Probabilistic Misconceptions Are Pervasive Among Communication Researchers

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Abstract

Across all areas of communication research, the most popular approach to generating insights about communication is the classical significance test (also called null hypothesis significance testing, NHST). The predominance of NHST in communication research is in spite of serious concerns about the ability of researchers to properly interpret its results. We draw on data from a survey of the ICA membership to assess the evidential basis of these concerns. The vast majority of communication researchers misinterpreted NHST (91%) and the most prominent alternative, confidence intervals (96%), while overestimating their competence. Academic seniority and statistical experience did not predict better interpretation outcomes. These findings indicate major problems regarding the generation of knowledge in the field of communication research.

Keywords: Statistical inference; misconceptions; confidence intervals; significance testing

Probabilistic Misconceptions Are Pervasive Among Communication Researchers

In communication, just as in many other academic disciplines, statistical inference is a central tool for drawing substantive conclusions from previously collected data. It would seem to go without saying that given their central role in the production of disciplinary knowledge, researchers should have a solid understanding of the techniques they routinely apply in addressing their research questions. Among the most widely used tool for statistical inference in communication research, without a doubt, is null hypothesis significance testing (NHST) (Levine, Weber, Hullett, Park, & Lindsey, 2008). However, despite its omnipresence in communication and other disciplines, its practice has been criticized for a variety of reasons (Kline, 2013). Levine et al. (2008) identified four major problems that bedevil the practice of NHST: (a) its sensitivity to sample size, (b) the fact that the tested null hypothesis is usually false from the beginning, (c) exceedingly high Type II error rates, and (d) widespread misunderstanding and abuse of the approach (see also Schmidt, 1996).

In this paper, we focus on the last of these problems and for the first time provide empirical insights into the magnitude of communication researchers' problems with understanding NHST. We do so by replicating earlier studies of the probabilistic misconceptions in psychology (Haller & Krauss, 2002; Oakes, 1986). In addition, we go beyond the interpretation of *p*-values and NHST and assess communication researchers' understanding of confidence intervals (CIs). CIs have often been advertised as an attractive alternative to NHST in communication (Levine, Weber, Park, & Hullett, 2008) as well as other fields (e.g., Fidler & Loftus, 2009; Schmidt & Hunter, 1997; Wilkinson & the Task Force on Statistical Inference, 1999), not least because they are expected to provide richer, more comprehensible information on which to base conclusions than *p*-values (Cumming & Fidler, 2009, p. 20). However, recent research in psychology has called into question the greater accessibility and comprehensibility of CIs for researchers as compared to NHST

(Hoekstra, Morey, Rouder, & Wagenmakers, 2014; Morey, Hoekstra, Rouder, Lee, & Wagenmakers, in press; Morey, Hoekstra, Rouder, & Wagenmakers, in press; see also Belia, Fidler, Williams, & Cumming, 2005).

We build on this research to assess the degree to which the understanding of both, NHST and CIs, poses problems to researchers in communication. In this paper, we provide the first empirical assessment of the degree to which misunderstandings of statistical inference are a problem in communication research. We conducted a survey of communication researchers to quantify the interpretation problems discussed by Levine, Weber, Hullet, et al. (2008) in absolute terms and replicate studies from psychology (Badenes-Ribera, Frías-Navarro, Monterde-I-Bort, & Pascual-Soler, 2015; Haller & Krauss, 2002; Hoekstra et al., 2014; Oakes, 1986) that allow for an assessment of the problem relative to that discipline and across time.

Method

Participants and procedure. Our sample consisted of 221 members of the International Communication Association (ICA).[1] Based on an overall ICA membership of

[1] A request was sent to the chairs of all ICA divisions and interest groups to forward the invitation to participate to their members. While not all chairs forwarded the invitation, the sample included members of all ICA divisions and interest groups existing at the time of study. The precise sample percentages for division/interest group membership were: Children, Adolescents and the Media (7.2%); Communication and Technology (33.9%); Communication History (3.2%); Communication Law and Policy (4.1%); Environmental Communication (6.3%); Ethnicity and Race in Communication (5.4%); Feminist Scholarship (3.2%); Game Studies (11.8%); Gay, Lesbian, Bisexual and Transgender Studies (3.2%); Global Communication and Social Change (6.3%); Health Communication (9.5%); Information Systems (14.0%); Instructional and Developmental Communication (5.9%); Intercultural Communication (6.3%); Intergroup Communication (9.1%); Interpersonal Communication (11.3%); Journalism Studies (8.6%); Language and Social Interaction

4,698 as of July 21, 2014 this makes for a coverage of 4.7% of all ICA members. The sample included communication researchers from all career stages: tenured faculty (*n* = 99; 44.8% of sample); non-tenured faculty (*n* = 13; 5.9%); post-docs (*n* = 9; 4.1%); graduate students (*n* = 92; 41.6%); undergraduate students (*n* = 2; 0.9%); and other researchers (*n* = 6; 2.7%).[2] In the analyses reported below, academic status groups were collapsed into a binary variable allowing for contrasts of predoc/student (undergraduate and graduate students) and postdoc/faculty researchers (post-docs, untenured and tenured faculty).[3]

ICA members were invited to participate in the online survey and were instructed on the first survey page to not consult any outside resources such as colleagues, literature, or websites when responding to the questions. The invitation message included only a generic statement that the survey would be about the interpretation of research findings. The survey was open from May 1 to May 21, 2014.

Materials

Knowledge about* p*-values and confidence intervals. Each participant was presented with a questionnaire opening with the six false statements representing common misinterpretations of significant statistical tests used by Oakes (1986) and Haller and Krauss (2002) followed by the six false statements representing common misinterpretations of

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(7.2%); Mass Communication (29.0%); Organizational Communication (10.4%); Philosophy, Theory and Critique (5.4%); Political Communication (19.0%); Popular Communication (4.5%); Public Relations (3.2%); Visual Communication Studies (3.6%); no division/interest group membership (5.9%).

[2] Answers to an open follow-up question indicated that the few cases in the “other” category included independent scholars and recent graduates on the job market.

[3] Since they could not reliably be identified as either pre- or postdoc researchers, participants in the “other” category were coded as missing for this binary indicator.

confidence intervals around a mean used by Hoekstra et al. (2014) (see Appendix for the complete questionnaire). Both sets of statements were preceded by a fictitious scenario that presented the finding of an experiment (*p*-value or 95% confidence interval, respectively). Participants were then asked to indicate for each statement whether they thought the statement was true or false by checking one of two corresponding boxes placed next to it. For both sets a “false” statement was defined as not following logically from the presented findings. This part of the questionnaire was designed to closely match the instruments used in the abovementioned studies.[4] The statements in both sets were phrased such that researchers aware of the correct interpretations of *p*-values and confidence intervals should have been able to reliably identify them as false. The false statements regarding the interpretation of a *p*-value of .01 read as follows:

1. You have absolutely disproved the null hypothesis (that there is no difference between the population means).
2. You have found the probability of the null hypothesis being true.

[4] However, we refrained from using the same story framework applied by Hoekstra et al. (2014). For the CI questions, they used (a) a fictitious professor called Bumbledorf, who looks like a mad scientist, (b) provided less information about the experiment (e.g., what kind of test statistics were computed and experimental designs were conducted), and (c) build the CI around “the” mean. Although this does not change anything about the interpretation of the answers, we thought that (a) not mentioning Prof. Bumbledorf removes possible context effects and makes it harder to find the Hoekstra et al. (2014) paper, if someone searches for the correct results on the Internet, (b) referring to the same design as in the *p*-value task makes it easier to have an idea what kind of experiment was conducted (e.g., a between-subjects and not a within-subjects design), and (c) using the description “true mean difference” makes it clear what kind of mean is meant (e.g., not the means of the control or experimental group but the mean of their difference). Thus, our modifications should lead to less interference that might be due to ambiguous context information.

3. You have absolutely proved your experimental hypothesis (that there is a difference between the population means).
4. You can deduce the probability of the experimental hypothesis being true.
5. You know, if you decided to reject the null hypothesis, the probability that you are making the wrong decision.
6. You have a reliable experimental finding in the sense that if, hypothetically, the experiment were repeated a great number of times, you would obtain a significant result on 99% of occasions.

Statements 1 and 3 are false because they ignore that significance tests provide probabilistic information and therefore can never prove (or disprove) hypotheses. Statements 2, 4, and 5 are false because significance tests (in the classical frequentist framework) do not allow for the assignment of probabilities to a hypothesis but to data only. Statement 6 represents the common “replication fallacy.” While in the frequentist framework $\alpha = .01$ can be interpreted as the relative frequency of rejections of the null hypothesis if it is true, the fictitious scenario, as in most real-world situations, does not provide evidence of that being the case (Haller & Krauss, 2002; Oakes, 1986, p. 80). The correct statement, not included in the set presented, is: “The probability of the available data, given that the null hypothesis is true, is 1%.”

The false statements regarding the interpretation of a 95% confidence interval ranging from 0.1 to 0.4 read as follows:

1. The probability that the true mean difference is greater than 0 is at least 95%.
2. The probability that the true mean difference equals 0 is smaller than 5%.
3. The “null hypothesis” that the true mean difference equals 0 is likely to be incorrect.
4. There is a 95% probability that the true mean difference lies between 0.1 and 0.4.
5. We can be 95% confident that the true mean difference lies between 0.1 and 0.4.

6. If we were to repeat the experiment over and over, then 95% of the time the true mean difference falls between 0.1 and 0.4.

Statements 1–4 correspond to *p*-value Statements 2, 4, and 5 and are false because they as well assign probabilities to hypotheses, which is not possible in the frequentist inferential framework. Statements 5 and 6 are false because CIs can only be used to evaluate the procedure generating them, not a specific interval. The correct statement, not included in the set presented, reads: “If we were to repeat the experiment over and over, then 95% of the time the confidence intervals contain the true mean [difference]” (Hoekstra et al., 2014, p. 1160).

Response certainty. After each set of statements, participants were asked to indicate how certain they were when marking the statements as true or false (7-point scale ranging from 1 = *completely guessing* to 7 = *completely certain*).

Training, practice, and teaching in statistics. After the knowledge and certainty questions, the questionnaire captured participants’ experience with statistics by asking for the number of university-level semester-length statistics courses they had taken (12-point scale ranging from *0* to *more than 10*, *M* = 4.1, *SD* = 2.5); whether they had ever applied inferential statistics in their own research (84.2% “yes”) and how many undergraduate- or graduate-level courses in quantitative data analysis or applied statistics they had taught as a primary instructor or instructor of record (12-point scale ranging from *0* to *more than 10*, *M* = 1.2, *SD* = 2.5).

Finally, participants were asked about their academic status (tenured, non-tenured, graduate student, etc.) and a few other questions not analyzed here (see Appendix for more details).

Results

Only responses from participants who completed the entire survey were used in the following analyses.

***P*-values and confidence intervals.** Table 1 shows the percentages of predoc and postdoc participants endorsing different numbers of the false *p*-value items. On average, predocs/students endorsed 2.49 statements (*SD* = 1.27), while postdoc/faculty researchers endorsed an average 2.19 false statements (*SD* = 1.26). As we can see, the distribution of false endorsements is unimodal and only slightly skewed, suggesting that the mean number of errors were not strongly influenced by badly performing outliers.

Table 1

Percentages of Predoc and Postdoc Participants Endorsing Different Numbers of p-*Value Items*

Endorsement count	Predoc/student researchers (n = 94)	Postdoc/faculty researchers (n = 121)
0	9%	11%
1	14%	21%
2	25%	23%
3	28%	32%
4	25%	11%
5	1%	3%
6	0%	0%

Note: All statements were false and none of them should have been endorsed.

Table 2 shows the percentages of endorsing predoc and postdoc respondents for the individual false *p*-value statements: Statements 4 and 5, representing probability-of-hypothesis errors, and Statement 6, representing the replication fallacy occurred among the absolute majority of both pre- and postdoc respondents.

Table 2

Percentages of Predoc and Postdoc Participants Endorsing Different p-*Value Items*

Statement	Predoc/student researchers (*n* = 94)	Postdoc/faculty researchers (*n* = 121)
You have absolutely disproved the null hypothesis (that there is no difference between the population means).	6%	5%
You have found the probability of the null hypothesis being true.	34%	28%
You have absolutely proved your experimental hypothesis (that there is a difference between the population means).	9%	7%
You can deduce the probability of the experimental hypothesis being true.	71%	65%
You know, if you decided to reject the null hypothesis, the probability that you are making the wrong decision.	68%	59%
You have a reliable experimental finding in the sense that if, hypothetically, the experiment were repeated a great number of times, you would obtain a significant result on 99% of occasions.	61%	56%

Note: All statements were false and none of them should be endorsed.

Turning to the false CI items, Table 3 shows the percentages of predoc and postdoc participants endorsing different numbers of the false statements. On average, predocs/students endorsed 3.69 (SD = 1.52), while postdoc/faculty researchers endorsed an average 3.62 of the false statements (*SD* = 1.72). Again, the distribution of the number of false endorsements suggests that the average errors count was not subject to excessive influence by outliers.

Table 3

Percentages of Predoc and Postdoc Participants Endorsing Different Numbers of Confidence Interval Items

Endorsement count	Predoc/student researchers (*n* = 94)	Postdoc/faculty researchers (*n* = 121)
0	2%	6%
1	8%	7%
2	10%	13%
3	28%	15%
4	19%	26%
5	21%	17%
6	13%	16%

Note: All statements were false and none of them should have been endorsed.

Table 4 shows the percentages of predoc and postdoc participants endorsing the individual confidence interval items. There are fewer differences in the proportion of endorsements across CI statements than for the *p*-value items. With only one exception (Statement 1 for predocs), all statements were endorsed by an absolute majority of respondents in both groups.

In sum, the data show that the level of competence in interpreting inferential statistics among the communication researchers surveyed was low.

Overall, only 9.5% (*n* = 21) of all participants correctly indicated that none of the *p*-value statements was true and only 4.1% (*n* = 9) were able to do the same for the statements interpreting a confidence interval. Conversely, more than 90% of the surveyed sample of communication researchers misinterpreted a given *p*-value, and more than 95% were not able to correctly interpret a confidence interval around a mean difference.

Table 4

Percentages of Predoc and Postdoc Participants Endorsing Different Confidence Interval Items

Statementb	Predoc/student researchers (*n* = 94)	Postdoc/faculty researchers (*n* = 121)
The probability that the true mean difference is greater than 0 is at least 95%.	44%	58%
The probability that the true mean difference equals 0 is smaller than 5%.	53%	52%
The “null hypothesis” that the true mean difference equals 0 is likely to be incorrect.	76%	72%
There is a 95% probability that the true mean difference lies between 0.1 and 0.4.	62%	65%
We can be 95% confident that the true mean difference lies between 0.1 and 0.4.	70%	60%
If we were to repeat the experiment over and over, then 95% of the time the true mean difference falls between 0.1 and 0.4.	65%	55%

Note: All statements were false and none of them should be endorsed.

Response certainty. Given this pattern of responses it is surprising that if we look at how certain respondents were about their answers, we find that they were rather certain they had given the correct responses regarding the interpretation *p*-values (M = 5.20, SD = 1.39) as well as, if somewhat less pronounced, regarding confidence intervals (M = 4.68, SD = 1.44).

Interestingly, certainty about their own answers was neither associated with the number of false *p*-value statements (r = .07) nor with the number of false CI statements endorsed (r = –.09). Confidence of communication researchers' own judgment did not appear to be a product of their actual knowledge.

Experience in training, practice, and teaching in statistics. Did experience with statistics as gathered through taking classes, applying them in one's own research, or even teaching them reduce the number of erroneous beliefs communication researchers held about the correct interpretation of inferential results?

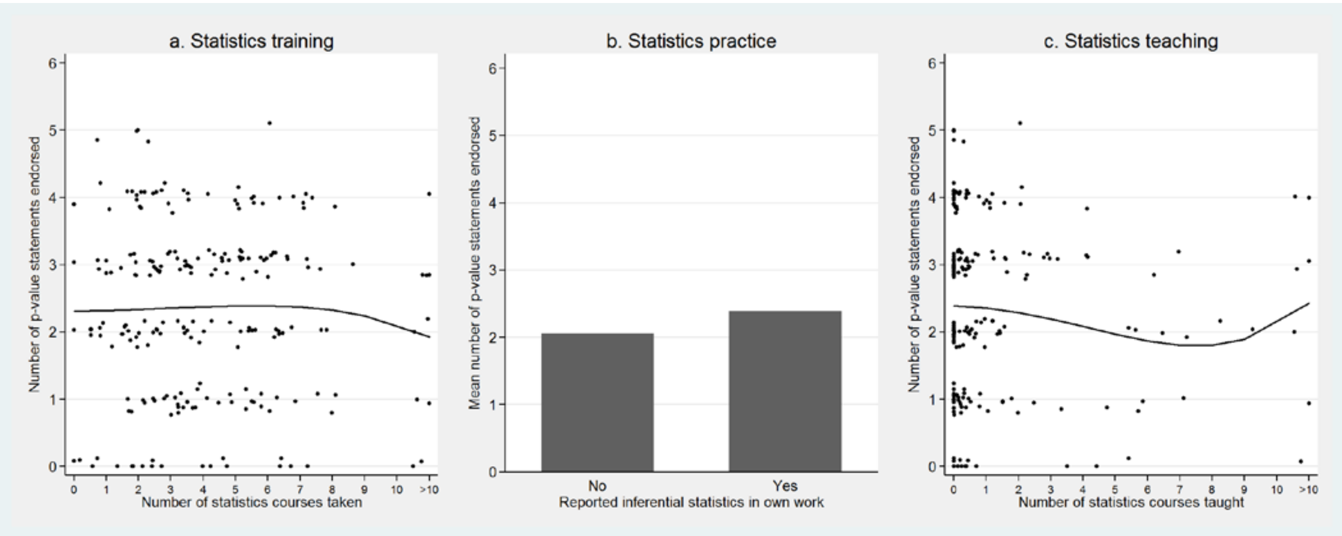

Figure 1. Number of false *p*-value statements endorsed, by statistics training, practice, and teaching. Note: Fitted lines are based on fractional polynomials of statistics training, practice, and teaching (two-degree with powers -2, -1, -.5, 0, .5, 1, 2, and 3). For a. R^2= .005, for c. R^2= .012.

Figure 1 plots the associations of statistics training, practice, and teaching with the number of falsely endorsed *p*-value statements. (Because many points in Figures 1 and 2 overlap, we "jittered" the observations to make it easier to see their distribution over the plotted categories.) As panels a. in Figures 1 and 2 show, we find that having taken a greater number of statistics classes was only slightly associated with a smaller number of errors for the interpretation of both *p*-values (r = –.04) and confidence intervals (r = –.09). This means that, in a linear model, training in statistics explains 0.1% of the overall variance in the number of falsely endorsed *p*-value statements and 0.9% of the variance in the number of falsely endorsed CI statements. If we relax the linearity constraint and fit the non-linear fractional polynomial model shown in Figures 1 and 2, the proportion of variance explained increases only very slightly to 0.5% and 1.8%, respectively.

Perhaps even more troubling, the surveyed researchers, who indicated they had reported inferential statistics (*p*-values or CIs) in their own work, endorsed a *greater* number of false statements about both *p*-values (M = 2.39 versus 2.06, respectively) and confidence intervals (M = 3.66 versus 3.60, respectively), indicating it was not those unengaged in quantitative data analysis using inferential statistics who were responsible for the dim overall picture reported above (see panels b. in Figures 1 and 2). Quite the contrary, those making use of these techniques exhibited greater problems with interpreting them correctly.

Finally, panels c. in Figures 1 and 2 show that experience in teaching quantitative data analysis or applied statistics did not lead to substantially better interpretation outcomes. The number of statistics classes taught correlated only weakly negatively with the number of interpretation errors committed for both *p*-values (r = –.05) and confidence intervals (r = –.10). In a linear model, experience with teaching statistics thus explained almost none of the overall variance in the number of falsely endorsed *p*-value and CI statements (0.2% and 1.0%, respectively). As was the case with statistics training, the proportion of variance explained by experience in teaching statistics did not increase considerably when fitting the non-linear fractional polynomial models in Figures 1 and 2 (*p*-value statements: 1.2%; CI statements: 1.5%).

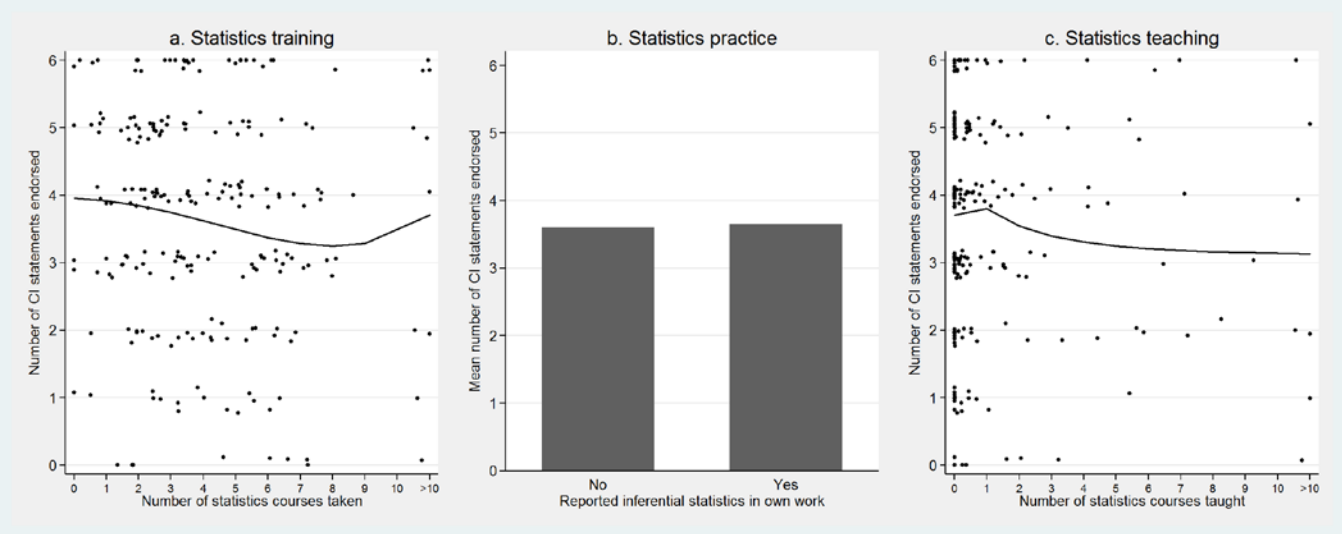

Figure 2. Number of false confidence interval statements endorsed, by statistics training, practice, and teaching. Note: Fitted lines are based on fractional polynomials of statistics training, practice, and teaching (two-degree with powers -2, -1, -.5, 0, .5, 1, 2, and 3). For a. R^2= .018, for c. R^2= .015.

Conclusion and Discussion

NHST continues to be the most frequently used approach to statistical inference in communication research (Levine, 2013). This study has shown for the first time that Levine, Weber, Hullet, et al.'s (2008, pp. 178–179) concerns about widespread misunderstandings of this most important statistical technique among communication researchers were far from unfounded. Not only did more than 90% of the surveyed communication researchers commit at least one error in interpreting the result of a significance test, echoing results from psychology and other disciplines (e.g., Badenes-Ribera et al., 2015; Haller & Krauss, 2002; Oakes, 1986; Westover, Westover, & Bianchi, 2011), but more than 95% were not able to correctly interpret the most frequently recommended alternative to NHST, confidence intervals, replicating recent findings from psychology (Hoekstra et al., 2014).

In stark contrast to their actual performance, most respondents indicated they were confident about their answers, suggesting a widespread self-illusion of communication researchers regarding their statistical competence.

Seniority played only a small role in explaining performance in interpreting inferential results, with faculty and other Ph.D.-owning respondents doing only slightly better than the surveyed students with regard to interpreting both *p*-values and confidence intervals. Statistical training and teaching practice also did little to improve performance. The most troubling result for the discipline as a whole, however, may be that those researchers who have used inferential statistics in their own research were not more proficient in interpreting inferential results than non-users, but in fact turned out to be slightly less competent.

It is important to note that the voluntary nature of participation in our survey entailed a high degree of self-selection into this study. However, for the purposes of our study such self-selection should not pose a major validity problem. We may expect that those who decided to complete the study were particularly interested in the subject of statistical inference, considered themselves competent in this area, and/or felt perhaps more certain about their correct answers. If anything, self-selection should thus have produced a hard test of the expectation that misinterpretations of inferential statistics are pervasive among communication researchers and rather underestimate the prevalence.

In sum, this study found little reliable knowledge among communication researchers about the correct interpretation of inferential statistics. Although these findings are consistent with findings in other disciplines (e.g., Castro Sotos, Vanhoof, Van den Noortgate, & Onghena, 2007; Falk & Greenbaum, 1995; Haller & Krauss, 2002; Hoekstra et al., 2014; Oakes, 1986), they do not bode well for communication as a scientific discipline and they call for change if the discipline is to make a claim to solid and well-grounded knowledge based on statistical analysis. Sound application of statistical tools for knowledge creation undoubtedly requires that the researchers who apply them also understand them. We thus have the following question before us: should we improve our understanding of our present ways of doing analysis or should we change these ways in the first place? The findings of this study suggest a clear picture: Misunderstandings of NHST and CIs are so pervasive and so independent of researchers' amount of statistical experience as well as their confidence in their own statistical knowledge that a vicious circle of self-perpetuating misconceptions regarding the meaning of inferential statistics, passed on from one generation to another, seems all but inevitable. We thus agree with Kline (2013, p. 104) when he finds that the cliché of "better teaching" is not particularly persuasive anymore as a response, given its decades-long history of failing to improve the situation substantially.

The failures in properly interpreting NHST and CIs are particularly consequential and problematic because they converge on an exaggeration of what can be learned from the results of a single study, coupled with an often mechanistic approach to the answering of substantive research questions and the analysis of data. The dim picture painted by our data suggests that a major reorientation will be necessary to minimize these problems for communication research in the future. Statistics reform as proposed by Kline (2013) and others (e.g., Cumming, 2014; Fidler, Geoff, Mark, & Neil, 2004; Sedlmeier, 2009) provides a promising framework in this regard. In line with this framework, we too suggest that communication researchers should generally refrain from the unjustified routine use of NHST—and CIs if falsely understood as just another way of conducting NHST. The word significant should indeed become gradually dissociated in our minds and everyday usage from the application of any particular statistical technique and instead be used again to denote an important or relevant finding. In other words, a concern for *substantive* significance should take the place presently occupied by a mechanistic concern for *statistical* significance of findings. Perhaps the most important implication of such a reorientation would be a greater focus on the size of effects and preregistered replications as the ultimate arbiter of any claim regarding the validity of a particular finding. Statistics education in line with these recommendations would amount not to *better* teaching but to a *different* teaching of statistics for communication research. In this approach to analyzing data, significance testing, including CIs misunderstood as a different flavor of it, would be much less central than it is today. Instead, more substantive concerns, replication, effect sizes, and better ways of drawing statistical inferences, including Bayesian methods, would take center stage.

In the end, communication research has been blessed to be a relatively young field of study. By mercy of its late birth it has a real chance of experiencing a rapid “coming of age,” if only it takes the experiences and lessons learned by its older sibling disciplines in the social and behavioral sciences seriously and resolutely turns towards the cutting-edge approaches to knowledge production that they have developed.

References

Badenes-Ribera, L., Frías-Navarro, D., Monterde-I-Bort, H., & Pascual-Soler, M. (2015). Interpretation of the p value: A national survey study in academic psychologists from Spain. *Psicothema*, *27*(3), 290–295. http://doi.org/10.7334/psicothema2014.283

Belia, S., Fidler, F., Williams, J., & Cumming, G. (2005). Researchers misunderstand confidence intervals and standard error bars. *Psychological Methods*, *10*(4), 389–396. http://doi.org/10.1037/1082-989X.10.4.389

Castro Sotos, A. E., Vanhoof, S., Van den Noortgate, W., & Onghena, P. (2007). Students' misconceptions of statistical inference: A review of the empirical evidence from research on statistics education. *Educational Research Review*, *2*(2), 98–113. http://doi.org/10.1016/j.edurev.2007.04.001

Cumming, G. (2014). The new statistics: Why and how. *Psychological Science*, *25*(1), 7–29. http://doi.org/10.1177/0956797613504966

Cumming, G., & Fidler, F. (2009). Confidence intervals: Better answers to better questions. *Zeitschrift Für Psychologie*, *217*(1), 15–26. http://doi.org/10.1027/0044-3409.217.1.15

Falk, R., & Greenbaum, C. W. (1995). Significance tests die hard: The amazing persistence of a probabilistic misconception. *Theory & Psychology*, *5*(1), 75–98. http://doi.org/10.1177/0959354395051004

Fidler, F., Geoff, C., Mark, B., & Neil, T. (2004). Statistical reform in medicine, psychology and ecology. *Journal of Socio-Economics*, *33*(5), 615–630. http://doi.org/10.1016/j.socec.2004.09.035

Fidler, F., & Loftus, G. R. (2009). Why figures with error bars should replace *p* values: Some conceptual arguments and empirical demonstrations. *Zeitschrift Für Psychologie, 217*(1), 27–37. http://doi.org/10.1027/0044-3409.217.1.27

Haller, H., & Krauss, S. (2002). Misinterpretations of significance: A problem students share with their teachers? *Methods of Psychological Research*, *7*(1), 1–20.

Hoekstra, R., Morey, R. D., Rouder, J. N., & Wagenmakers, E.-J. (2014). Robust misinterpretation of confidence intervals. *Psychonomic Bulletin & Review*, *21*(5), 1157–1164. http://doi.org/10.3758/s13423-013-0572-3

Kline, R. B. (2013). *Beyond significance testing: Statistics reform in the behavioral sciences* (2nd ed.). Washington, DC: American Psychological Association.

Levine, T. R. (2013). Quantitative communication research: Review, trends, and critique. *Review of Communication Research*, *1*(1), 69–84. http://doi.org/10.12840/issn.2255-4165_2013_01.01_003

Levine, T. R., Weber, R., Hullett, C., Park, H. S., & Lindsey, L. L. M. (2008). A critical assessment of null hypothesis significance testing in quantitative communication research. *Human Communication Research*, *34*(2), 171–187. http://doi.org/10.1111/j.1468-2958.2008.00317.x

Levine, T. R., Weber, R., Park, H. S., & Hullett, C. R. (2008). A communication researchers' guide to null hypothesis significance testing and alternatives. *Human Communication Research*, *34*(2), 188–209. http://doi.org/10.1111/j.1468-2958.2008.00318.x

Morey, R. D., Hoekstra, R., Rouder, J. N., Lee, M. D., & Wagenmakers, E.-J. (in press). The fallacy of placing confidence in confidence intervals. *Psychonomic Bulletin & Review*. http://doi.org/10.3758/s13423-015-0947-8

Morey, R. D., Hoekstra, R., Rouder, J. N., & Wagenmakers, E.-J. (in press). Continued misinterpretation of confidence intervals: Response to Miller and Ulrich. *Psychonomic Bulletin & Review*. http://doi.org/10.3758/s13423-015-0955-8

Oakes, M. W. (1986). *Statistical inference: A commentary for the social and behavioural sciences*. Chichester, UK: Wiley.

Schmidt, F. L. (1996). Statistical significance testing and cumulative knowledge in psychology: Implications for training of researchers. *Psychological Methods*, *1*(2), 115–129. http://doi.org/10.1037/1082-989X.1.2.115

Schmidt, F. L., & Hunter, J. E. (1997). Eight common but false objections to the discontinuation of significance testing in the analysis of research data. In L. L. Harlow, S. A. Mulaik, & J. H. Steiger (Eds.), *What if there were no significance tests?* (pp. 37–64). Mahwah, NJ: Erlbaum.

Sedlmeier, P. (2009). Beyond the significance test ritual: What is there? *Zeitschrift Für Psychologie*, *217*(1), 1–5. http://doi.org/10.1027/0044-3409.217.1.1

Westover, M. B., Westover, K. D., & Bianchi, M. T. (2011). Significance testing as perverse probabilistic reasoning. *BMC Medicine*, *9*(1), 20. http://doi.org/10.1186/1741-7015-9-20

Wilkinson, L., & the Task Force on Statistical Inference. (1999). Statistical methods in psychology journals: Guidelines and explanations. *American Psychologist*, *54*(8), 594–604. http://doi.org/10.1037/0003-066X.54.8.594

Appendix: Questionnaire

Welcome page

Dear Sir or Madam,

Thank you very much for your interest and for taking the time to participate in our study!

Completion of the survey should not take longer than 5 minutes. Please make sure to answer all questions spontaneously without consulting any resource such as colleagues, literature, or websites.

Please press "Continue" to start the questionnaire.

varname: pval	**label:** A1: *p*-value assessment performance

Display notes: forced response

Split:

Filter:

Question wording:
Suppose you have a treatment which you suspect may alter performance on a certain task. You compare the means of your control group and experimental group (say 20 subjects in each sample). Further, suppose you use a simple independent means *t*-test and your result is ($t = 2.7$, $df = 18$, $p = 0.01$).

Please mark each of the statements below as “true” or “false”. “False” means that the statement does not follow logically from the above premises. Also note that several or none of the statements may be correct.

Items:
(A) You have absolutely disproved the null hypothesis (that there is no difference between the population means).
(B) You have found the probability of the null hypothesis being true.
(C) You have absolutely proved your experimental hypothesis (that there is a difference between the population means).
(D) You can deduce the probability of the experimental hypothesis being true.
(E) You know, if you decided to reject the null hypothesis, the probability that you are making the wrong decision.
(F) You have a reliable experimental finding in the sense that if, hypothetically, the experiment were repeated a great number of times, you would obtain a significant result on 99% of occasions.

Scale/categories:
(1) True
(2) False

varname: pvalcert	**label:** A1: Response certainty

Display notes: forced response

Split:

Filter:

Question wording:
How certain (as opposed to guessing) were you when answering the questions on the page before?

Items:

Scale/categories:
(1) 1 completely guessing
(2) 2
(3) 3
(4) 4
(5) 5
(6) 6
(7) 7 completely certain

varname: ci	**label:** A2: CI assessment performance

Display notes: forced response

Split:

Filter:

Question wording:
Again, suppose you have conducted an experiment and compare the means of your control and experimental groups. You find that the 95% confidence interval for the differences between the two means ranges from 0.1 to 0.4.

Please mark each of the statements below as “true” or “false”. “False” means that the statement does not follow logically from this finding. Also note that several or none of the statements may be correct.

Items:
(A) The probability that the true mean difference is greater than 0 is at least 95 %.
(B) The probability that the true mean difference equals 0 is smaller than 5 %.
(C) The “null hypothesis” that the true mean difference equals 0 is likely to be incorrect.
(D) There is a 95%probability that the true mean difference lies between 0.1 and 0.4.
(E) We can be 95 % confident that the true mean difference lies between 0.1 and 0.4.
(F) If we were to repeat the experiment over and over, then 95 % of the time the true mean difference falls between 0.1 and 0.4.

Scale/categories:
(1) True
(2) False

varname: cicert	**label:** A2: Response certainty

Display notes: forced response

Split:

Filter:

Question wording:
How certain (as opposed to guessing) were you when answering the questions on the page before?

Items:

Scale/categories:
(1) 1 completely guessing
(2) 2
(3) 3
(4) 4
(5) 5
(6) 6
(7) 7 completely certain

varname: stattr	**label:** Statistical training

Display notes: forced response

Split:

Filter:

Question wording:
How many undergraduate- and graduate-level courses in quantitative data analysis/applied statistics have you completed?

Include ALL **semester-length** courses and **equivalent** intensive courses (three days minimum). Exclude any non-equivalent short courses.

Items:

Scale/categories:
(1) 0
(2) 1
(3) 2
(4) 3
(5) 4

(6) 5
(7) 6
(8) 7
(9) 8
(10) 9
(11) 10
(12) more than 10

varname: statpr	**label:** Statistical practice

Display notes: forced response

Split:

Filter:

Question wording:
Have you ever applied inferential statistics (i.e., reported statistical test results like *p* values or confidence intervals) in your own research?

Items:

Scale/categories:
(1) Yes
(2) No

varname: statte	**label:** Statistical teaching

Display notes: forced response

Split:

Filter:

Question wording:
How many undergraduate- or graduate-level courses in quantitative data analysis/applied statistics have you taught as a primary instructor/instructor of record?

Items:

Scale/categories:
(1) 0
(2) 1
(3) 2
(4) 3
(5) 4
(6) 5
(7) 6
(8) 7
(9) 8
(10) 9
(11) 10
(12) more than 10

varname: acstat	**label:** Academic status

Display notes: forced response; offer text box to specify “other” response in ≤ 50 characters

Split:

Filter:

Question wording:
Are you a…

Items:

Scale/categories:
(1) Faculty member (tenure/tenure-track)

(2) Faculty member (non-tenure/non-tenure-track)
(2) Post-doc
(3) Graduate student
(4) Undergraduate student
(5) Other (please specify)?

varname: icadiv	**label:** ICA division memberships

Display notes:

Split:

Filter: If (1) to (25) > 1 → gen, if (1) to (25) = 1 or (26) → icaimp

Question wording:
Which ICA division(s)/interest group(s) are you currently a member of?

Items:

Scale/categories:
(1) Children, Adolescents and the Media
(2) Communication and Technology
(3) Communication History
(4) Communication Law and Policy
(5) Environmental Communication
(6) Ethnicity and Race in Communication
(7) Feminist Scholarship
(8) Game Studies
(9) Gay, Lesbian, Bisexual and Transgender Studies
(10) Global Communication and Social Change
(11) Health Communication
(12) Information Systems
(13) Instructional and Developmental Communication
(14) Intercultural Communication
(15) Intergroup Communication
(16) Interpersonal Communication
(17) Journalism Studies
(18) Language and Social Interaction
(19) Mass Communication
(20) Organizational Communication
(21) Philosophy, Theory and Critique
(22) Political Communication
(23) Popular Communication
(24) Public Relations
(25) Visual Communication Studies

(26) I am not a member of an ICA division or interest group.

varname: icaimp	**label:** ICA membership importance

Display notes: forced response

Split:

Filter: Only if icadiv (1) to (25) > 1

Question wording:
If you are a member of more than one division/interest group, please select the one that is most important to you.

Items:
[dynamic answers dependent on selection in icadiv]

Scale/categories:

varname: sex	**label:** sex

Display notes: forced response

Split:

Filter:

Question wording:
What is your biological sex?

Items:

Scale/categories:
(1) Female
(2) Male

varname: yob | **label:** Year of birth

Display notes: forced response; offer text box for response with 4 characters

Split:

Filter:

Question wording:
What is your year of birth?

Items:

Scale/categories:

varname: cor | **label:** Country of residence

Display notes: forced response; offer drop down menu with list of UN member states and “other (please specify)” option

Split:

Filter:

Question wording:
What is your current country of residence?

Items:
[List of UN countries + “other (please specify)]

Scale/categories: