Overview on the Null Hypothesis Significance Test: A Systematic Review on Essay Literature on its Problems and Solutions

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Abstract

For decades, waxing and waning, there has been an ongoing debate on the values and problems of the ubiquitously used null hypothesis significance test (NHST). With the start of the replication crisis, this debate has flared-up once again, especially in the psychology and psychological methods literature. Arguing for or against the NHST method usually takes place in essay and opinion pieces that cover some, but not all the qualities and problems of the method. The NHST literature landscape is vast, a clear overview is lacking, and participants in the debate seem to be talking past one another. To contribute to a resolution, we conducted a systematic review on essay literature concerning NHST published in psychology and psychological methods journals between 2011 and 2018. We extracted all arguments in defense of (20) and against (70) NHST, and we extracted the solutions (33) that were proposed to remedy (some of) the perceived problems of NHST. Unfiltered, these 123 items form a landscape that is prohibitively difficult to keep in one's sights. Our contribution to the resolution of the NHST debate is twofold. 1) We performed a thematic synthesis of the arguments and solutions that carves the landscape in a framework of three zones: mild, moderate, and critical. This reduction summarizes groups of arguments and solutions, thus offering a manageable overview of NHST's qualities, problems, and solutions. 2) We provide the data on the arguments and solutions as a resource for those who will carry-on the debate and/or study the use of NHST.

Keywords: null hypothesis significance test; systematic review; essay literature; opinion literature; thematic synthesis

1. Introduction

In 2015, the social sciences, psychology in particular, were dealt a devastating blow. The Open Science Collaboration (2015) replicated 100 landmark studies in the field of psychology, from which less than half yielded sufficiently similar results. Replication attempts in other academic fields showed comparable results (Prinz, Schlange, & Asadullah, 2011; Begley & Ellis, 2012; Camerer et al., 2016; Camerer et al., 2018). In addition, Simmons, Nelson, and Simonsohn (2011) had shown how surprisingly easy it can be to increase the probability of obtaining positive results for a(n obviously) false hypothesis, using research practices that were considered conventional. According to many, a major culprit of this state of crisis was the *Null Hypothesis Significance Test* procedure for statistical inference, or at least the misuse of this method (e.g., Wagenmakers, Wetzels Borsboom, & Van Der Maas, 2011).

The Null Hypothesis Significance Test (NHST from now on) is the procedure that is ubiquitously used in the social sciences for the analysis of quantitative data. Roughly summarizing NHST, the data that are produced by a study are compared to a null hypothesis of no-effect (e.g., no difference between two groups on the investigated measure). The null hypothesis is rejected if the observed data are sufficiently improbable according to this null hypothesis. Specifically, the null hypothesis is rejected if, under the assumption that the null hypothesis is true, the probability of observing the obtained data or data more extremely deviating from the null hypothesis is below a certain threshold (i.e., 5% probability; $p < .05$). In such a case, the null hypothesis is generally rejected in favor of an unspecified alternative hypothesis (e.g., there is a

difference between the two groups). Otherwise, the null hypothesis is retained, though one is not supposed to consider this as evidence in its favor.

This seemingly simple procedure is associated with two major problems: 1) is easily misused and 2) it possesses (hidden) deficiencies. There is abundant empirical evidence (e.g., see Engman, 2013) of scientists unwittingly misusing the method and misinterpreting its results (e.g., interpreting the probability of the data under H_0 as the probability of H_0 given the data). With regard to the second problem, deficiencies and flaws of NHST that are independent of misuse have been brought into the limelight (e.g., ease of rejecting H_0 with a large enough sample; Wagenmakers, 2007). These issues, in combination with publication bias (Sutton, 2009) and a publish-or-perish incentive structure are expected to be at the root of the low replicability rate of social science research (Szucs & Ioannidis, 2017).

As a response to the first mentioned problem, NHST's misuse, several proposals have been made in the literature. People have called for and are starting to implement more transparency (e.g., open data and methods; Munafò, 2016; Freese & King, 2018), and design and analysis specification prior to data collection (i.e., preregistration; Lindsay, Simons, Lilienfeld, 2016; van 't Veer, Giner-Sorolla, 2018). For instance, registered reports have, at the moment of writing, been adopted by more than 250 journals (Center for Open Science, 2020). Roughly speaking, a registered report is a study design and analysis plan that is submitted for peer review at a journal (that accepts registered reports) prior to the data collection and accepted on its methodological merits and general theoretical relevance alone. Early meta-scientific results on the effectiveness of registered reports are promising (Scheel, Schijen, & Lakens, 2020)

In response to the second mentioned problem, NHST's deficiencies, researchers and statisticians have called for reform in statistical methodology. Some have proposed that, if we were to retain NHST, we should at least lower the threshold for statistical significance (Benjamin et al., 2018), which would reduce the problem of inflated false-positive rates to some extent. This view is opposed by those that think that there should not be a default threshold and that the critical value should be set and justified by the study design, the research question, etc. (Lakens, et al., 2018). Then there are others who want to abandon the statistical significance threshold all together (McShane, Gal, Robert, Tackett, & Gelman, 2019). In this case, the advice is to refrain from hypothesis tests and use, for instance, only estimation methods instead (e.g., Cumming, 2014). This perspective is, in turn, opposed by those who see the merits of hypothesis testing and binary decision-making in science (e.g., Morey, Rouder, Verhagen, & Wagenmakers, 2014). Instead of estimation, they propose a Bayesian version of hypothesis testing that is supposed to be less prone to error and misuse (e.g., Wagenmakers et al., 2017). All these groups agree that the current practice involving NHST is detrimental to science. However, there is a worrisome absence of opinions and suggestions of these groups converging on a semblance of consensus about how these problems should be addressed.

The literature on the problems of the significance test goes back to the 1940s (Berkson, 1942) and a steadily increasing stream has been published on the topic. The current attempt at methodological reformation is also not the first time that scientists have tried to change the NHST system. For instance, around 2000 there was a serious collective attempt to change the way in which scientists analyze data and report results (e.g., Meehl, 1990, 1992; Cohen, 1994; Gigerenzer, 2002). Meehl (1990, p.139) put it succinctly when he wrote:

"Let me say as loudly and clearly as possible that what we critics of weak significance testing are advocating is not some sort of minor statistical refinement (e.g., one-tailed or two-tailed test? unbiased or maximum likelihood statistics? pooling higher order uninterpretable and marginal interactions into the residual?). It is not a reform of significance testing as currently practiced in soft psychology. We are making a more heretical point than any of these: *We are attacking the whole tradition of null-hypothesis refutation as a way of appraising theories*. The argument is intended to be revolutionary, not reformist.

It seems that all these events did however not inspire the intended methodological revolutions and that they have not left many traces in academia's collective memory. This could be because papers about (how to solve) NHST's problems are focused only a small number of issues and are contradicted in other papers by authors who disagree, instead of forming a coherent structure that provides a clear plan of attack. For instance, Cohen (1994) claimed that we, scientists, are interested in the probability that the hypothesis is true and should thus use (something akin to) Bayesian statistics. This was then contradicted in responses to Cohen's paper (e.g., Baril & Cannon, 1995; Frick 1995; McGraw, 1995; Parker, 1995). In turn, Cohen tempered his claim in a rejoinder (Cohen, 1995).

As it appears, many authors agree on the fact that there is problem to be addressed concerning NHST, but most differ in which deficiencies and misuses of the method they address. The papers seem to talk past each other, each vying for attention, and in doing so, inhibiting improvement of the practice of statistical inference. A clear over view of the perspectives on NHST is absent and without such an overview - a map of NHST's qualities, problems, its solutions

- it will be neigh impossible to plot a course of action away from the replication crisis and towards methodological health. To this end, a framework is required in which the different perspectives on NHST can be placed side-by-side, compared, and evaluated. Such a framework will allow us to assess the veracity of each argument for or against NHST and assess the potential consequences of proposed methodological reform prior to implementation. With the systematic review reported in this paper, we aim to provide the foundations of such framework of NHST and its practice. Furthermore, the overview of the discussion and the dataset that is established through this research, can provide valuable information and data for other researchers to continue with.

2. Methods

We reviewed opinion literature describing the misconceptions and limitations of the Null Hypothesis Significance Test (NHST). We synthesized essays and opinion pieces, because we are interested in the arguments researchers use to make their point for or against NHST and the solutions they provide. To our knowledge, at the moment of writing, there are no specific guidelines for the synthesis of opinion literature yet. Since our review question is mainly exploratory and open, we made use of existing guidelines for reviews of qualitative and mixed methods studies. To ensure transparency, extension, and reproducibility, we adhere to the ENTREQ transparency statement for qualitative research (Tong, Flemming, McInnes, Oliver, & Craig, 2012). To aid this endeavor, Table 1. provides the list of applicable ENTREQ items and in which sections the information is given that pertains to that item. Five out of 21 ENTREQ items were not addressed. One item (ENTREQ: 18.) is concerned with study comparison, which is not

applicable to our review. Four items (ENTREQ: 10. - 13.) are concerned with the quality appraisal of the data, which is absent from our review. We considered the checklist for text and opinion tools from the Joanna Briggs Institute (2017), but we preferred to focus on the quality of the individual arguments that make up the opinion that is to be evaluated which this tool does not provide. Furthermore, using the tool in despite of this deficiency could have led to the exclusion of papers based on their overall opinion, whereas articles with 'illogical' opinions could still contain arguments with interesting information for our analysis (e.g., Carroll, Booth, & Lloyd-Jones, 20212). The rest of this section contains the formulation of the review question, the search strategy, the selection of studies, the data extraction, and the data analysis plan.

Table 1. ENTREQ items adhered to and where they can be found in the text.

No.	Item	Location
1	Aim	Section 2.1.
2	Synthesis methodology	Section 2.5.
3	Approach to searching	Section 2.2.
4	Inclusion criteria	Section 2.2., Appendix S
5	Data sources	Section 2.2., Appendix S
6	Electronic search strategy	Section 2.2., Appendix S
7	Study screening methods	Section 2.4., Appendix S
8	Study characteristics	Section 3.1.
9	Study selection results	Section 2.2.
14	Data extraction	Appendix E

15	Software	Section 2.5.
16	Number of reviewers	Section 2.4., Section 2.5.
17	Coding	Section 2.5.
19	Derivation of themes	Section 2.5.
20	Quotations	Section 3.2.
21	Synthesis output	Section 3.2.

2.1 Review question

We used the acronym SPIDER (Cooke, Smith & Booth, 2012) to aid us in the focus on a review question. The SPIDER acronym allows the reviewer to specify the sample, phenomena of interest design, evaluation, and research type. We specified the components of the SPIDER acronym as follows Sample: *Opinion statements* (conclusions) supported by *arguments* for or against the Null Hypothesis Significance Test method and proposed *solutions* to problems, which in turn are based on *evidence* in the form of literature references, examples, mathematical proofs, and/or data simulations. Phenomena of Interest: *deficiencies* of NHST, *misconceptions* about NHST, *defenses* of NHST, *solutions* to problems pertaining to NHST, and overall *conclusions* about NHST. *NHST deficiencies*: Intrinsic properties of the method that are considered undesirable, limiting or pernicious (e.g., p-value is not an absolute measure of evidence, but relative to the sample size and effect-size of the population). *NHST misconceptions*: Misconceptions about the results of the Null Hypothesis Significance Test are specific misinterpretations of the results produced by the NHST method that are linked to (elements of) the method (e.g., interpreting a p-value as the

probability of the null hypothesis on the observed data instead of the probability of the data on the assumption that the null hypothesis is true). *NHST defenses*: Properties of NHST that speak to its qualities or counterarguments to the misconceptions and deficiencies. *Solutions to NHST*: Solutions that are purported to mitigate or remedy the mentioned problem. Examples of such solutions are: a) alternative methods of statistical inference that supposed to suffer less from limitations and potential for misconception than the NHST procedure; b) safeguards or policy changes that mitigate or remedy the purported problems; c) changes to the NHST method mitigate or remedy the purported problems. *Conclusions*: The particular conclusions about, perspectives on, or positions to NHST the writers have that follow from / are built on the arguments they use in their paper. Design: Discussions / essay on the phenomena of interest using arguments supported by evidence. Evaluation: Identification and description of perspectives and opinions on the NHST. Research type: Essays and opinion pieces (i.e., non-empirical scientific publications) in the psychological science and the accompanying methodological literature published between 2011 and 2018. This boils down to the following two general review questions:

What are the deficiencies, misconceptions, and defenses of NHST?

What are the proposed solutions to problems pertaining to NHST?

2.2 Search strategy

Although this is a novel type of systematic review, we tried to adhere as much as possible to reporting standards already in existence. We adopted the STARTLITE reporting standard for literature searches (Booth, 2006). We explicate the items that make up the STARLITE mnemonic: *Sampling strategy*: We used purposive sampling. Specifically, we restricted our search to papers published in psychology or psychological methods literature published between 2011 and 2018. We choose this restriction because 2011 is recognized as the year the replication crisis started and psychology is the field in which it takes place or, at least, is most engaged with investigating and remedying the situation. *Type of study*: As indicated in section 2.1, we limited this review to essays and opinion pieces. We choose these types of papers because this is where the pros, cons, and solutions of NHST are presented. *Approaches*: We used electronic subject searches. No other approaches were used, because we expected that all published papers on the subject are reachable through electronic searches on online databases. *Range of years*: We included papers published from 1 January 2011 up to 31 December 2018. We selected this starting date because Bem's paper *Feeling the Future* on precognition, which triggered the replication crisis,¹ was published in January 2011 and had received some media coverage at the end of 2010 (e.g., Lehrer, 2010). We performed the search in January 2019. *Limits*: The functional limits that were applied concern English language and publication in peer reviewed scientific journals. The literature was limited to peer reviewed journal publications because an adequate quality

¹ We acknowledge that there are several prior papers that contributed to the commencement of what is now called the replication crisis. However, Bem's *Feeling the Future* paper can be considered the proverbial straw that broke the camel's back. It elicited a flurry of comments and was a major motivator for the first large replication project in psychological science, which started in November 2011 (Open Science Collaboration, 2015).

assessment instrument is lacking for essay literature and peer review offers some quality control.

Inclusion and exclusion: Papers were included if they were about the Null Hypothesis Significance Test inference procedure (i.e., the correct *Type of study*); either wholesale or parts of the procedure. Specifically, papers were included if they were about the concepts ‘p-value’, ‘statistical significance’, ‘significance tests’, or ‘null hypothesis’. Papers were excluded if they were about empirical research instead of the opinion or arguments of the author(s); if the concepts were used in the paper, but the papers were not about these concepts (e.g., “the results were statistically significant at the $p < 0.05$ level”); or if the papers were about another statistical procedure that has similar concepts (e.g., Bayesian hypothesis test) Figure 1 depicts more specific information about the reasons for exclusion of papers. *Terms used:* We used the following search terms: ‘null hypothesis’, ‘hypothesis test’, ‘statistical significance’, ‘significance test’, ‘p-value’, and ‘p value’. We used these terms, because these are the concepts most commonly associated with NHST. All search terms with syntax and operators are provided in **Appendix S. Electronic sources:** We used two databases for the literature search, PsycInfo (via EBSCOhost) and Web of Science Core (via EndNote 8). We limited our search to these two databases, because they cover the width of psychological literature. The schematic representation of the selection process is presented in Figure 1. The initial search yielded 6221 potential paper and the final selection consisted of 42 papers.

2.4 Data extraction

We extracted descriptive information on the articles and descriptive information concerning the authors' opinion on NHST. The descriptive information on the article consisted of the name of the (first) author, year of publication and journal, and whether or not the article was part of a special issue. Furthermore, we extracted the *purpose* of the article if explicitly stated by the author(s) in the abstract or introduction; the *readability* for non-expert (i.e., absence of advanced mathematics and assumed technical know-how in the argumentation); the *applicability of solutions* (i.e., solutions do not require costly statistical software or mathematical experience); and the *conclusion* if explicitly stated at in the last section of the article.

Descriptive information concerning the authors' opinion on NHST consists of arguments and solutions related to NHST was extracted from all parts of the papers. Arguments and solutions were identified in terms of explicit claims pertaining to the phenomena of interest (as specified in Section 2.1). Specifically, a description in one or more sentences on their position (or the views/position of others they endorse) with respect to, for instance a particular deficiency of NHST. An example of data extraction of and argument from one of the papers is as follows. On the first page, Trafimow (2013) states: "p-values generally are inaccurate estimators of probabilities of null hypotheses." This claim indicates NHST's deficiency that its outcome measure, the p-value, does not provide an accurate estimation of the probability of the null hypothesis. It was therefore interpreted as a deficiency of NHST.

Evidence used to support these claims was also extracted. Empirical research, examples, other literature, simulations, and/or mathematical proofs were extracted as evidence if they were referenced for that claim. For example, on page 13, Cumming (2014) makes the claim:

"[w]hatever the N, a [p -value] gives only extremely vague information about replication (Cumming, 2008)." In this case, "(Cumming, 2018)" is used as support for this claim. We interpreted this information as evidence of the type: reference to other literature. The extraction form, provided as Appendix E, gives further details concerning what was extracted the indicators that were for their classification.

The data were extracted by [NVD] and the data extraction procedure was checked for errors and inconsistencies by [LVG]. Identified errors and inconsistencies were discussed upon agreement.

Figure 1. Selection process of essay and opinion pieces pertaining to the qualities and problem of NHST.

2.5 Data analysis

The purpose of our systematic review is to provide an overview of the qualities, deficiencies, and misconceptions of, and solutions to NHST. The collection of extracted arguments, arguments, proposed solutions, conclusions, and their supporting evidence provide this overview, but it is to vast interpret without some kind of focus or filter. To this end, we conducted an initial qualitative thematic synthesis (Thomas & Harden, 2008) in which we identified clusters of arguments and solutions described in the articles.

2.5.1. Thematic synthesis

The thematic synthesis contains four steps: identification of claims in the papers, development of descriptive themes, the development of analytical themes within the phenomena of interest, development of overarching analytical clusters. These four steps were as follows. Firstly, [NVD] identified pertinent text fragments (i.e., the claims pertaining to arguments, solutions, or conclusions) from all sections of the articles. Secondly, [NVD] developed *descriptive* themes (Thomas & Harden, 2008) by clustering fragments into groups: using the software program EPPI-reviewer 4.11.4.0 (Thomas, Graziosi, Brunton, Ghouze, O'Driscoll, & Bond, 2020). [NVD] and [LVG] discussed the descriptive themes upon agreement. Text fragments were grouped in descriptive themes based on interpreted overlap in content, meaning, or intention.² These descriptive themes were the individual arguments concerning NHST's deficiencies, misconceptions, and qualities, and solutions and conclusions. Thirdly, from the 137 descriptive

² Note that this is a slight deviation from Thomas and Harden (2008). We adopted this deviation to make the method amendable to the unorthodox nature of our systematic review.

themes, *analytical themes* were developed (Thomas & Harden (2008). Analytical themes go beyond the information from the primary studies in order to address our review question directly. During this step, the analysis was done separately for each phenomena of interest as specified in the SPIDER research question: Deficiencies, misconceptions, NHST defense arguments, solutions, and conclusions. The descriptive themes were first grouped in analytical subthemes, based on similarities in their semantic content. These analytical subthemes were then grouped in overarching analytical themes within each phenomenon of interest (see Figure 2. for a graphical representation of this process). Fourthly, overarching analytical clusters³ were developed from the analytical themes identified within the phenomena of interest. These overarching clusters form semantically coherent zones within the landscape of NHST, containing its qualities, problems and the solution to these problems.

³ We adopted this term to add an additional layer in the hierarchy that provide some conceptual distinction.

Figure 2. Example of the analysis hierarchy within a phenomenon of interest. A text fragment is first labeled with a descriptive theme. These descriptive themes are then clustered in analytical subthemes based on their similarity in semantic content. These were then clustered into higher order analytical themes within each phenomenon of interest.

3. Results

The results section describes the descriptive information concerning the included papers and the themes from generated in the thematic synthesis.

3.1. Descriptive results

A total of 42 articles were included in the analysis. Of these, 34 were regular articles, two editorials and six commentaries. Eleven articles were part of a special issue; of which eight were

published in “Perspectives on the Use of Null Hypothesis Statistical Testing (NHST)” a three-part special issue edited by *Educational and Psychological Measurement*. Most papers (12 out of 42) were published in 2017 and only a few papers were published in 2012, 2014, and 2018 (respectively, 1, 3, and 2 out of 42). All but one of the papers were considered readable. The exception was a paper published in *Statistica Sinica* (Martin, 2014) and required the understanding of mathematical notation, the stated mathematical theorems and their proofs. Out of 42 articles, 29 offered one or more potential solutions to the problems pertaining to NHST. In only three out of these 29 cases, no relevant information was given on how to implement the suggested solution(s). A complete overview of the paper characteristics can be found is presented in Table 2.

Table 2. Overview of the papers and their characteristics. The details on the special issues and the subjects of the commentaries can be found in the online dataset. The cells in the ‘Useful’ column are empty when the paper in question does not contain a solution.

First author	Year	Journal	Context	Special issue	Readable	Solutions	Useful
Gelman	2013	Journal of Mathematical Psychology	Commentary	Yes	Yes	No	
Rouse	2016	Psi Chi Journal of Psychological Research	Editorial	No	Yes	Yes	Yes
Gelman	2018	Personality and Social Psychology Bulletin	Article	No	Yes	Yes	Yes
Dienes	2018	Psychonomic Bulletin and Review	Article	Yes	Yes	Yes	Yes
Campitelli	2017	Educational and Psychological Measurement	Article	Yes	Yes	Yes	Yes

Haig	2017	Educational and Psychological Measurement	Article	Yes	Yes	Yes	Yes
Haggstrom	2017	Educational and Psychological Measurement	Article	Yes	Yes	No	
Schneider	2015	Scientometrics	Article	No	Yes	Yes	Yes
Wilcox	2017	Educational and Psychological Measurement	Article	Yes	Yes	Yes	Yes
Trafimow	2016	Basic and Applied Social Psychology	Editorial	No	Yes	No	
Chen	2017	NeuroImage	Article	No	Yes	Yes	Yes
Trafimow	2013	Frontiers in Psychology	Commentary	No	Yes	No	NA
Marsman	2017	Educational and Psychological	Article	Yes	Yes	No	NA
Lu	2015	Shanghai Archives of Psychiatry	Article	No	Yes	Yes	Yes
Hupé	2015	Frontiers in Neuroscience	Article	No	Yes	Yes	Yes
Laber	2017	Journal of the American Statistical Association	Commentary	No	Yes	No	
Rao	2016	Journal of Modern Applied Statistical Methods	Article	No	Yes	Yes	No
Goddard	2015	METODE Science Studies Journal	Article	No	Yes	Yes	No
Cumming	2014	Psychological Science	Article	No	Yes	Yes	Yes
Cumming	2013	Australian Psychologist	Article	No	Yes	Yes	Yes
Klugkist	2011	International Journal of Behavioral Development	Article	No	Yes	Yes	Yes
Garcia-Perez	2017	Educational and Psychological Measurement	Article	Yes	Yes	Yes	Yes
van Helden	2016	Nature Methods	Commentary	No	Yes	No	
Perezgonzalez	2014	Theory & Psychology	Article	No	Yes	Yes	Yes

Citrone	2011	Bulletin of Clinical Psychopharmacology	Article	No	Yes	Yes	Yes
Konijn	2015	Communication Methods and Measures	Article	Yes	Yes	Yes	Yes
Hasley	2015	Nature Methods	Article	No	Yes	Yes	Yes
Chang	2017	Educational and Psychological Measurement	Article	Yes	Yes	No	
LeBel	2011	Review of General Psychology	Article	No	Yes	Yes	Yes
Miller	2017	Educational and Psychological Measurement	Article	Yes	Yes	Yes	Yes
Lambdin	2012	Theory & Psychology	Article	No	Yes	No	
Hofmann	2011	Psychotherapy	Commentary	No	Yes	No	
Perezgonzalez	2015	Frontiers in Psychology	Article	No	Yes	Yes	Yes
Szucs	2017	Frontiers in Human Neuroscience	Article	No	Yes	Yes	Yes
Savalei	2015	Frontiers in Psychology	Article	No	Yes	Yes	Yes
Bradley	2016	Psychological Reports	Article	No	Yes	No	
Baird	2016	Journal of Modern Applied Statistical Methods	Article	No	Yes	Yes	Yes
Garamszegi	2017	Trends in Neuroscience and Education	Commentary	No	Yes	Yes	Yes
Martin	2014	Statistica Sinica	Article	No	No	Yes	Yes
Hubbard	2011	Journal of Applied Statistics	Article	No	Yes	No	NA
Johanson	2011	Scandinavian Journal of Psychology	Article	No	Yes	Yes	No
Engman	2013	Quality & Quantity: International Journal of Methodology	Article	No	Yes	No	

3.2 Arguments, solutions, conclusions, and evidence

We identified a total of 90 arguments, 33 proposed solutions and 14 conclusions across the 42 articles that were included. Concerning the arguments, we identified 39 deficiencies of NHST, 31 arguments about how NHST is misinterpreted and misused, and 20 on the defense of NHST. These 137 items provide a first step in answering the review question: they describe the NHST landscape. A rough overview of the distribution of arguments and solutions across the papers is presented in Table 3. The complete lists of these arguments, solutions, and conclusions, their descriptions, and from which papers they originate can be found in Appendix A. The complete dataset that contain further details can be accessed <https://osf.io/bktdfx/>). As is shown in Table 2., the range in the number of items per paper is large (i.e., from 1 to 30 per paper). One paper contained as many as 11 deficiencies. Another paper contained as many as 14 misconceptions. The maximum number of NHST defenses was 8. The highest number of solutions was 11. Not a single paper had the highest count on more than a single category.

Table 3. Overview of the number of arguments and solutions per paper. See Appendix A for details on which argument or solution is present in which paper and in how many papers each item is present.

First author	Year	Deficiencies	Misconceptions	NHST defenses	Solutions	Total
Gelman	2013	3	0	0	0	3

Rouse	2016	0	3	4	0	7
Gelman	2018	1	2	0	5	8
Dienes	2018	3	0	0	1	4
Campitelli	2017	0	0	0	1	1
Haig	2017	1	3	0	2	6
Haggstrom	2017	0	8	0	0	8
Schneider	2015	11	8	0	10	29
Wilcox	2017	0	0	0	1	1
Trafimow	2016	0	3	0	0	3
Chen	2017	2	3	2	1	8
Trafimow	2013	4	0	0	0	4
Marsman	2017	2	0	0	0	2
Lu	2015	1	1	0	1	3
Hupé	2015	6	1	0	3	10
Laber	2017	0	0	1	0	1
Rao	2016	2	0	0	1	3
Goddard	2015	1	0	0	1	2
Cumming	2014	2	0	0	3	5
Cumming	2013	2	0	0	2	4
Klugkist	2011	2	1	0	1	4
Garcia-Perez	2017	0	0	8	0	8
van Helden	2016	0	0	1	0	1
Perezgonzalez	2014	2	0	0	1	3
Citrone	2011	1	0	0	1	2
Konijn	2015	2	3	0	1	6

Hasley	2015	4	0	0	1	5
Chang	2017	1	0	3	0	4
LeBel	2011	5	0	0	4	9
Miller	2017	1	0	4	1	6
Lambdin	2012	5	14	0	1	20
Hofmann	2011	2	0	0	0	2
Perezgonzalez	2015	0	3	0	2	5
Szucs	2017	7	12	0	11	30
Savalei	2015	0	0	3	3	6
Bradley	2016	3	1	0	1	5
Baird	2016	4	1	0	4	9
Garamszegi	2017	7	2	0	1	10
Martin	2014	1	1	0	1	3
Hubbard	2011	1	1	0	0	2
Johanson	2011	6	0	0	1	7
Engman	2013	3	5	0	0	8

In total, we identified 508 unique pieces of evidence that were referenced in the 42 papers to support the 123 arguments and solutions. 15 were published before 1950; 139 were published between 1950 and 1999; 181 were published between 2000 and 2010; and 173 were published between 2011 and 2017 (see Figure 3. for the distribution of publication dates). The body of evidence is diverse. For instance, some references that were used as evidence for the arguments in the papers came from journals such as *Journal of Wildlife Management*, *The Journal of Experimental Education*, *Philosophy of science*, *Political Analysis*, *Biological Psychiatry*,

Seminars in Hematology, Ecology, and Biology of Blood and Marrow Transplantation. See the online supplements for further details on the extracted evidence, <https://osf.io/ayf56/>.

Figure 3. Distribution of publications dates of the pieces of evidence extracted from the papers. These pieces of evidence were referenced in the papers to support the particular claims that were extracted as the descriptive themes.

3.3. Thematic synthesis results

The opinions on NHST as presented in the literature were analyzed using thematic synthesis. We generated three *overarching analytical clusters* from the analysis that can be identified as three *zones* in the (problems and solutions concerning) NHST landscape: 1) the mild problems zone 2) the moderate problems zone and 3) the critical problems zone. For all three zones, we describe the identifying element(s) and we specify the associated arguments, solutions and conclusions, and provide quotes from the papers to support our synthesis. The terms in *italic* represent the

analytical subthemes generated during the analysis (see Section 2.5.). See Figure 4, 5, and 6 for an overview of the mild, moderate, and critical zone of the NHST landscape respectively.

Figure 4. The mild zone in the NHST landscape: *NHST itself is not the problem*. This zone consists of three NHST defenses themes (orange), one misconceptions theme (green); one solution theme (blue), and one conclusion theme (yellow). 14 of the 42 papers ascribe to a conclusion that is part of this zone. There are an additional four papers that at least contain one misconception and at least one solution that are part of this zone. There are seven papers that only have one or more misconceptions, one or more deficiencies, or one or solutions that are part of this zone while also containing descriptive themes belonging to the other phenomena of interest whose analytic theme(s) are part of another zone (these papers are: Bradley, 2016; Engman, 2013; Gelman, 2013; Konijn, 2015; Trafimov, 2016; Cumming, 2013; Cumming, 2014).

3.3.1. The mild zone

The mild problem zone of NHST (see Figure 4) can be labeled as: NHST itself is not the problem. The problems with statistical inference, such as inflated false-positive rates and biased results, have to do with misconceptions and faulty practice due to the psychology of the researchers and the research culture, not with the method that is being used. Specifically, these problems result from *psychological heuristics that lead to misunderstanding, the tendency to dichotomous reasoning, and bad research practices that are considered acceptable by the community*. This means that the problems have not so much to do with the method per se, but with peripheral aspects, like the *language* of NHST in relation human reasoning and behavior. For instance, Rouse (2016, p.129) writes

... the dichotomous language of NHST promotes unrealistic and simplistic dichotomous thinking styles. Many aspects of human behavior are too complex to be boiled down to “True or Not True” conclusions, and yet the language of NHST subtly communicates fallacious and absolutist approaches to evaluating claims.

Within this zone, solutions are geared towards leaving the method as it is, but adding *supplements and safeguards to NHST*, that mitigate the psychological and cultural problems. These solutions consist of policy changes (e.g., in education, funding, publication), focus on proper use of NHST (e.g., high enough power, adherence to strict guidelines), and additions to NHST, such as procedure verification, meta-analyses, and direct replication. For instance, Rouse (2016, p.132) writes:

"As the research community is examining and debating the most appropriate use of inferential statistics, we recommend that researchers continue to use the tools of NHST, but to use these tools carefully and effectively."

This zone also contains the analytical themes of defenses of NHST and its use. These themes are 1) *other methods are just as bad or worse*: Bayesian hypothesis tests and estimations methods either come with additional and more pernicious problems (for the former) or are based on the same principles and thus suffer from the same problems (for the latter). 2) *NHST does what it is supposed to do*: the shortcomings, such as reliance on sampling plan, are actually qualities and what NHST is supposed to do, control error rates, it does well. 3) *NHST is good enough for what scientists need and can do/have*: NHST is actually quite intuitive to understand or at least not more misunderstood than other methods and can be unproblematically operated when certain precautions are taken (e.g., sufficient power and replication studies). For instance, Miller (2017, p.664) writes:

To the contrary, the heart of NHST is a simple, intuitive, and familiar "common sense" logic that most people routinely use when they are trying to decide whether something they observe might have happened by coincidence (a.k.a., "randomly," "by accident," or "by chance").

This zone can be seen containing the milder conclusions concerning NHST, such as the analytical subthemes *use NHST with care and proper practice*, *use complete reporting*, and *improve general practice*. In other words, from within this zone, there is nothing actually wrong with NHST.

Specifically, the method works as it is supposed to work when used correctly. Policy and education changes are all that is required to remedy the existing problems.

Figure 5. The moderate zone: *Moderate, non-fundamental changes are needed*. This zone consists of one deficiency theme (purple), one misconceptions theme (green); one solution theme (blue), and one conclusion theme (yellow). 9 of the 42 papers ascribe to a conclusion that is part of this zone. There are an additional six papers that contain at least one misconception, deficiency or one solution that is part of this zone and also on item that is part of another theme in this zone. There are ten papers that only have one or more misconceptions, one or more deficiencies, or one or solutions that are part of this zone while also containing descriptive themes belonging to the other phenomena of interest whose analytic theme(s) are part of another zone (these papers are: Häggström, 2017; Chen, 2017; Garamszegi, 2017; Gelman, 2013; Hasley, 2015; Hupé, 2015; Johanson, 2011; LeBel, 2011; Perezgonzalez, 2014; Trafimow, 2013).

3.3.1. The moderate zone

The second zone (see Figure 5.) within the NHST landscape contains the proposals for moderate, but not fundamental, changes in light of serious misuse of NHST and mild shortcomings of the methods. Within the borders of this zone, the general conclusion is that researchers should *stick with frequentist hypothesis testing*, just in a different form than NHST. This differs from the mild zone in the sense that the NHST approach of sole reliance on p-values to accept unspecified alternative hypotheses should be dropped in favor of approach that are still based on the frequentist philosophy of probability, but have a different approach to hypothesis testing (e.g., interval-null hypothesis testing). Scientists misunderstand how NHST works which leads to wrongfully interpreted results. This misunderstanding is caused by deficiencies concerning the input for the analysis and the output. To illustrate, within this zone, the use of NHST is problematic because, for instance, if the sample size is large enough, the null hypothesis will always be rejected as a result (e.g., "Berkson (1938) was the first to notice dependence of significance testing on the sample size. He objected that it is possible to obtain a statistically significant chi-square test merely by increasing sample size"; Rao & Lovric, 2016, p.13) and, as LeBel (2011, p.374) states, it outputs ambiguous evidence:

Thus, although it is well known that negative (null) results are ambiguous and difficult to interpret, exclusive reliance on NHST makes positive results equally ambiguous, because they can be explained by flaws in the way NHST is implemented rather than by a more theoretically interesting mechanism (Meehl, 1967).

Although these are important criticisms on NHST as it is currently practiced, not all frequentist hypothesis of statistical significance testing need to be sensitive for these deficiencies. As another example, the misconceptions, such as that statistical significance comes in degrees (e.g., ' $0.05 < p < 0.1$ ' marginally significant, ' $p < 0.001$ ' highly significant and that high p-values indicate that the null hypothesis is true, can be addressed by reconceptualizing several components of NHST (i.e., what error probabilities are); as Haig (2017, p.496) writes about adopting Error statistics theory of Mayo (1999):

In her initial formulation of the error-statistical philosophy, Mayo (1999) modified, and built upon, the classical Neyman–Pearsonian approach to ToSS [tests of statistical significance]. However, in later publications with Spanos (e.g., Mayo & Spanos, 2011), and in writings with David Cox (Cox & Mayo, 2010; Mayo & Cox, 2010), her error-statistical approach has come to represent a coherent blend of many elements, including both Neyman–Pearsonian and Fisherian thinking. For Fisher, reasoning about p values is based on postdata, or after-trial, consideration of probabilities, whereas Neyman and Pearson's Type I and Type II errors are based on predata, or before-trial, error probabilities. The error-statistical approach assigns each a proper role that serves as an important complement to the other (Mayo & Spanos, 2011; Spanos, 2010). Thus, the error- statistical approach partially resurrects and combines, in a coherent way, elements of two perspectives that have been widely considered to be incompatible. In the post- data element of this union, reasoning takes the form of severe testing, a notion to which I now turn.

From which Haig (2017, p.504) concludes:

In more than 50 years of preoccupation with these tests, psychology has concentrated its gaze on teaching, using, and criticizing NHST in its muddled hybrid form. It is high time for the discipline to bring itself up-to-date with best thinking on the topic, and employ sound versions of ToSS in its research.

In addition, deficiencies, such as that the null hypothesis is always false or that NHST overestimates the evidence against the null hypothesis, are remedied when minor structural changes are made. These changes are, for instance, using context dependent Type I and Type II errors (i.e., incorporating the costs of making a Type I and/or Type II error for the particular test at hand); interval null hypothesis testing (i.e., using a range of values around the null effect instead of a point null hypothesis); and using a minimum effect-size of interest null hypothesis (i.e., using as null hypothesis the smallest effect-size that would be of interest for the particular research question). As an example, Rao (2016, p.15) writes:

So, what should we do? This article is an initial contribution to making a paradigm shift in testing statistical hypotheses. Instead of testing highly problematic and almost surely false point null hypotheses, as a natural replacement, test a negligible null hypothesis.

This collection of suggested solutions, and this zone in general, is succinctly expressed by Baird (2016, p.113):

By implementing the concepts from these sources, both traditional and contemporary, researchers are engaged in what could be described as “context-driven NHST” or CD-NHST. Instead of being driven by convention, which may or may not have much relevance, CD-NHST places the researcher in the driver’s seat of inference.

Consequently, the deficiencies of NHST do require adjustments to the method, but the underlying assumption of falsification and controlling error rates remains intact.

Figure 6. The critical zone on NHST: *fundamental change is needed*. This zone consists of two deficiency themes (purple), one misconceptions theme (green); one solution theme (blue), and one conclusion theme (yellow). 19 of the 42 papers ascribe to a conclusion that is part of this zone. There are an additional five papers that contain at least one misconception, deficiency, or one solution that

is part of this zone and also on item that is part of another theme in this zone. There are ten papers that only have one or more misconceptions, one or more deficiencies, or one or solutions that are part of this zone while containing any descriptive themes belonging to the other phenomena of interest whose analytic theme(s) are part of another zone (these papers are: Häggström, 2017; Haig, 2017; Lu, 2015; Martin, 2014; Perezgonzalez, 2015; Rourse, 2016; Baird, 2016; Chang, 2017; Garamszegi, 2017; Perezgonzalez, 2014)

3.3.3. The critical zone

The critical zone (see Figure 6) calls for fundamental changes in the way science practices statistical inference. This is because the foundational problems of NHST, such as its insensitivity to the specifics of the alternative hypothesis, are severe. If the alternative hypothesis is what the researcher is actually interested in, then a method is required that take the characteristics of this hypothesis into account when evaluating the data. As Dienes and Mclatchie (2018, p.214) write:

Bayes factors are sensitive to how vague or precise the theory is; P-values are not. But, normatively, precise theories should be favored over vague ones when data appear within the predicted range.

In addition, NHST is incapable of providing that which research misconceive it to provide, such as interpreting p-values as the probability of the null hypothesis, the replication probability of the results, the realized Type I error probability, the methodological quality of the study, or that the results are due to chance. This is because, the method only provides, under the assumption that the null hypothesis is true, the probability of observing the data at hand or data deviating more strongly from the null hypothesis. As an example, Schneider (2015, p.423) writes:

Another variant is to believe that p indicates the probability that a result is due to chance alone (i.e., sampling error). This is also not so, as p values are calculated on the assumption that H_0 is true, this is the assumed 'chance model', so the probability that chance is the only explanation of the result is already taken to be 1. It is therefore illogical to view p as somehow measuring the probability of chance (Carver 1978).

Other methods might not suffer these deficiencies, making their result interpretations correct that would have been wrong for NHST results. For example, estimation methods and other types of hypothesis tests (e.g., Bayesian hypothesis tests) do not have a dichotomous decision rule (i.e., reject H_0 *versus* retain H_0) nor do they provide the probability of the data under the null hypothesis. They are said not suffer from the problems mention above, because these methods are not about testing a single null hypothesis and evidence comes in degrees. As Scheinder (2015, p.427) writes:

First of all, there are inferential alternatives, which contrary to NHST do in fact assess the degree of support that data provide for hypotheses, [...] [such as] likelihood inference (e.g., Royall 1997).

The perspective on NHST from this zone is finds a clear expression in Szucs and Ioannidis (2017, p.13):

NHST [...] does not allow for systematic knowledge accumulation. In addition, both because of its shortcomings and because it is subject to major misunderstandings it facilitates the production of

non-replicable false positive reports. Such reports ultimately erode scientific credibility and result in wasting perhaps most of the research funding in some areas.

In summary of this zone, the deficiencies and their resulting misconception concerning NHST are severe to the extent that scientific progress is impeded to dangerous levels and radical methodological change is required. The online available data (<https://osf.io/bktdfx/>) gives a complete breakdown of the three zones from their analytic themes and subthemes to descriptive themes (i.e., arguments, solutions, conclusions).

4. Discussion

4.1. Summary

As this systematic review shows, NHST and its practice are diverse and intricate. We extracted data from 42 papers published between 2011 and 2018 in psychology and psychological methods journals. Combined, the papers discussed 39 deficiencies of NHST, 31 misconceptions or misuses, 20 arguments in defense of NHST, and 33 solutions to NHST problems in particular or statistical inference problems in general. Across the papers, these 123 items were supported by 508 unique pieces of evidence (i.e., references to other papers, examples, simulation studies, or mathematical proofs). The 123 arguments and solutions are employed to reach 14 types of conclusions. Collectively, these 137 items make up the landscape NHST within which the author's positions, or perspective if you will, on NHST – in terms of its qualities, problems, and their

solutions – can be interpreted as that which is visible to the author within this landscape from his/her point of view.

Within this landscape, we identified general zones. Based on their content, the arguments, solutions, and conclusions can be synthesized into three overarching zones enclosing certain practices and problems of NHST. The mild zone houses that which is actually in favor of NHST and only encloses problems in and solutions for policy, education, human psychology, and research culture. The moderate zone contains acknowledgments of some defects and misuse of NHST in combination with structural but not fundamental change in statistical inference (i.e., continue with frequentist hypothesis testing in a different form than NHST). The critical zone incorporates fundamental deficiencies and a systematic desire in the researchers that NHST will never be able to satisfy, in any shape or form. In this case, a complete break from NHST is required and a different statistical inference method needs to be adopted.

4.2. Embedding and Implications

At the moment, the replication crisis is not (yet) considered solved, there is still fierce debate on how to address the misuse of NHST, and disagreement continues on if and how NHST should be changed or replaced by which alternative. The contribution of our systematic review to this situation is twofold.

Firstly, our results offer a possible explanation of why these debates have not been resolved. The NHST landscape is vast. Vast enough that no single paper on the topic provides a complete overview of NHST's machination, its application, its consequences, and how it is

perceived. There is more than enough space for its inhabitants to hold incompatible views without the threat of overt conflict, because their perspectives do not or minimally overlap and they have the internal coherence of their standpoint to fall back on. For instance, the proponents of and open science (Lindsay, Simons, Lilienfeld, 2016; van 't Veer, Giner-Sorolla, 2018; Munafò, 2016; Freese & King, 2018) build their position on arguments of psychology and research culture, which entail the improvement of replication rates. From another position in the landscape, these solutions are insufficient, because the inference method is considered at fault and these superficial cosmetic fixes only give a false sense of betterment (e.g., Szollosi et al., 2019). However, they are too far apart for an actual conflict to ensue. Their positions are not built on the same or neighboring arguments, thus their opposing conclusions not threaten that on which it is founded. Conflicts that do concern these foundations would be dialectic: each needs to improve or move (i.e., change) their positions in response to the other's attack, eventually leading to surrender/victory or consensus. Without such threats to one's position, one can continue to feel safe; out of the reach of the arguments of others and where there is the internal consistency of one's own arguments to fall back.

As a result, published denouncements of each other's positions do not have to be perceived as carrying the force that would motivate change in one's position. As another example, there are several many-authors papers that call for different changes in the application of statistical methods. One such paper suggests leaving NHST as it is, but only lowering the threshold of statistical significance (Benjamin et al., 2018),⁴ which is consistent with our mild

⁴ It needs to be noted that (many of) the authors actually prefer Bayesian hypothesis tests, but see this solution as more feasible for the near future. However, taking this into account does not change the argument.

zone. Another suggests taking both Type I and Type II error rates into account and have scientist sets them with respect to the particularities of their research aim and subject (i.e., the Neyman-Pearson approach to frequentist hypothesis testing; Lakens et al., 2018), which is consistent with our moderate zone. A third paper suggest abandoning hypothesis tests and thresholds in favor of continues measures of estimation and model adequacy (McShane, et al., 2019), which is consistent with our critical zone. Hence, these papers draw on different parts of the NHST landscape (i.e., arguments). As a result, they argue more past each other than against each other. Consequently, as long as those trying to resolve these problems do not consider each other's position in the NHST landscape and do not target those areas where their confliction positions overlap, it is likely that conflicts will not be treating enough to motivate defense or change.

Secondly, our data can be used to move towards a resolution of these debates on how scientific practice should be improved. The overview our data provides could serve as a starting point for statisticians and methodologists to formulate alternatives that are more likely to have the support from a large group of researchers. Moreover, it provides a complete and neutral classification for academic researchers using NHST to reflect upon their own position and account for the advantages and drawbacks of using NHST. More particular, our results can be used to identify where in the NHST landscape particular positions overlap. The arguments and solutions in these overlapping areas could be the focus of evaluation or the subject of empirical research. This would allow a systematic comparison and assessment of the particular debate positions.

In addition, our data provides some indication of relevance and interconnection. Some deficiencies and misconceptions are more prevalent in the papers than other. One explanation for this prevalence is that these problems are more relevant and severe and thus garner more

attention. Within the papers and our zones, these potentially relevant problems are connected to particular solutions, which could therefore be favored over their alternatives. Concretely, this, and the dataset in general, could be of assistance to those intent on improving science (e.g., policy makers, journal editors, educators, methodologists, etc.) when deciding on how to allocate limited resource. For instance, those working towards the improvement of scientific practice through better statistics education could benefit from selecting those misconceptions of NHST that are most prevalent and evaluate if these curricular changes reduce these misconceptions.

Furthermore, an overview such as this could prove useful for those developing research methods and want to take its adequate application by fallible human scientists into account. Scientists might be perceived by lay people and other scientists as more rational, objective, and open-minded than non-scientists (Veldkamp, Hartgerink, van Assen, & Wicherts, 2017). Even if this is the case, scientists are not infallible. As our data shows, there are many misconceptions and misuses possible when it comes to statistical inference via NHST, which might result from psychological biases and research cultures that do not incentivize methodological rigor. Also, research show that reporting error in statistical results are prevalent in published papers (e.g., Veldkamp, Nuijten, Dominguez-Alvarez, van Assen, & Wicherts, 2014). It is thus advisable that these fallibilities of scientists should to be taken into account, to which our overview can be of assistance, when developing or implementing alternatives to NHST with the aim of improving the quality of scientific inference.

4.3. Limitations

This review suffers from several limitations. First and foremost, the methodology for the systematic review of opinion literature is not yet fully developed. We adopted methods for mixed-methods and qualitative systematic reviews, which offered guidelines. However, on several occasions, choices had to be made that had no precedent in the current methodological literature. The most prominent of these choices were the exclusion of empirical papers; using claims in the papers as our data; and categorizing the phenomena of interest in deficiencies, misconceptions, NHST defenses, solutions, and conclusions. Empirical studies of NHST and its use might also contain arguments and solutions; other types of text fragments could have been used as data; and the phenomena of interest could have been combined, further sub-divided, or differently delineated. For instance, the requirement of a positive element or alternative in a proposed solution would have precluded 'stop using NHST' from being an instance of that phenomenon of interest. Different choices would have led to different result. However, without proper methodological guidelines it is impossible to predict if these alternative choices would have let to meaningful differences in results and if these alternative results would be better or worse.

Secondly, a quality assessment of the included literature is lacking. It is general practice for systematic reviews to evaluate the quality of the data and either only includes data that meet certain quality criteria (e.g., Tong et al., 2012) or conduct sensitivity analysis of the review results with respect to the quality assessments of the data (e.g., Patsopoulos, Evangelou, & Ioannidis, 2008). However, at the moment, there is no tool available for the evaluation of the quality of particular arguments, nor the structure of a set of arguments to their conclusion. Thus, we

included all arguments even though some would consider them to be clearly false or of such a low quality that they should not be included in the overview. When comparing the arguments, some clearly contradict each other, such as Miller claiming that “the heart of NHST is a simple, intuitive, and familiar “common sense” logic” (Miller, 2017, p. 664) while others claim that NHST is incoherent (and thus illogical). This is a clear indication that at least one of them must be wrong. In such a case, a quality assessment might be able to arbitrate between conflicting cases.

Thirdly, although the identified zones within the NHST landscape generally overlap with the perspectives of the authors, there is lack of complete correspondence. However, it does not have to be unexpected that some authors use arguments or solutions across more than one zone. It is not necessary that the authors’ positions are exclusively dependent on what is present in the landscape. For instance, personal agenda, position within their academic field, or their particular education might play a role as well. To extent the landscape metaphor, borders are not always drawn along structure in the landscape, such as rivers, but logistic, political, historical, and other factors are also taken into account. Consequently, this does not necessarily have to be considered as a limitation, but could be seen as highlighting the diversity and intricacies of the NHST landscape.

Finally, the scope of our review is limited. Time and resources required constraints. We only included essay and opinion literature from psychology and methodological journals, published between 2011 and 2018. The replication crisis and the consequent attention for methodological evaluation and reform made this, in our opinion, the most promising boundaries to work in. However, other fields might have a different perspective on NHST. Specifically, researchers in those fields might differ from psychologists in their misconceptions and misuses.

Or, the authors of NHST papers in these fields might emphasize deficiencies of NHST that are ignored by authors of such papers working in psychology and vice versa. Furthermore, different deficiencies and misconceptions might have been in the spotlight before the advent of the replication crisis in 2011 and it could be possible that different problems are addressed in empirical literature concerning NHST. In short that is ample room for broadening and deepening the understanding of NHST in particular and statistical inference in general via systematic literature review.

4.4. Suggestions for further research

Our paper offers handholds for the extension of our review and the development of systematic review methodology for essay and opinion literature. The access we provide to our methods and progress notes will not only allow others to evaluate our work, but also extend and improve it. Specifically, this review can be extended to other academic fields and further back in time. These extensions will allow us to gain insight in the differences and similarities between fields and across time on the perspectives and practice of NHST. Such a nuanced overview will be of value in the continuing debate on how statistical inference is and should be practiced.

This paper also counts as a proof of principle. As far as we know, this is the first systematic review of essay and opinion literature. Its successful completion is an indication that such reviews are possible in principle. We expected that our methods can be developed into a systematic review methodology with general application, which itself can be investigated and evaluated. The academic literature is teeming with essays on a wide variety of topics. Many of them have a

shared topic and argue against or support each other. At the moment, essays concerning open science, the replication crisis, and preregistration and methodological rigor are prime examples of topics on which many such essays are published. An adequate systematic review methodology could be used to catalog the copious amounts of such papers and get a clear perspective on topics that are of clear current relevance.

4.5. Concluding remarks

In this paper we provided an overview on the perspectives on NHST and its practice. The extensive dataset that resulted from our review contains more information than we could properly describe and analyze in one paper. Thus we conclude with the wish that others might use our data and further investigate this fascinating topic.

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Appendix S

Search strategy

As stated in the research question, the systematic review was limited to psychological science and methodological literature. We choose PsycINFO and Web of Science Core as databases to search. In general, we used the same search strategy for both databases. However, differences in technical details between both databases forced us to adopt two slightly different search strategies:

Search strategy PsycInfo (via EBSCOhost)

- searched in: “title” and “keywords”,
- limited to: ‘articles’,
- in: ‘English’,
- for the following words connected by an OR operator:
 - null hypothesis
 - hypothesis test
 - statistical significance
 - significance test
 - p value AND⁵ “statistic*

⁵ The ‘AND’ operator between ‘value’ and ‘statistic’ was necessary, because EBSCOhost identifies ‘p’ as a stop word and ignores it in the search (which turns up very many results on emotion research).

- p-value AND² “statistic”

Search strategy for Web of Science Core (via EndNote X8)

- searched in: ‘key terms’ (title / abstract / keywords),
- limited to ‘articles’
- in ‘English’,
- for the following words connected by an OR operator:
 - null hypothesis
 - hypothesis test
 - statistical significance
 - significance test
 - p-value
 - p value
- A second search in EndNote X8 on these entries was necessary to identify those with titles or keywords (excluding abstracts) that contained one or more of the following terms:
 - null hypothesis
 - hypothesis test
 - statistical significance
 - significance test
 - p-value
 - p value

Papers were excluded from the review if 1) they were about empirical studies; 2) they were published in a journal not pertaining to psychological science, statistics or research methodology; or 3) lacked a description of one or more problems with / quality of NHST, or NHST related concepts in the abstract.

Papers about the weakness and drawbacks of NHST are a subclass of papers about NHST in general. Terms that are related to or identify NHST are 'null hypothesis', 'hypothesis test', 'statistical significance', 'significance test', 'p-value', and 'p value'. However, papers that contain reports of quantitative research can include these terms (e.g., 'the results were significant [p-value<.05]') without actually being about those concepts. We choose to limit our search to titles and keywords of paper, because it is conventional that the subject of the paper is mentioned there.

Appendix E

Extraction form

General information. The following items are relevant for all papers.

Item name	Item explanation	Possible values or examples
Author	Surname of the first author	EXAMPLE: Cohen If there are first author sharing a surname, add the initial after the surname. EXAMPLE: Cohen, J.
Year	Year of publication	1992
Journal	Journal in which the paper was published	American Psychologist
Context	Context in which the paper was published. Specifically, indicate if the paper was published as in (invited) editorial, response to a previous paper, regular/unprompted article.	POSSIBLE VALUES: Editorial Commentary to (indicate paper) Article

Special issue	Is the paper part of a special issue	POSSIBLE VALUES: Yes No
Name of special issue	Name of the special issue if the paper is part of a special issue	EXAMPLE: Perspectives on the Use of Null Hypothesis Statistical Testing (NHST) (part III of special issue)
Url of special issue	Website url of the special issue if the paper is part of a special issue	EXAMPLE: https://journals.sagepub.com/toc/epma/77/5
Purpose	The purpose of the paper as specified in its introduction or abstract. Quote the purpose if it is 3 sentences or shorter. Otherwise paraphrase the purpose. Indicate if its a quote or paraphrase by using quotation marks on page number for the former and only a page number for the latter. If no purpose is given, leave it blank	EXAMPLE: “The primary goal of this article is to promote awareness of the various statistical problems associated with the use of p value null-hypothesis significance testing (NHST).” (p.779)
Type	What kind of paper is it? We distinguish between discussion	POSSIBLE VALUES:

	and criticism (of a method or responded to paper), exposition of problems and solutions, advocacy (for a particular solution, by discussing problems that the suggested solution solves)	Discussion Exposition Advocacy
Consistency	Is the reported purpose consistent with the type of article. For instance, when the reported goal of the paper is to create awareness, then the paper should be of the type “Discussion” or “Exposition”. If the paper’s reported goal is to show/discuss that method A is bad (has certain problems) and method B is good (does not suffer from these problems), then the paper should be of the type “Advocacy”.	POSSIBLE VALUES: Yes No NA (if the article does not have a clear type, it’s consistency cannot be reported)
Readable	Is the paper understandable for researchers without a strong	POSSIBLE VALUES:

	<p>mathematical or formal statistical background? Concretely, are mathematical formulas and proofs absent, are they irrelevant for understanding the main claim and arguments of the paper, or are the main claim and arguments also given in a non mathematical form.</p>	<p>Yes</p> <p>No</p>
Solutions	<p>Does the paper offer one or more solutions to methodological problems discussed in the paper</p>	<p>POSSIBLE VALUES:</p> <p>Yes</p> <p>No</p>
Useful	<p>Can what is discussed and suggested in the paper be implemented by researchers without a strong mathematical or formal statistical background and without expensive software or extensive education requirements.</p>	<p>POSSIBLE VALUES:</p> <p>Yes</p> <p>No</p> <p>Unclear</p> <p>NA (if no solutions are proposed)</p>
Main conclusion	<p>A brief summary of the main conclusion of the paper as either</p>	<p>EXAMPLE</p>

	<p>give in the abstract or conclusion/discussion. Quote the main conclusion if it is 3 sentences or shorter. Otherwise paraphrase it. Indicate if its a quote or paraphrase by using quotation marks on page number for the former and only a page number for the latter. If no clear main conclusion can be given, indicate this and briefly explain why.</p>	<p>As it stands, NHST is an incoherent and misleading tool, which results are unfit to be used as evidence for or against the null hypothesis. (p. 26)</p>
Stance	<p>Bottom-line conclusion that can be expressed in a few words or a short sentence. These stances are to group paper according to general similarities in their conclusion. The list of (possible) stances will be identified as the papers are read and data are extracted.</p>	<p>EXAMPLE</p> <p>Use estimation</p> <p>Stop using NHST and p-values</p> <p>Use Bayesian methods</p>

Argument content of the papers. The papers contain arguments against NHST in the form of *deficiencies of the method* and *misinterpretations of the results, concepts, and procedures*. The papers can also contain

arguments in favor of NSHT and solutions that remedy one, some, or all of the problems of NHST discussed in the paper.

An argument is constituted as a claim defended by appeal to some evidence and is generally embedded in rhetoric. Arguments can span from one sentence to several paragraphs, though can be summarized as, for instance, 'NHST is/has ...' which is supported by an reference to (assumed) common knowledge, other literature, mathematical proof, empirical research, or data simulations.

The list of (possible) arguments will be identified as the papers are read and data are extracted. Data on the arguments per paper are extracted by indicating if the arguments are presented in the paper and what kind of evidence is given in the paper to support each argument.

Item name	Item description	Possible values or examples
Presence of <Deficiency argument #x against NHST>	Is this deficiency discussed as an argument against NHST?	POSSIBLE VALUES: Yes No
Evidence for <Deficiency argument #x against NHST>	What kind of support is given for the argument and/or how is the argument explained. This can be done via reference to other published research, examples, mathematical proofs, data simulations	POSSIBLE VALUES: References

		<p>Example(s)</p> <p>Mathematics</p> <p>Simulation(s)</p>
<p>Presence</p> <p>of <Misconception</p> <p>argument #x against</p> <p>NHST></p>	<p>Is this misconception discussed as an argument against</p> <p>NHST?</p>	<p>POSSIBLE</p> <p>VALUES:</p> <p>Yes</p> <p>No</p>
<p>Evidence for</p> <p><Misconception</p> <p>argument #x against</p> <p>NHST></p>	<p>What kind of support is given for the argument and/or</p> <p>how is the argument explained. This can be done via</p> <p>reference to other published research, examples,</p> <p>mathematical proofs, data simulations. Give each</p> <p>individual piece of evidence its own cell in the data set. If</p> <p>references are used, specify each individual reference in</p> <p>APA style (author names and year of publication)</p>	<p>POSSIBLE</p> <p>VALUES:</p> <p>References</p> <p>Example(s)</p> <p>Mathematics</p> <p>Simulation(s)</p>
<p>Presence of <Argument</p> <p>#x in favor or NHST></p>	<p>Is this argument that defends or supports NHST discussed</p> <p>in the paper?</p>	<p>POSSIBLE</p> <p>VALUES:</p> <p>Yes</p> <p>No</p>

Evidence for <Argument #x in favor or NHST>	What kind of support is given for the argument and/or how is the argument explained. This can be done via reference to other published research, examples, mathematical proofs, data simulations	POSSIBLE VALUES: References Example(s) Mathematics Simulation(s)
Presence of <Solution #x for NSHT problem(s)>	Is this solution presented in the paper	POSSIBLE VALUES: Yes No
Evidence for <Solution #x for NSHT problem(s)>	What kind of support is given for the solution and/or how is the solution explained. This can be done via reference to other published research, examples, mathematical proofs, data simulations	POSSIBLE VALUES: References Example(s) Mathematics Simulation(s)

Appendix A

Arguments, solutions, and conclusions

Table A contains the labels and descriptions of the arguments, solutions, and conclusions, and in which paper they are present. The online dataset contains additions information, such as example quotes and the results of the thematic synthesis. The dataset can be accessed through <https://osf.io/bkftfx/>

Table A. Overview of the deficiencies, misconceptions, NHST defenses, solutions, and conclusions. Each item has a label, a description and a list of the papers in which the item is present.

Deficiencies		
Label	Description	Present in
P-values underestimate the probability of the data	P-values do not exactly represent the probability of observing these results or more extreme based on chance, but overestimate it some degree. This is due to regular use of researcher's degrees of freedom ('Garden of forking paths) in the optimistic case and optional stopping, file drawer problem, and p-hacking in the pessimistic case.	Gelman, 2013 Bradley, 2016 Garamszegi, 2017
P-values overestimate the effect size	If there is an effect, analysis results with mathematically correct p-values overestimate this effect (to more than an order of magnitude for small effects).	Gelman, 2013 Chen, 2017 Hasley, 2015 Szucs, 2017 Bradley, 2016 Garamszegi, 2017
P-values by themselves are insufficient for inference and decisions	P-values are not sufficient for making decisions, because they do not take into account the effect size, costs, benefits, etc. Also, p-values are a very rough summary of the data; they do not provide a complete enough picture of the data.	Hupé, 2015 Chang, 2017
NHST only provides information against the null hypothesis	NHST inference based on p-values is incapable of distinguishing between evidence of absence and absence of evidence.	Hupé, 2015 Konijn, 2015 Garamszegi, 2017 Johanson, 2011
NHST inference neglects possible alternative hypotheses.	The results from the NHST procedure are indifferent to the plausibility of alternative hypotheses that are being considered.	Hofmann, 2011
NHST needs sufficient precision	NHST inference only functions properly when, one has enough precision to confidently reject the null hypothesis. Specifically, one needs a large sample of measurements with low bias and low variance.	Gelman, 2018 Hasley, 2015
Statistical significance does not guarantee practical/theoretical significance.	Rejecting H0 based on a low p-value does not guarantee that the measured effect size is large or meaningful. Results from data showing meaningless discrepancies (e.g., treating 1000 people for one extra positive result) can be statistically significant.	Dienes, 2018 Chen, 2017 Cumming, 2013 Citrone, 2011
NHST is insensitive to the specificity of H1	NHST inference is insensitive to how precise or vague the alternative hypothesis (H1) is that followed from the theory with respect to the null hypothesis (H0).	Dienes, 2018 Baird, 2016
NHST is an incoherent hybrid of two schools of statistics	NHST is an incoherent hybrid of two school of statistics, the Fisher's inductive test of statistical significance and Neyman and Pearson's decision theoretic hypothesis testing. For instance, the former is concerned with a single hypothesis and a continuous inference indicator. The latter is concerned with two hypotheses and decisions between the two are based data falling in a pre-	Haig, 2017 Schneider, 2015 Perezgonzalez, 2014 Lambdin, 2012

	specified critical region, which is determined by the hypotheses and acceptable Type I and Type II error probabilities.	Bradley, 2016 Hubbard, 2011 Engman, 2013 Schneider, 2015
The Neyman-Pearson hypothesis test has limited applicability	Neyman-Pearson's test (part of NHST) is considered to be theoretically consistent and is generally accepted as 'frequentist orthodoxy' in mathematical statistics. However, the price for theoretical clarity leads to restricted utility in applied scientific work. For instance, it does not allow inference from the observed data.	Schneider, 2015
P-values rely on unobserved results	P-values are based on the tail area of probabilities under the hypothesis. They are probabilities of the observed results and more extreme results, results that have not actually occurred, which is considered problematic. In the words of Jeffreys' "[a] hypothesis that may be true may be rejected because it has not predicted ... results which have not occurred"	Schneider, 2015 Johanson, 2011
The 'stopping- rule' paradox	When there are two similar studies - the same number of observations, the same treatments, and the same results - there can be different p-values and thus different conclusions, just because the two researchers had different sampling plans for their respective studies.	Schneider, 2015
P-values do not measure evidence	P-values do not measure evidence, because their calculation involves only one hypothesis and are based on unobserved data. As defined, an inductive measure of statistical evidence is the relative support given to two hypotheses by the observed data. The sample space has become irrelevant after the data is observed.	Schneider, 2015 Johanson, 2011
NHST violates the hypothesis imperative	For certain statistical models, the p-value is considered a transformation of the likelihood ratio, where the likelihood of H0 is compared to a post hoc, data-suggested H1 (i.e., the maximum likelihood versus H0). This approach violates the imperative to specify hypotheses before the data are observed.	Schneider, 2015
P-values overestimate the evidence against H0	From the perspective of likelihood and Bayesian methods, p-values overstate the evidence against H0. Especially in the interval between significance levels 0.01 and 0.05 odds against H0 can be far removed from 1:100 and 1:20 respectively, and can therefore can highly misleading indicators of evidence.	Schneider, 2015 Marsman, 2017 Konijn, 2015 LeBel, 2011 Johanson, 2013
NHST requires data to be IID	Paramount to frequentist tests is randomization (i.e., random assignment and probability sampling). Such randomization ensures a known probability distribution for the possible results under a specified hypothesis. It capitalizes on what, in principle, would happen if one were to generate independent repeated samples by the same process, because it then becomes possible to represent the uncertainty in the parameter estimates. For this notion of "repeated random sampling", it is required that the data come from an ongoing stream of independent, identically distributed (IID) values. In some cases nature is capable of producing such an ongoing stream of iid values and in theory an infinite number of identical experimental trials could be setup to mirror this. However, much research in the social sciences cannot fulfill this IID requirement.	Schneider, 2015
H0 is (almost) always false	Nil null hypotheses are in general implausible to begin with in non-experimental studies. Even in experimental studies, they are never perfectly true. It could be argued that H0 is just a 'straw man' and that it is most likely false to begin with. However, in either case (H0 is false or assumed to be false), the practice of NHST becomes uninformative and resulting p-values meaningless.	Schneider, 2015 Trafimov, 2013 Marsman, 2017 Hupé, 2015 Rao, 2016 Klugkist, 2011 Hasley, 2015 LeBel, 2011 Lambdin, 2012 Szucs, 2017 Baird, 2016
NHST is sensitive to assumption violation	When one or more of the model assumptions are violated, p-values are biased and difficult to interpret for NHST inference.	Schneider, 2015 Garamszegi, 2017
P-values are inaccurate estimators of the probability of H0	P-values are generally inaccurate estimators of probabilities of null hypotheses. Only under very specific circumstances do the probability of the data under H0 and the probability of H0 given the data match.	Trafimov, 2013 Hupé, 2015 Goddard, 2015
NHST results are not informative about the probability of H0	If one were to meet the conditions necessary to make p-values valid indicators of probabilities of H0, then this would preclude one from gaining much information from the NHST inference procedure.	Trafimov, 2013 Lambdin, 2012
Low correlation between p-values and the probability of H0	There is a low correlation between the continuous measure of p-values and probabilities of null hypotheses. This correlation is decreased to triviality when p-values are dichotomized into "accept" ($p \geq 0.05$) or "reject" ($p < 0.05$) regions.	Trafimov, 2013
P-values are highly variable	P-values are highly variable between similar tests of the same true effect. Specifically, an identical replication of a test with which reported a one-sided p-value of 2.5% would have a 95% confidence-interval for the p-value ranging from 0 to 79%.	Lu, 2015 Cumming, 2014 Cumming, 2013 Klugkist, 2011 Hasley, 2015

NHST does not condition on the data	When performing NHST on a particular dataset, the results do not tell us the probabilities of committing a Type I when H0 is rejected or a Type II error when H0 is not rejected in this particular case.	Hupé, 2015
Multiple testing paradox	When there are two similar studies - the same number of observations, the same treatments, and the same outcomes - there can be different p-values and thus different conclusions on the same hypotheses, because one researcher had one or more additional hypotheses to test on the data or performed some extra exploratory analyses.	Hupé, 2015
Large N problem	The problem is that for any discrepancy from the H0, however small, there is a sample size that one can be (almost) certain that a test will the rejection of H0 for any significance levels, however small.	Rao, 2016 Szucs, 2017 Baird, 2016
P-values are only vague indicators of replicability	Independent of the sample size, if an original experiment that gives a two-tailed p-value of 0.05, then an 80% prediction interval for a one-tailed p-value in a replication study is [0.00008, 0.44].	Cumming, 2014
Fisher's and Neyman and Pearson's theories are made to be confusion	The theories of Fisher and Neyman and Pearson use the same tests, similar procedures, and similar concepts. It is therefore hard to keep them apart and disentangle them. Better education and careful use is thus hindered by this superficial overlap.	Perezgonzalez, 2014
NHST follows a flawed logic	NHST operates by modus tollens: one rejects the antecedent (the hypothesis) if the consequent is false (predicted observation). However, if the consequent is unlikely (e.g., the probability of the data), this does not mean that this is sufficient for the rejection of the antecedent.	Hofmann, 2011 Szucs, 2017
NHST provides only ambiguous evidence	The exclusive reliance on NHST makes positive results (i.e., rejection of H0 in favor of an H1) ambiguous, because such results can be explained by flaws in the way NHST is implemented rather than by a more theoretically interesting mechanism.	LeBel, 2011 Garamszegi, 2017
NHST does not provide the probability of H0	NHST on its own does not tell us what many researchers are interested in, namely the probability of H0 given the new data. It gives us something much less informative, namely, the probability of the data given that H0 is true.	LeBel, 2011 Garamszegi, 2017 Engman, 2013
NHST only provides a weak test	NHST does not provide strong tests of theoretical hypotheses, because it only requires the rejection based on the data of what the theory does not predict.	LeBel, 2011 Baird, 2016
Multiple comparison correction is problematic	In most cases, Type 1 error adjustment across tests only leads to power reduction and an overestimation of the population effect size	Lambdin, 2012
NHST does not allow knowledge integration	NHST does not offer a formal mechanism for systematic knowledge accumulation and integration. It specifically requires that tests are independent.	Szucs, 2017
The null hypothesis often does not make sense	With NHST, H0 is a statement about the absence of an effect. However, in many cases such a hypothesis embodies nonsensical situations. In these situations, small p-values merely indicate that a silly H0 was considered to evaluate the data.	Garamszegi, 2017
NHST is based on questionable logic	H0 is considered to be true for the calculation of p-values. If H0 is rejected this means that H0 is considered to be false from a calculation that assumes it to be true.	Szucs, 2017 Martin, 2014 Engman, 2013
NHST violates the likelihood principle	NHST is based on unobserved results and sampling plan, which violates the likelihood principle.	Johanson, 2011
NHST has hidden and unknowable subjectivity	The fact that NHST relies on unobserved data in a sampling distribution has curious consequences. For instance, the intentions of what the researcher actually did and would have done in certain circumstances determine the sample space and thus the outcome of the test. This means that the resulting p-values are affected by what is locked in the researcher's head.	Johanson, 2011
NHST is useless	Although many have repeatedly called for evidence, to this moment no one has shown that decision making improves or scientific knowledge advance due to the application of NHST.	Lambdin, 2012
False protection against false positive results	NHST with a low alpha (significance threshold) does not protect us from false positive results. The ratio of false positive results can only be minimized by keeping bias and probability odds of H0 and H1 low and power high, which is not offered by the NHST procedure.	Szucs, 2017

Misconceptions

Label	Description	Present in
P-values as effect sizes	Small p-values (statistical significance) are often equated with high effect sizes of practical/theoretical significance.	Rourse, 2016 Haggsrom, 2017 Schneider, 2015 Chen, 2017 Lu, 2015 Perezgonzalez, 2015 Engman, 2013
Statistical significance dichotomy	P-values below the significance threshold are often equated with the truth of H1, while p-values above this threshold are equated with the truth of H0.	Rourse, 2016 Gelman, 2013 Häggström, 2017 Schneider, 2015 Trafimov, 2016

		Chen, 2017 Lambdin, 2012 Perezgonzalez, 2015 Szucs, 2017 Engman, 2013
P-hacking is acceptable	If H1 is true, whatever H1 might be, when $p < 0.05$ it is often considered acceptable to run multiple tests on the data and only report those that produced such a small p-value. Other practices are also considered acceptable, such as different criteria for outlier exclusion or binning of variable to reach a significant p-value.	Rouse, 2016 Häggström, 2017 Konijn, 2015 Szucs, 2017 Garamszegi, 2017
Chasing noise	People have the tendency to see structure in data where there is none, when p-values are low but the sample size is so high as to make a negligible effect statistically significant. Or they fail to see structure where there is structure, when p-values are high, but the sample size is too small to make a meaningful effect statistically significant.	Gelman, 2018 Häggström, 2017
P-values as the probability of H0	P-values, the probability of these data or more extreme given H0, are often misconceived as the probability that H0 is true given these data.	Haig, 2017 Häggström, 2017 Schneider, 2015 Chen, 2017 Klugkist, 2011 Lambdin, 2012 Szucs, 2017 Engman, 2013
Confidence interval misinterpretation	X% Confidence intervals, the product of a procedure that ensures that X% of the confidence intervals contain the true parameter value, are interpreted as X% credible intervals, the X% probability that the parameter values lies within the interval.	Häggström, 2017
Unwarranted comparison	Often comparisons are made between tests that are not warranted by the procedure. For instance, when there is statistical significance in a test for one group, but not the other, it is assumed that the difference between the groups is also significant.	Häggström, 2017
Neglect of multiple testing	The necessity of correction for multiple testing is often neglected. Specifically, p-values are considered to retain their meaning when more than one test is used on the same data.	Häggström, 2017 Garamszegi, 2017
P-values as replication index	Many researchers believe that 1 minus the p-value is the probability that the findings will replicate in a follow-up study.	Haig, 2017 Trafimov, 2016 Lambdin, 2012
H0 Likelihood as its credibility	Often researchers mistake the likelihood of H0 or the likelihood ratio of H0 and the maximum likelihood as the credibility of H0	Haig, 2017 Lambdin, 2012
Conceptual confusion of p-values	Researchers often confuse the meaning of 'statistical significance'. Routinely, p-values are misinterpreted as both the 'observed' Type I error probability and at the same time the amount of evidence against H0.	Schneider, 2015
Logic violations	Researchers often misconceive the NHST procedure as being based on solid deductive logic of modus tollens. However, a) modus tollens is concerned with non-probabilistic propositions (not probabilities of data under H0) and b) rejection the antecedent (H0) in favor of an alternative (H1) is only allowed when this alternative is its complement (not-H0) and not one of many possible alternatives.	Schneider, 2015
Assuming that H0 is true when the p-value is high	Many researchers, after finding that $p > \alpha$, commit the mistake of concluding that H0 is true (e.g., there is no effect / no difference). However, this is inconsistent with Fisher's theory where one is supposed to conclude that the results are inconclusive. It is also inconsistent with the Neyman-Pearson theory where one is supposed to behave as if H0 is true when one fails to reject it, but is not concerned with its actual truth.	Schneider, 2015 Konijn, 2015 Szucs, 2017
P-values as the probability that results are due to chance	Many researchers believe that the p-value is the probability that a result is due to chance alone (i.e., sampling error). If H0 is considered the 'chance model' and p-values are calculated based on this model, then the probability of these data resulting from chance alone is taken to be 1. It is thus illogical to view p-values as somehow being the probability of chance.	Schneider, 2015 Trafimov, 2016 Lambdin, 2012
P-values as the realized Type I error probability	Often researchers interpret the p-value as the conditional probability of committing a Type I error when rejecting H0. Alpha is pre-data fixed probability of Type I error that applies only to infinitely random selections from the same finite population. It does not apply to any actual result of a single experiment. A p-value is the probability of observing the result from this single experiment or more extreme if H0 is true. Thus it is a mistake to believe that $p < 0.05$ given $\alpha = 0.05$ means that there is a 5% probability that the decision to reject H0 in this a Type I error.	Schneider, 2015 Lambdin, 2012 Szucs, 2017 Martin, 2014 Hubbard, 2011
Power overestimation	In general, scientists underestimate the number of observations (amount of data) needed to observe a particular effect with an acceptable probability. Almost in all cases more data is needed than people expect to obtain sufficient power.	Hupé, 2015 Lambdin, 2012
Hypothesizing after the results are known	Many researchers do not see any problem with performing several analyses on their data and reporting significant as if they were hypothesized before the data was collected.	Szucs, 2017
Non-random sampling	Often researchers use and see no problem with using convenience samples, systematic samples, or even entire populations even though NHST requires random sampling.	Engman, 2013

Low p-value bias	Many researchers often see high p-values as uninteresting and not worthy of publication.	Szucs, 2017 Bradley, 2016
Continued sampling	Many researchers have the tendency to add additional participants to a sample if the p-value is not yet below 0.05, but appears to be close.	Konijn, 2015 Szucs, 2017
False sense of objectivity	Although believed, the NHST procedure does not lend objectivity to the process of making inferences. Sampling plan intentions and decisions during data management and analysis affect the eventual p-value.	Lambdin, 2012 Engman, 2013
Large sample confidence	Generally, scientists place more confidence in p-values obtained with larger sample sizes than smaller sample sizes. This is a misconception, because large studies with p-values just below 0.05 are more indicative for than against H0.	Lambdin, 2012
Inference mismatch	Many researchers see p-value as a tool for inference from population parameters to their research hypothesis and scientific theory, while it is concerned with inference from sample statistics to population parameters.	Lambdin, 2012 Szucs, 2017
P-values for information about individual sample members	In many cases, scientists take p-value as telling something about the individual members of the sample. This is a misconception, because p-values are about the sample as a whole, not the specifics of individual members.	Lambdin, 2012
P-values as the conditional probability of H1	Often, p-value are interpreted as the probability that H1 is false based on the observed data.	Lambdin, 2012
P-values as a measure of confidence	The misconception that p-value quantify the confidence one should have in the veracity of H0 or, similarly, the confidence one should have that the researcher's hypothesis is false.	Lambdin, 2012
Levels of statistical significance	Scientists divide p-values in level of significance, from 'marginally significant' ($0.05 > p > 0.1$) to 'highly significant' ($p < 0.001$) and pick their level of significance after the p-value is calculated, even though alpha should be fixed in advance.	Lambdin, 2012 Szucs, 2017
P-values as indicator of methodological quality	A significant result is taken to exonerate the methodology used. A non-significant result is taken to be explainable by bad methodology (not a wrong research hypothesis).	Perezgonzalez, 2015 Szucs, 2017
P-values and true/false positive probability	This misconception concerns the confusing a p-value (1 minus p-value) with the with the post-experiment probability of False Discovery Rate (True Discovery Rate) given a significant test result, $\Pr(H0 p)$ ($\Pr(H1 1-p)$).	Szucs, 2017
Rituals and blind procedures	In most cases, the NHST application is ritualistic. The null hypothesis value and critical value are predetermined by convention and many important conditions are ignored, such as the hypothesized effect size and the relative seriousness of Type I versus Type II error.	Baird, 2016

NHST defenses

Label	Description	Present in
Add confidence intervals to NHST results	Inferences from p-values are okay if they are accompanied by confidence interval, because they express the uncertainty around the effect size estimate.	Rouse, 2016
Combine NHST with replications	P-values as inference criterion are okay if studies replicate. Specifically, the use of low p-values as evidence against H0 and in favor of H1 is okay when results are shown to reproduce and replicate.	Rouse, 2016
NHST with high power and reliability	Using high p-values as evidence in favor of H0 is okay when the a-priori power for the expected effect was high and the scores/study/data is found to be reliable.	Rouse, 2016 Chen, 2017
NHST with rich null model	The null hypothesis should be interesting and meaningful in itself. Specifically, when the default "null model" is a rich and complex model, fit using efficient methods to large and carefully modeled data, a NHST targeted to the effects of interest can become quite compelling.	Laber, 2017
Use NHST for what it is supposed to	NHST was never designed to find out whether or not a hypothesis is true or quantify the probability of this hypothesis, but works fine when used properly. The NHST procedure is supposed to derive the probability distribution that a test statistic computed from the data would have if the null hypothesis were true. This result is then to be used as a reference to make a decision to reject or not to reject H0.	García-Pérez, 2017
NHST serves another purpose than quantifying confidence	NHST results cannot be used to quantify confidence or to indicate whether believing the null to be false is meaningful. However, NHST is not supposed to quantify this confidence, but it serves its given purpose just fine.	García-Pérez, 2017
NHST cannot be replaced by estimation	Effect-size estimates and confidence intervals serve another purpose than hypothesis testing, namely estimation. Therefore, they cannot be considered a universal substitute for NHST.	García-Pérez, 2017
NHST offers something that Bayes factors do not	More often than not, we would want to know, quantify, and control the rates of false positives and false negatives. For instance, one wants to keep faulty decisions to an acceptable minimum when it comes to allowing new medication in circulation. Hypothesis testing via Bayes factors comes with a continuous measure of evidence and approach intentionally avoids dichotomous decisions. In so doing, it forfeits the possibility of quantifying error rates.	García-Pérez, 2017
P-values offer as much as Bayes factors	When it comes to one-sided p-values, Bayes factors do not carry any information that is not also in the p-value for a given sample size. The Bayes factor is only a transformation of the p-	García-Pérez, 2017

	value. This can be anticipated, for instance in the case of a t-test, from the fact that the Bayes factor is determined by the value of the test statistic and the sample size, just like the p-value..	
Scientists draw inferences, NHST provides a framework	Switching to using only descriptive statistics in scientific papers does not stop scientists from drawing inductive inferences from their results. The problematic difference is, without the NHST there is not inferential framework for the guidance and control of such inferences.	García-Pérez, 2017
NHST is well suited to assess goodness-of-fit	NHST procedures are well suited to assessing goodness-of-fit and model comparisons via the empirical proportion of significant p-values across replicates, which are readily computed when models are fitted individually to each participant and condition within or across studies. On the other hand, that model-comparison approaches based on metrics detached from an inferential framework are bound to render incorrect dichotomous decisions that capitalize on sampling variability and do not do justice to the data.	García-Pérez, 2017
Point hypothesis are always false, not just for NHST	The objection raised against NHST that H_0 (whether null or non-null) is always false is also an objection against all other hypothesis testing procedures that test point hypotheses. Any hypothesis involving a single value of a continuous parameter is false by definition.	García-Pérez, 2017
If confidence interval are fine, then so are p-values	There is a mathematical equality between CI boundaries and the acceptance limits of the null hypothesis.	van Helden, 2016 Savalei, 2015
NHST controls false discovery rate	Having a hard criterion like fixed acceptable Type I error probability α for the approval of such things as drugs developed by companies that have a vested interest without allowing prior knowledge or subjective judgment caps the rate at which false positives are put on the market or introduced into the academic literature.	Chang, 2017
NHST is intuitive	At the heart of NHST is a simple, intuitive, and familiar “common sense” logic. A logic which most people routinely use when they are trying to decide whether what they have observed might have happened by coincidence. Something one observes might be unexpected based on one’s model of the world (e.g., $p < 0.5$), but not so unexpected that one would change this model (e.g., $p > 0.05$).	Miller, 2017
NHST not more misused	There is no empirical evidence that NHST is more often misused than any other procedure.	Miller, 2017 Savalei, 2015
NHST is not necessarily more easily hackable than others	When questionable research practices are used to artificially reduce the p-value below the significance threshold, it is called p-hacking. Other methods, like hypothesis testing with Bayes factors are just as vulnerable; they are b-hacked just as easy.	Savalei, 2015
Sampling plans must be taken into account	If one wants to assess if something will happen “by chance”, then this is only possible within a well-defined set of possible outcomes. In turn, these outcomes are determined by the sampling plan. Thus, the sampling plan must influence the probability assessment. It follows that any conclusion about the presence of data pattern that is unusual enough to warrant further investigation would depend on both the sampling plan and the actual observations.	Miller, 2017
Probabilities of the data is often all we have	If one is interested in the probability of an explanation/hypothesis given observed data, one needs to take into account all relevant alternative explanations and their probabilities prior to observing the data. In many cases, the complete set of other possible explanations of the observed data and their probabilities are simply unknown. In these situations, it is impossible to compute the probability of these explanations given the data. All that can be done is compute the probability of these data given a hypothesis. NHST should therefore not be criticized for failing to provide something that cannot be determined with any other technique either.	Miller, 2017

Solutions

Label	Description	Present in
Open post-publication review	Move from flagship-journal pre-publication closed review to an (Arxiv and PubPeer) open post-publication review.	Gelman, 2018
Preregistration	Preregister data collection and analysis plan	Gelman, 2018 Lu, 2015 Cumming, 2014 Szucs, 2017
Increase measurement quality	Reduction of measurement error (e.g., from between to within-subject design)	Gelman, 2018
Display data	Show as much of the data as possible and use things like multiverse analysis	Gelman, 2018 Hupé, 2015
Bayesian parameter estimation	Use Bayesian methods for estimation, uncertainty quantification, inference.	Gelman, 2018 Schneider, 2015 Szucs, 2017
Bayes factor hypothesis testing	Use Bayesian hypothesis testing via Bayes factors	Dienes, 2018 Klugkist, 2011

		Konijn, 2015 LeBel, 2011 Campitelli, 2017
Visualization Model Comparison	A process combined from three strategies: 1) visualization of the theoretical process and data predications; 2) visual representation of data distributions and choice of appropriate distribution of analysis; and 3) model comparison (e.g., GAMLSS, multilevel, Generalized Linear Model, etc.)	
Neo Fisherian test of significance	A reformulation of Fisher's original perspective. 1) No Type I error rate is specified; 2) p-values are used as a continuous measure; 3) judgment is suspended based on high p-values; 4) "three-valued logic" that gives information about the direction of the effect being tested is adopted (see Tukey's Three Decision Rule); 5) information about effect-size and confidence interval is provided; and 6) a clear distinction is made between statistical and substantive significance.	Haig, 2017
Error statistical theory	A perspective on probability and statistics from Deborah Mayo that combines the perspectives of Fisher and Neyman and Pearson in a way that complement each other instead of forming something incoherent.	Haig, 2017
Stop using NHST	The best solution is to simply stop using NHST as practiced, at least with non-experimental data.	Schneider, 2015
NHST with strict guidelines	If NHST is used, it should be done in a judicious way where its influence is restricted to its rightful epistemic level.	Schneider, 2015 Szucs, 2017
Information theoretic inference	Comparing of data to model fit between models based on information theoretic criteria (e.g., AIC, BIC, K-L distance, etc.)	Schneider, 2015 Szucs, 2017
Likelihood ratio inference	Assessing relative evidence for simple hypotheses based on the likelihood of the data.	Schneider, 2015 Szucs, 2017 Johanson, 2011
Graphical display without hypotheses	Simple, flexible, informal and largely graphical techniques of exploratory data analysis, aim to enable data to be interpreted without statistical tests of any kind	Schneider, 2015
Frequentist parameter estimation	If we stick to the frequentist philosophy, we should switch to parameter estimation. Specifically, scientists need to report estimates of effect sizes with CIs and discuss in greater detail the sampling process and perhaps even other possible biases such as measurement errors.	Schneider, 2015 Hupé, 2015 Cumming, 2014 Cumming, 2013 Hasley, 2015 Szucs, 2017
Much larger samples	To address the problem of sampling error we need to use large samples. The need for NHST primarily exists in low power situations. If one increases power, sampling error decreases, and the need for NHST diminishes.	Schneider, 2015 Savalei, 2015
Meta-analyses	Single p-values tells you nothing about the reliability of a specific result. For knowledge accumulation we need meta-analyses of several well-performed studies to assess the veracity of certain results. NHST should play a little or no role in meta-analyses.	Schneider, 2015 Chen, 2017 Hupé, 2015 Cumming, 2014 Cumming, 2013 Lambdin, 2012 Perezgonzalez, 2015
Tukey's Three Decision Rule	Use a setup where one test the point H0 and two directional alternative hypotheses. One first test if one can reject H0 based on some decision rule. If this is the case, one decides that the parameter of interest is larger (smaller) than H0 predicted based on the observed results. So the actual goal is not to test H0, but determine whether it is reasonable to make a decision about whether the parameter value is greater or less than H0 predicted.	Wilcox, 2017
Interval null hypothesis	Use an interval null hypothesis that contains the values that are considered negligible and excludes the values that are considered practically meaningful	Rao, 2016 Baird, 2016
Uniformly Most Powerful Bayesian Test	Set prior assumptions / assumed parameter value / prior distribution of the alternative model/hypothesis so that it maximizes the probability that the posterior probability of H0 will fall below a certain threshold (e.g., 0.05)	Goddard, 2015 Szucs, 2017
Reconceptualization	Reconceptualize Fishers' significance test and N-P's hypothesis test to ensure they do not share concepts and reduce the likelihood of their confusion and increase the likelihood of appropriate use	Perezgonzalez, 2014
Number Needed to Treat	Transform effect-sizes to an NNT (number needed to treat). This is a number that is intuitive and makes clear how meaningful the observed effect size is.	Citrone, 2011
Require direct replications	The scientific literature would benefit greatly from a stronger emphasis on close (relative to conceptual) replication.	Schneider, 2015 Lebel, 2011 Perezgonzalez, 2015 Szucs, 2017 Savalei, 2015
Verify procedure	More emphasis should be placed on verifying the integrity of empirical procedures (e.g., validation, reliability assessment, pilot studies).	Lebel, 2011

Strong NHST	A switch should be made to a form of NHST in which the null hypothesis is a theoretically derived point value of the variable of interest. The researcher then attempts to reject this hypothesis based on the observed data	Lebel, 2011
Open science	We should require authors to make all raw data and/or a detailed documentation of all analytical steps (including data transformations, etc.) publicly available.	Szucs, 2017 Savalei, 2015
Improve education	Better education is the best path to solving the myriad and persisting misunderstandings of NHST.	Miller, 2017 Szucs, 2017
Context dependent Type I and Type II error probabilities	The NHST Type I and Type II error thresholds should be set based on the particular context of the study.	Bradley, 2016 Baird, 2016
Minimum-effect testing	In this framework one tests against a "negligibly small or trivial" effect, instead of a null effect. Thus, minimum effects testing can test against more realistic hypotheses.	Baird, 2016
Context dependent NHST	This is a combination of "Minimum-effect testing", "Interval null hypothesis", and "Context dependent Type I and Type II error probabilities"	Baird, 2016
Proper use of NHST	A) Make sure that auxiliary assumptions (normality, homoscedasticity, etc ...) are carefully checked before applying a statistical test. B) Use adequate multiple testing corrections. C) Use a H0 that makes sense. D) correct interpretation of p-values. E) Report all relevant information and statistics. F) report non-significant results.	Garamszegi, 2017
P-values as indicators of plausibility	p-value can be interpreted as a plausibility that the null hypothesis is true. "plausibility" is precisely defined within the inferential model (IM) framework and is built upon two fundamental principles for valid and efficient statistical inference.	Martin, 2014
Include statisticians	Enhance the training of professional applied statisticians and to ensure that all research involves knowledgeable statisticians or equivalent methodologists.	Szucs, 2017

Conclusions

Label	Description	Present in
Disentangle N-P and Fisher	The statistical approaches of Fisher and Neyman-Pearson should be separated from each other and used distinct from each other	Perezgonzalez, 2014 Bradley, 2016 Hubbard, 2011
Use context dependent NHST	The Type I and Type II error rates and the specification of H0 should depend on the (context of) the particular research question and study design at hand	Baird, 2016
Improve general research practice	The general research practices of scientists should be improved. This extends to research design and protection against biases, such as preregistration and replication studies	Gelman, 2018 LeBel, 2011 Savalei, 2015
Use NHST with care and proper practice	We should continue to use NHST, but this should be done by adhering to the assumptions of method and following guidelines of analysis and reporting	Rouse, 2016 Häggström, 2017 Lu, 2015 Laber, 2015 Garcia-Perez, 2017 van Helden, 2016 Chang, 2017 Miller, 2017 Perezgonzalez, 2015 Garamszegi, 2017
Use estimation	We should use some form of frequentist estimation; for instance confidence intervals	Hupé, 2015 Cumming, 2014 Cumming, 2013 Citron, 2011 Hasley, 2015
Use Bayesian methods	We should use a type of Bayesian inference, either estimation based on posteriors or hypothesis testing based on Bayes factors	Dienes, 2018 Goddard, 2015 Klugkist, 2011 Konijn, 2015 Engman, 2013
Stop using NHST and p-values	We should stop using NHST and p-values all together, period	Gelman, 2013 Schneider, 2015 Trafimov, 2016 Trafimov, 2013 Lambdin, 2012
Use sound version of test of statistical significance	We should conceptualize and restructure to ensure a sound and coherent frequentist test of statistical significance	Haig, 2017

Use Likelihood ratios	We should use likelihood ratios to test our statistical hypotheses	Johanson, 2011
Use interval-null hypothesis testing	We should use an interval to test our null hypothesis in NHST	Rao, 2016
Use something else than NHST	We should use something else than NHST (papers of this persuasion recommended numerous and distinct alternatives without favoring one of them)	Campitelli, 2017 Hofmann, 2011 Szucs, 2017
Use robust version of NHST	Use techniques that do not result in misleading p-values, such as 'Tukey's three decision rule' (This is a particular conclusion from a particular paper that could not be meaningfully grouped with any of the conclusions of the other papers)	Wilcox, 2017 Marsman, 2017
Use NHST with complete reporting	We should continue to use NHST, though with the complete reporting of all analyses and statistics	Chen, 2017
Reinterpret p-values	P-values should be reinterpreted as the plausibility of an inferential model ((This is a particular conclusion from a particular paper that could not be meaningfully grouped with any of the conclusions of the other papers)	Martin, 2014