/10.1038/d41586-019-02674-6>
- Chartier, C. R., Riegelman, A., & McCarthy, R. J. (2018). StudySwap: A platform for interlab replication, collaboration, and resource exchange. *Advances in Methods and Practices in Psychological Science*, *1*, 574–579. <https://doi.org/10.1177/2515245918808767>
- Chen, E. E., & Wojcik, S. P. (2016). A practical guide to big data research in psychology. *Psychological Methods*, *21*, 458–474. <https://doi.org/10.1037/met0000111>
- Church, T. A. (2010). Current perspectives in the study of personality across cultures. *Perspectives on Psychological Science*, *5*, 441–449. <https://doi.org/10.1177/1745691610375559>
- Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Erlbaum.
- Cook, P. J., Dodge, K., Farkas, G., Fryer, R. G., Guryan, J., Ludwig, J., & Mayer, S. (2015). *Not too late: Improving academic outcomes for disadvantaged youth* (Working paper WP-15-01). Institute for Policy Research Northwestern University.
- De Boeck, P., & Jeon, M. (2018). Perceived crisis and reforms: Issues, explanations, and remedies. *Psychological Bulletin*, *144*, 757–777. <https://doi.org/10.1037/bul0000154>
- Donnelly, P. (2008). Progress and challenges in genome-wide association studies in humans. *Nature*, *456*, 728–731. <https://doi.org/10.1038/nature07631>
- Duncan, G. J., & Magnuson, K. (2007). Penny wise and effect size foolish. *Child Development Perspectives*, *1*, 46–51. <https://doi.org/10.1111/j.1750-8606.2007.00009.x>
- Eisenberg, N., Duckworth, A. L., Spinrad, T. L., & Valiente, C. (2014). Conscientiousness: Origins in childhood? *Developmental Psychology*, *50*, 1331–1349. <https://doi.org/10.1037/a0030977>
- Fanelli, D., Costas, R., & Ioannidis, J. P. A. (2017). Meta-assessment of bias in science. *Proceedings of the National Academy of Sciences, USA*, *114*, 3714–3719. <https://doi.org/10.1073/pnas.1618569114>

- Fischer, R., Lee, A., & Verzijden, M. N. (2018). Dopamine genes are linked to extraversion and neuroticism personality traits, but only in demanding climates. *Scientific Reports*, *8*, Article 1733. <https://doi.org/10.1038/s41598-017-18784-y>
- Frisvold, D. E. (2015). Nutrition and cognitive achievement: An evaluation of the School Breakfast Program. *Journal of Public Economics*, *124*, 91–104. <https://doi.org/10.1016/j.jpubeco.2014.12.003>
- Funder, D. C., Levine, J. M., Mackie, D. M., Morf, C. C., Sansone, C., Vazire, S., & West, S. G. (2014). Improving the dependability of research in personality and social psychology. *Personality and Social Psychology Review*, *18*, 3–12. <https://doi.org/10.1177/1088868313507536>
- Funder, D. C., & Ozer, D. J. (2019). Evaluating effect size in psychological research: Sense and nonsense. *Advances in Methods and Practices in Psychological Science*, *2*, 156–168. <https://doi.org/10.1177/2515245919847202>
- Furnham, A., & Cheng, H. (2018). Early predictors of trait extraversion in adulthood: Findings from a nationally representative sample. *Personality and Individual Differences*, *135*, 242–247. <https://doi.org/10.1016/j.paid.2018.07.026>
- Garretsen, H., Stoker, J. I., Soudis, D., Martin, R. L., & Rentfrow, P. J. (2018). Brexit and the relevance of regional personality traits: More psychological openness could have swung the regional vote. *Cambridge Journal of Regions, Economy and Society*, *11*, 165–175. <https://doi.org/10.1093/cjres/rsx031>
- Gelman, A., & Carlin, J. (2014). Beyond power calculations: Assessing type s (sign) and type m (magnitude) errors. *Perspectives on Psychological Science*, *9*, 641–651. <https://doi.org/10.1177/1745691614551642>
- Gignac, G. E., & Szodorai, E. T. (2016). Effect size guidelines for individual differences researchers. *Personality and Individual Differences*, *102*, 74–78. <https://doi.org/10.1016/j.paid.2016.06.069>
- Gladstone, J. J., Matz, S. C., & Lemaire, A. (2019). Can psychological traits be inferred from spending? Evidence from transaction data. *Psychological Science*, *30*, 1087–1096. <https://doi.org/10.1177/0956797619849435>
- Götz, F. M., Gvirtz, A., Galinsky, A. D., & Jachimowicz, J. M. (2021). How personality and policy predict pandemic behavior: Understanding sheltering-in-place in 55 countries at the onset of COVID-19. *American Psychologist*, *76*(1), 39–49. <https://doi.org/10.1037/amp0000740>
- Götz, F. M., Stieger, S., Gosling, S. D., Potter, J., & Rentfrow, P. J. (2020). Physical topography is associated with human personality. *Nature Human Behaviour*, *4*, 1135–1144. <https://doi.org/10.1038/s41562-020-0930-x>
- Götz, F. M., Yoshino, S., & Oshio, A. (2020). The association between walkability and personality: Evidence from a large socioecological study in Japan. *Journal of Environmental Psychology*, *69*, Article 101438. <https://doi.org/10.1016/j.jenvp.2020.101438>
- Grand, J. A., Rogelberg, S. G., Banks, G. C., Landis, R. S., & Tonidandel, S. (2018). From outcome to process focus: Fostering a more robust psychological science through registered reports and results-blind reviewing. *Perspectives on Psychological Science*, *13*, 448–456. <https://doi.org/10.1177/1745691618767883>
- Greenwald, A. G., Banaji, M. R., & Nosek, B. A. (2015). Statistically small effects of the Implicit Association Test can have societally large effects. *Journal of Personality and Social Psychology*, *108*, 553–561. <https://doi.org/10.1037/pspa0000016>
- Harari, G. M., Lane, N. D., Wang, R., Crosier, B. S., Campbell, A. T., & Gosling, S. D. (2016). Using smartphones to collect behavioral data in psychological science. *Perspectives on Psychological Science*, *11*, 838–854. <https://doi.org/10.1177/1745691616650285>
- Hardwicke, T. E., & Ioannidis, J. P. (2018). Mapping the universe of registered reports. *Nature Human Behaviour*, *2*, 793–796. <https://doi.org/10.1038/s41562-018-0444-y>
- Harris, D. N. (2009). Toward policy-relevant benchmarks for interpreting effect sizes: Combining effects with costs. *Educational Evaluation and Policy Analysis*, *31*, 3–29. <https://doi.org/10.3102/0162373708327524>
- Hill, C. J., Bloom, H. S., Black, A. R., & Lipsey, M. W. (2008). Empirical benchmarks for interpreting effect sizes in research. *Child Development Perspectives*, *2*, 172–177. <https://doi.org/10.1111/j.1750-8606.2008.00061.x>
- Hindorff, L. A., Sethupathy, P., Junkins, H. A., Ramos, E. M., Mehta, J. P., Collins, F. S., & Manolio, T. A. (2009). Potential etiologic and functional implications of genome-wide association loci for human diseases and traits. *Proceedings of the National Academy of Sciences, USA*, *106*, 9362–9367. <https://doi.org/10.1073/pnas.0903103106>
- Hoffman, L. W. (1991). The influence of the family environment on personality: Accounting for sibling differences. *Psychological Bulletin*, *110*, 187–203. <https://doi.org/10.1037/0033-2909.110.2.187>
- Hufer, A., Kornadt, A. E., Kandler, C., & Riemann, R. (2020). Genetic and environmental variation in political orientation in adolescence and early adulthood: A nuclear twin family analysis. *Journal of Personality and Social Psychology*, *118*, 762–776. <https://doi.org/10.1037/pspp0000258>
- Hutteman, R., Nestler, S., Wagner, J., Egloff, B., & Back, M. D. (2015). Wherever I may roam: Processes of self-esteem development from adolescence to emerging adulthood in the context of international student exchange. *Journal of Personality and Social Psychology*, *108*, 767–783. <https://doi.org/10.1037/pspp0000015>
- Jokela, M. (2020). Selective residential mobility and social influence in the emergence of neighborhood personality differences: Longitudinal data from Australia. *Journal of Research in Personality*, *86*, Article 103953. <https://doi.org/10.1016/j.jrp.2020.103953>
- Jokela, M., Bleidorn, W., Lamb, M. E., Gosling, S. D., & Rentfrow, P. J. (2015). Geographically varying associations between personality and life satisfaction in the London metropolitan area. *Proceedings of the National Academy of Sciences, USA*, *112*, 725–730. <https://doi.org/10.1073/pnas.1415800112>
- Kazdin, A. E. (1999). The meanings and measurement of clinical significance. *Journal of Consulting and Clinical*

- Psychology*, 67, 332–339. <https://doi.org/10.1037/0022-006x.67.3.332>
- Kerr, N. L. (1998). HARKing: Hypothesizing after the results are known. *Personality and Social Psychology Review*, 2, 196–217. https://doi.org/10.1207/s15327957pspr0203_4
- Kitayama, S., Conway, L. G., Pietromonaco, P. R., Park, H., & Plaut, V. C. (2010). Ethos of independence across regions in the United States: The production-adoption model of cultural change. *American Psychologist*, 65, 559–574. <https://doi.org/10.1037/a0020277>
- Klein, R. A., Vianello, M., Hasselman, F., Adams, B. G., Adams, R. B., Jr., Alper, S., Aveyard, M., Axt, J. R., Babalola, M. T., Bahník, S., Batra, R., Berkics, M., Bernstein, M. J., Berry, D. R., Bialobrzeska, O., Binan, E. D., Bocian, K., Brandt, M. J., Busching, R., . . . Nosek, B. A. (2018). Many Labs 2: Investigating variation in replicability across samples and settings. *Advances in Methods and Practices in Psychological Science*, 1, 443–490. <https://doi.org/10.1177/2515245918810225>
- Kosinski, M., Matz, S. C., Gosling, S. D., Popov, V., & Stillwell, D. (2015). Facebook as a research tool for the social sciences: Opportunities, challenges, ethical considerations, and practical guidelines. *American Psychologist*, 70, 543–556. <https://doi.org/10.1037/a0039210>
- Kraft, M. A. (2020). Interpreting effect sizes of education interventions. *Educational Researcher*, 49, 241–253. <https://doi.org/10.3102/0013189x20912798>
- Kramer, A. D. I., Guillory, J. E., & Hancock, J. T. (2014). Experimental evidence of massive-scale emotional contagion through social networks. *Proceedings of the National Academy of Sciences, USA*, 111, 8788–8790. <https://doi.org/10.1073/pnas.1320040111>
- Krapohl, E., Rimfeld, K., Shakeshaft, N. G., Trzaskowski, M., McMillan, A., Pingault, J.-B., Asbury, K., Harlaar, N., Kovas, Y., Dale, P. S., & Plomin, R. (2014). The high heritability of educational achievement reflects many genetically influenced traits, not just intelligence. *Proceedings of the National Academy of Sciences, USA*, 111, 15273–15278. <https://doi.org/10.1073/pnas.1408777111>
- Krauss, S., Orth, U., & Robins, R. W. (2020). Family environment and self-esteem development: A longitudinal study from age 10 to 16. *Journal of Personality and Social Psychology*, 119, 457–478. <https://doi.org/10.1037/pspp0000263>
- Lakens, D. (2019). The value of preregistration for psychological science: A conceptual analysis. *Japanese Psychology Review*, 62, 272–280. <https://doi.org/10.31234/osf.io/jbh4w>
- Lee, J. J., Wedow, R., Okbay, A., Kong, E., Maghazian, O., Zacher, M., Nguyen-Viet, T. A., Bowers, P., Sidorenko, J., Karlsson Linnér, R., Fontana, M. A., Kundu, T., Lee, C., Li, H., Li, R., Royer, R., Timshel, P. N., Walters, R. K., Willoughby, E. A., . . . Cesarini, D. (2018). Gene discovery and polygenic prediction from a genome-wide association study of educational attainment in 1.1 million individuals. *Nature Genetics*, 50, 1112–1121. <https://doi.org/10.1038/s41588-018-0147-3>
- Levin, H. M., & Belfield, C. (2015). Guiding the development and use of cost-effectiveness analysis in education. *Journal of Research on Educational Effectiveness*, 8, 400–418. <https://doi.org/10.1080/19345747.2014.915604>
- Lindsay, D. S. (2020). Seven steps toward transparency and replicability in psychological science. *Canadian Psychology/Psychologie canadienne*, 61, 310–317. <https://doi.org/10.1037/cap0000222>
- Liu, M., Jiang, Y., Wedow, R., Li, Y., Brazel, D. M., Chen, F., Datta, G., Davila-Velderrain, J., McGuire, D., Tian, C., Zhan, X., Choquet, H., Docherty, A. R., Faul, J. D., Foerster, J. R., Fritsche, L. G., Gabrielsen, M. E., Gordon, S. D., Haessler, J., . . . Tian, C. (2019). Association studies of up to 1.2 million individuals yield new insights into the genetic etiology of tobacco and alcohol use. *Nature Genetics*, 51, 237–244. <https://doi.org/10.1038/s41588-018-0307-5>
- Lu, J. G., Quoidbach, J., Gino, F., Chakroff, A., Maddux, W. W., & Galinsky, A. D. (2017). The dark side of going abroad: How broad foreign experiences increase immoral behavior. *Journal of Personality and Social Psychology*, 112, 1–16. <https://doi.org/10.1037/pspa0000068>
- Ludwig, J., Duncan, G. J., Gennetian, L. A., Katz, L. F., Kessler, R. C., Kling, J. R., & Sanbonmatsu, L. (2012). Neighborhood effects on the long-term well-being of low-income adults. *Science*, 337, 1505–1510. <https://doi.org/10.1126/science.1224648>
- Luhmann, M., Hofmann, W., Eid, M., & Lucas, R. E. (2012). Subjective well-being and adaptation to life events: A meta-analysis. *Journal of Personality and Social Psychology*, 102, 592–615. <https://doi.org/10.1037/a0025948>
- Mackay, T. F. C., Stone, E. A., & Ayroles, J. F. (2009). The genetics of quantitative traits: Challenges and prospects. *Nature Reviews Genetics*, 10, 565–577. <https://doi.org/10.1038/nrg2612>
- Matz, S. C., Gladstone, J. J., & Stillwell, D. (2016). Money buys happiness when spending fits our personality. *Psychological Science*, 27, 715–725. <https://doi.org/10.1177/0956797616635200>
- Matz, S. C., Gladstone, J. J., & Stillwell, D. (2017). In a world of big data, small effects can still matter: A reply to Boyce, Daly, Hounkpatin, and Wood (2017). *Psychological Science*, 28, 547–550. <https://doi.org/10.1177/0956797617697445>
- Matz, S. C., Kosinski, M., Nave, G., & Stillwell, D. J. (2017). Psychological targeting as an effective approach to digital mass persuasion. *Proceedings of the National Academy of Sciences, USA*, 114, 12714–12719. <https://doi.org/10.1073/pnas.1710966114>
- McCrae, R. R., Costa, P. T., Ostendorf, F., Angleitner, A., Hřebíčková, M., Avia, M. D., Sanz, J., Sánchez-Bernardos, M. L., Kusdil, M. E., Woodfield, R., Saunders, P. R., & Smith, P. B. (2000). Nature over nurture: Temperament, personality, and life span development. *Journal of Personality and Social Psychology*, 78, 173–186. <https://doi.org/10.1037/0022-3514.78.1.173>
- Meyer, G. J., Finn, S. E., Eyde, L. D., Kay, G. G., Moreland, K. L., Dies, R. R., Eisman, E. J., Kubiszyn, T. W., & Reed, G. M. (2001). Psychological testing and psychological assessment: A review of evidence and issues. *American Psychologist*, 56, 128–165. <https://doi.org/10.1037/0003-066x.56.2.128>

- Miller, D. I. (2019). When do growth mindset interventions work? *Trends in Cognitive Sciences*, 23, 910–912. <https://doi.org/10.1016/j.tics.2019.08.005>
- Moshontz, H., Campbell, L., Ebersole, C. R., IJzerman, H., Urry, H. L., Forscher, P. S., Grahe, J. E., McCarth, R. J., Musser, E. D., Atfolk, J., Castille, C. M., Evans, R. R., Fiedler, S., Flake, J. K., Forero, D. A., Janssen, S. M. J., Keene, J. R., Protzko, J., Aczel, B., & Chartier, C. R. (2018). The psychological science accelerator: Advancing psychology through a distributed collaborative network. *Advances in Methods and Practices in Psychological Science*, 1, 501–515. <https://doi.org/10.1177/2515245918797607>
- Möttus, R., Kandler, C., Bleidorn, W., Riemann, R., & McCrae, R. R. (2017). Personality traits below facets: The consensual validity, longitudinal stability, heritability, and utility of personality nuances. *Journal of Personality and Social Psychology*, 112, 474–490. <https://doi.org/10.1037/pspp0000100>
- Munafò, M. R., Nosek, B. A., Bishop, D. V. M., Button, K. S., Chambers, C. D., Percie du Sert, N., Simonsohn, U., Wagenmakers, E.-J., Ware, J. J., & Ioannidis, J. P. A. (2017). A manifesto for reproducible science. *Nature Human Behaviour*, 1, Article 0021. <https://doi.org/10.1038/s41562-016-0021>
- Murray, S. L., Lamarche, V., Seery, M. D., Jung, H. Y., Griffin, D. W., & Brinkman, C. (2021). The social-safety system: Fortifying relationships in the face of the unforeseeable. *Journal of Personality and Social Psychology*, 120(1), 99–130. <https://doi.org/10.1037/pspi0000245>
- Nelson, L. D., Simmons, J., & Simonsohn, U. (2018). Psychology's renaissance. *Annual Review of Psychology*, 69, 511–534. <https://doi.org/10.1146/annurev-psych-122216-011836>
- Noftle, E. E., & Robins, R. W. (2007). Personality predictors of academic outcomes: Big five correlates of GPA and SAT scores. *Journal of Personality and Social Psychology*, 93, 116–130. <https://doi.org/10.1037/0022-3514.93.1.116>
- Nosek, B. A., Ebersole, C. R., DeHaven, A. C., & Mellor, D. T. (2018). The preregistration revolution. *Proceedings of the National Academy of Sciences, USA*, 115, 2600–2606. <https://doi.org/10.1073/pnas.1708274114>
- Nosek, B. A., & Lakens, D. (2014). Registered reports: A method to increase the credibility of published results. *Social Psychology*, 45, 137–141. <https://doi.org/10.1027/1864-9335/a000192>
- Nosek, B. A., Spies, J. R., & Motyl, M. (2012). Scientific utopia: II. Restructuring incentives and practices to promote truth over publishability. *Perspectives on Psychological Science*, 7, 615–631. <https://doi.org/10.1177/1745691612459058>
- Obschonka, M., Stuetzer, M., Rentfrow, P. J., Shaw-Taylor, L., Satchell, M., Silbereisen, R. K., Potter, J., & Gosling, S. D. (2018). In the shadow of coal: How large-scale industries contributed to present-day regional differences in personality and well-being. *Journal of Personality and Social Psychology*, 115, 903–927. <https://doi.org/10.1037/pspp0000175>
- Ofofu, E. K., Chambers, M. K., Chen, J. M., & Hehman, E. (2019). Same-sex marriage legalization associated with reduced implicit and explicit antigay bias. *Proceedings of the National Academy of Sciences, USA*, 116, 8846–8851. <https://doi.org/10.1073/pnas.1806000116>
- Okbay, A., Baselmans, B. M., De Neve, J. E., Turley, P., Nivard, M. G., Fontana, M. A., Meddens, S. F. W., Linnér, R. K., Rietveld, C. A., Derringer, J., Gratten, J., Lee, J. J., Liu, J. Z., de Vlaming, R., Ahulawalia, T. S., Buchwald, J., Cavadino, A., Frazier-Wood, A. C., Furlotte, N. A., . . . Gratten, J. (2016). Genetic variants associated with subjective well-being, depressive symptoms, and neuroticism identified through genome-wide analyses. *Nature Genetics*, 48, 624–633. <https://doi.org/10.1038/ng.3552>
- Open Science Collaboration. (2015). Estimating the reproducibility of psychological science. *Science*, 349, Article aac4716. <https://doi.org/10.1126/science.aac4716>
- Orth, U. (2018). The family environment in early childhood has a long-term effect on self-esteem: A longitudinal study from birth to age 27 years. *Journal of Personality and Social Psychology*, 114, 637–655. <https://doi.org/10.1037/pspp0000143>
- Ozer, D. J., & Benet-Martínez, V. (2006). Personality and the prediction of consequential outcomes. *Annual Review of Psychology*, 57, 401–421. <https://doi.org/10.1146/annurev.psych.57.102904.190127>
- Paluck, E. L. (2009). Reducing intergroup prejudice and conflict using the media: A field experiment in Rwanda. *Journal of Personality and Social Psychology*, 96, 574–587. <https://doi.org/10.1037/a0011989>
- Plomin, R. (1999). Genetics and general cognitive ability. *Nature*, 402, C25–C29. <https://doi.org/10.1038/35011520>
- Plomin, R., Owen, M., & McGuffin, P. (1994). The genetic basis of complex human behaviors. *Science*, 264, 1733–1739. <https://doi.org/10.1126/science.8209254>
- Polderman, T. J. C., Benyamin, B., de Leeuw, C. A., Sullivan, P. F., van Bochoven, A., Visscher, P. M., & Posthuma, D. (2015). Meta-analysis of the heritability of human traits based on fifty years of twin studies. *Nature Genetics*, 47, 702–709. <https://doi.org/10.1038/ng.3285>
- Prentice, D. A., & Miller, D. T. (1992). When small effects are impressive. *Psychological Bulletin*, 112, 160–164. <https://doi.org/10.1037/0033-2909.112.1.160>
- Revelle, W. (1995). Personality processes. *Annual Review of Psychology*, 46, 295–328. <https://doi.org/10.1146/annurev.ps.46.020195.001455>
- Richard, F. D., Bond, C. F., & Stokes-Zoota, J. J. (2003). One hundred years of social psychology quantitatively described. *Review of General Psychology*, 7, 331–363. <https://doi.org/10.1037/1089-2680.7.4.331>
- Roberts, B. W., Kuncel, N. R., Shiner, R., Caspi, A., & Goldberg, L. R. (2007). The power of personality: The comparative validity of personality traits, socioeconomic status, and cognitive ability for predicting important life outcomes. *Perspectives on Psychological Science*, 2, 313–345. <https://doi.org/10.1111/j.1745-6916.2007.00047.x>
- Robertson, A. A., Grimes, P. W., & Rogers, K. E. (2001). A short-run cost-benefit analysis of community-based interventions for juvenile offenders. *Crime & Delinquency*, 47, 265–284. <https://doi.org/10.1177/0011128701047002006>

- Rosenthal, R. (1990). How are we doing in soft psychology? *American Psychologist*, *45*, 775–777. <https://doi.org/10.1037/0003-066x.45.6.775>
- Rosenthal, R., & DiMatteo, M. R. (2001). Meta-analysis: Recent developments in quantitative methods for literature reviews. *Annual Review of Psychology*, *52*, 59–82. <https://doi.org/10.1146/annurev.psych.52.1.59>
- Rosnow, R. L., & Rosenthal, R. (2003). Effect sizes for experimenting psychologists. *Canadian Journal of Experimental Psychology/Revue canadienne de psychologie expérimentale*, *57*, 221–237. <https://doi.org/10.1037/h0087427>
- Rothbart, M. K., Ahadi, S. A., & Evans, D. E. (2000). Temperament and personality: Origins and outcomes. *Journal of Personality and Social Psychology*, *78*, 122–135. <https://doi.org/10.1037/0022-3514.78.1.122>
- Sawaoka, T., & Monin, B. (2018). The paradox of viral outrage. *Psychological Science*, *29*, 1665–1678. <https://doi.org/10.1177/0956797618780658>
- Schäfer, T., & Schwarz, M. A. (2019). The meaningfulness of effect sizes in psychological research: Differences between sub-disciplines and the impact of potential biases. *Frontiers in Psychology*, *10*, Article 813. <https://doi.org/10.3389/fpsyg.2019.00813>
- Schooler, J. (2011). Unpublished results hide the decline effect. *Nature*, *470*, Article 437. <https://doi.org/10.1038/470437a>
- Shrout, P. E., & Rodgers, J. L. (2018). Psychology, science, and knowledge construction: Broadening perspectives from the replication crisis. *Annual Review of Psychology*, *69*, 487–510. <https://doi.org/10.1146/annurev-psych-122216-011845>
- Sisk, V. F., Burgoyne, A. P., Sun, J., Butler, J. L., & Macnamara, B. N. (2018). To what extent and under which circumstances are growth mind-sets important to academic achievement? Two meta-analyses. *Psychological Science*, *29*, 549–571. <https://doi.org/10.1177/0956797617739704>
- Smith-Woolley, E., Selzam, S., & Plomin, R. (2019). Polygenic score for educational attainment captures DNA variants shared between personality traits and educational achievement. *Journal of Personality and Social Psychology*, *117*, 1145–1163. <https://doi.org/10.1037/pspp0000241>
- Son, H.-Y., Hwangbo, Y., Yoo, S.-K., Im, S.-W., Yang, S. D., Kwak, S.-J., Park, M. S., Kwak, S. H., Cho, S. W., Ryu, J. S., Kim, J., Jung, Y.-S., Kim, T. H., Kim, S.-j., Lee, K. E., Park, D. J., Cho, N. H., Sung, J., Seo, J.-S., . . . Kim, J.-I. (2017). Genome-wide association and expression quantitative trait loci studies identify multiple susceptibility loci for thyroid cancer. *Nature Communications*, *8*, Article 15966. <https://doi.org/10.1038/ncomms15966>
- Soto, C. J. (2019). How replicable are links between personality traits and consequential life outcomes? The life outcomes of personality replication project. *Psychological Science*, *30*, 711–727. <https://doi.org/10.1177/0956797619831612>
- Specht, J., Egloff, B., & Schmukle, S. C. (2011). Stability and change of personality across the life course: The impact of age and major life events on mean-level and rank-order stability of the Big Five. *Journal of Personality and Social Psychology*, *101*, 862–882. <https://doi.org/10.1037/a002495>
- Spellman, B. A. (2015). A short (personal) future history of revolution 2.0. *Perspectives on Psychological Science*, *10*, 886–899. <https://doi.org/10.1177/1745691615609918>
- Steering Committee of the Physician's Health Study Research Group. (1988). Preliminary report: Findings from the aspirin component of the ongoing physicians' health study. *New England Journal of Medicine*, *318*, 262–264. <https://doi.org/10.1056/nejm198801283180431>
- Sun, B. B., Maranville, J. C., Peters, J. E., Stacey, D., Staley, J. R., Blackshaw, J., Burgess, S., Jiang, T., Paige, E., Surendran, P., Oliver-Williams, C., Kamat, M. A., Prins, B. P., Wilcox, S. K., Zimmerman, E. S., Chi, A., Bansal, N., Spain, S. L., Wood, A. M., . . . Butterworth, A. S. (2018). Genomic atlas of the human plasma proteome. *Nature*, *558*, 73–79. <https://doi.org/10.1038/s41586-018-0175-2>
- Sutin, A. R., Luchetti, M., Stephan, Y., Robins, R. W., & Terracciano, A. (2017). Parental educational attainment and adult offspring personality: An intergenerational life span approach to the origin of adult personality traits. *Journal of Personality and Social Psychology*, *113*, 144–166. <https://doi.org/10.1037/pspp0000137>
- Szucs, D., & Ioannidis, J. P. A. (2017). Empirical assessment of published effect sizes and power in the recent cognitive neuroscience and psychology literature. *PLOS Biology*, *15*, Article e2000797. <https://doi.org/10.1371/journal.pbio.2000797>
- Tajfel, H. (1970). Experiments in intergroup discrimination. *Scientific American*, *223*, 96–102. <https://doi.org/10.1038/scientificamerican1170-96>
- Talhelm, T., Zhang, X., Oishi, S., Shimin, C., Duan, D., Lan, X., & Kitayama, S. (2014). Large-scale psychological differences within China explained by rice versus wheat agriculture. *Science*, *344*, 603–608. <https://doi.org/10.1126/science.1246850>
- Tankard, M. E., & Paluck, E. L. (2017). The effect of a supreme court decision regarding gay marriage on social norms and personal attitudes. *Psychological Science*, *28*, 1334–1344. <https://doi.org/10.1177/0956797617709594>
- Turkheimer, E., Pettersson, E., & Horn, E. E. (2014). A phenotypic null hypothesis for the genetics of personality. *Annual Review of Psychology*, *65*, 515–540. <https://doi.org/10.1146/annurev-psych-113011-143752>
- Uhlmann, E. L., Ebersole, C., Chartier, C., Errington, T., Kidwell, M., Lai, C. K., McCarthy, R., Riegelman, A., Silberzahn, R., & Nosek, B. A. (2019). Scientific utopia III: Crowdsourcing science. *Perspectives on Psychological Science*, *14*, 711–733. <https://doi.org/10.1177/1745691619850561>
- Uskul, A. K., Kitayama, S., & Nisbett, R. E. (2008). Ecocultural basis of cognition: Farmers and fishermen are more holistic than herders. *Proceedings of the National Academy of Sciences, USA*, *105*, 8552–8556. <https://doi.org/10.1073/pnas.0803874105>
- Van de Vliert, E., & Van Lange, P. A. M. (2019). Latitudinal psychology: An ecological perspective on creativity, aggression, happiness, and beyond. *Perspectives on Psychological Science*, *14*, 860–884. <https://doi.org/10.1177/1745691619858067>
- Visscher, P. M., Wray, N. R., Zhang, Q., Sklar, P., McCarthy, M. I., Brown, M. A., & Yang, J. (2017). 10 years of GWAS discovery: Biology, function, and translation. *The American Journal of Human Genetics*, *101*, 5–22. <https://doi.org/10.1016/j.ajhg.2017.06.005>
- Wagenmakers, E.-J., Wetzels, R., Borsboom, D., van der Maas, H. L. J., & Kievit, R. A. (2012). An agenda for purely

- confirmatory research. *Perspectives on Psychological Science*, 7, 632–638. <https://doi.org/10.1177/1745691612463078>
- Weedon, M. N., Lango, H., Lindgren, C. M., Wallace, C., Evans, D. M., Mangino, M., Freathy, R. M., Perry, J. R. B., Stevens, S., Hall, A. S., Samani, N. J., Shields, B., Prokopenko, I., Farrall, M., Dominiczak, A., Johnson, T., Bergmann, S., Beckmann, J. S., Vollenweider, P., . . . Frayling, T. M. (2008). Genome-wide association analysis identifies 20 loci that influence adult height. *Nature Genetics*, 40, 575–583. <https://doi.org/10.1038/ng.121>
- Wei, W., Lu, J. G., Galinsky, A. D., Wu, H., Gosling, S. D., Rentfrow, P. J., Yuan, W., Zhang, Q., Guo, Y., Zhang, M., Gui, W., Guo, X.-Y., Potter, J., Wang, J., Li, B., Li, X., Han, Y.-M., Lv, M., Guo, X.-Q., . . . Wang, L. (2017). Regional ambient temperature is associated with human personality. *Nature Human Behaviour*, 1, 890–895. <https://doi.org/10.1038/s41562-017-0240-0>
- Weston, S. J., Gladstone, J. J., Graham, E. K., Mroczek, D. K., & Condon, D. M. (2018). Who are the scrooges? Personality predictors of holiday spending. *Social Psychological and Personality Science*, 10, 775–782. <https://doi.org/10.1177/1948550618792883>
- Wicherts, J. M., Veldkamp, C. L. S., Augusteijn, H. E. M., Bakker, M., van Aert, R. C. M., & van Assen, M. A. L. M. (2016). Degrees of freedom in planning, running, analyzing, and reporting psychological studies: A checklist to avoid *p*-hacking. *Frontiers in Psychology*, 7, Article 1832. <https://doi.org/10.3389/fpsyg.2016.01832>
- Yarkoni, T., & Westfall, J. (2017). Choosing prediction over explanation in psychology: Lessons from machine learning. *Perspectives on Psychological Science*, 12, 1100–1122. <https://doi.org/10.1177/1745691617693393>
- Yeager, D. S., Hanselman, P., Walton, G. M., Murray, J. S., Crosnoe, R., Muller, C., Tipton, E., Schneider, B., Hulleman, C. S., Hinojosa, C. P., Paunesku, D., Romero, C., Flint, K., Roberts, A., Trott, J., Iachan, R., Buontempo, J., Yang, S. M., Carvalho, C. M., . . . Dweck, C. S. (2019). A national experiment reveals where a growth mindset improves achievement. *Nature*, 573, 364–369. <https://doi.org/10.1038/s41586-019-1466-y>