Adopting a Meta-Generative Way of Thinking in the Field of Education via the Use of Bayesian Methods: A Multimethod Approach in a Post-Truth and COVID-19 Era

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Abstract

In this editorial, we introduce the multimethod concept of *thinking meta-generatively*, which we define as directly integrating findings from the extant literature during the data collection, analysis, and interpretation phases of primary studies. We demonstrate that meta-generative thinking goes further than do other research synthesis techniques (e.g., meta-analysis) because it involves meta-synthesis not only *across* studies but also *within* studies—thereby representing a multimethod approach. We describe how meta-generative thinking can be maximized/optimized with respect to quantitative research data/findings via the use of *Bayesian methodology* that has been shown to be superior to the inherently flawed null hypothesis significance testing. We contend that Bayesian meta-generative thinking is essential, given the potential for divisiveness and far-reaching sociopolitical, educational, and health policy implications of findings that lack generativity in a post-truth and COVID-19 era.

Keywords: Bayesian, statistical education, graduate education, meta-generative thinking, methodology, multimethod, multiple methods, post-truth, coronavirus pandemic, COVID-19

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Higher education has a long history. In 859 AD, Princess Fatima al-Fihri, the daughter of a wealthy merchant, established the first degree-granting university in the world, namely, the Al-Karaouine mosque and university in Fez, Morocco. At this university, which was founded on Islamic tradition, grammar, mathematics, astronomy, and medicine were taught (Glenday, 2013). Since then, institutions of higher education worldwide have been deemed as representing the premier source for specialized knowledge and essential expertise, containing faculty members who produce theory and disseminate research findings pertaining to issues that serve the needs of various segments of society (Gleason, 2018). However, in recent years, the authority of higher education faculty members in general and their knowledge production in particular have been undermined and delegitimized in a contemporary period that is referred to in social and political discourse in the United States and beyond as the *post-truth era*. In support of our contention, in 2016, the Oxford Dictionaries selected *post-truth* as its word of the year, which the Oxford Dictionaries publisher defines as an adjective “relating to or denoting circumstances in which objective facts are less influential in shaping public opinion than appeals to emotion and personal belief” (Oxford Dictionaries, 2018, ¶1). Interestingly, simply Googling the phrase “post-truth” reveals an array of academic works, news stories, essays, and Web 2.0 posts that explain how and why we are now operating in a post-truth era.

This post-truth era is characterized by discourses that are no longer moored in T/truth. As examples, this era has witnessed important unsubstantiated claims that is shaping Governmental policy, such as the unwarranted denial of the scientific consensus on climate change (i.e., global warming denial), and most recently, the initial downplaying of the novel coronavirus pandemic by some cable television news channels as well as the claim that 5G mobile technology is the cause of coronavirus (i.e., COVID-19). As a result, it has led at least some, if not many, academicians not only to rethink education policy and methodology (cf. Wolgemuth, Koro-Ljungberg, Marn, Onwuegbuzie, & Dougherty, 2018a), but also to rethink data, fact, evidence, and validity/legitimation in education policy-making, as well as the onto-ethico-epistemology of (educational) research and evaluation ethics. More specifically, in this recent and still emerging era of post-truth, T/truth has been problematized, amidst continuously shifting and unstable intersections among policy, methodology, and evidence (cf. Wolgemuth et al., 2018a). Moreover, this era has generated both challenges and opportunities for scholars to rethink the purpose, justification, and value of their work, as well as the validity/legitimation of their knowledge claims (Wolgemuth, Koro-Ljungberg, Marn, Onwuegbuzie, & Dougherty, 2018b). Foucault (2003) warned against the field of social sciences—which includes the field of education—being subjected to abuse wherein certain experiences, knowledges, and wisdom traditions are marginalized or eliminated in order to produce partial elements of truth and to effect governmental power. Thus, in this post-truth era, it is essential that the politics of *all* research and evaluation undergo close scrutiny. However, bearing in mind that the role of education is not only to prepare students for the challenges of life within the career world but also to empower citizens to become active agents in the transformation of their societies, and that, even more importantly, education provides a pathway to success for disadvantaged groups (Bobbitt-Zeher, 2007), no social science research area warrants closer scrutiny than does the field of educational research in general and educational policy analysis in particular.

According to the American Educational Research Association (AERA), AERA "is concerned with improving the educational process by encouraging scholarly inquiry related to education and evaluation and by promoting the dissemination and practical application of research results" (AERA, 2018). Central to AERA's statement here is the phrase "by promoting the dissemination and practical application of research results." An effective way to promote this application is by ensuring that research findings—whether they be quantitative, qualitative, or mixed methods research findings—are *connected*. And the most effective way of connecting findings is by promoting *generativity*, which Shulman (1999) defines as the capacity to build on previous research—which leads to a cumulative approach to conducting research.

In the field of medicine, generativity represents a life-and-death issue—no more than in this COVID-19 era that is being characterized by a scramble worldwide to find both a treatment and a vaccine—with the failure to adopt a cumulative approach to research having dire consequences, for example, if findings that show adverse or fatal side effects of a trial drug are not built on present and future research (e.g., the promotion of hydroxychloroquine to treat COVID-19 infection; see, for e.g., Kim et al., 2020). Although, in the field of education, generativity typically does not represent a life-and-death issue, lack of maximal "knowledge integration, collaboration, and translation of research findings" (Ball, 2012, p. 288), still can have dire consequences. In particular, lack of generative research can prevent the closing of the research-to-practice gap (Carnine, 1997)—or what Ball (2012) referred to as the "knowledge—doing gap" (p. 283) in education, as well as what Onwuegbuzie and Hitchcock (2018) referred to as the practice-to-research gap in education.

An effective way that education researchers can connect findings is by *thinking meta-generatively*. We define meta-generative thinking as the direct integration of findings from the extant literature during the data collection, data analysis, and data interpretation phases of a primary (i.e., quantitative, qualitative, or mixed methods) research study. In the context of qualitative research in general and qualitative findings in particular, a part of *meta-generative thinking* includes meta-syntheses. As described by Sandelowski and Barroso (2003), a meta-synthesis, coined by Stern and Harris (1985), is an interpretive analysis that involves the integration (i.e., synthesis) of qualitative findings for the hermeneutic purpose of theory development aimed at understanding and explaining phenomena. With respect to quantitative research, a part of *meta-generative thinking* includes meta-analyses. A meta-analysis involves combining or aggregating the quantitative findings from as many available individual quantitative research studies as possible in order to integrate the findings (Glass, 1976). Finally, in the context of mixed methods research, a part of *meta-generative thinking* includes meta-summaries. Sandelowski and Barroso (2003) define a meta-summary as "a form of systematic review or integration of qualitative findings in a target domain that are themselves topical or thematic summaries or surveys of data" (p. 227) and that involves the conversion of qualitative data to quantitative data, a mixed methods analysis technique referred to as *quantitizing* (Miles & Huberman, 1994; Onwuegbuzie & Teddlie, 2003; Sandelowski, Voils, & Knafl, 2009; Tashakkori & Teddlie, 1998).

However, these three classes of syntheses neither maximize nor optimize meta-generative thinking because although they all involve meta-generative thinking *across* studies, they do not involve meta-generative thinking *within* studies. Thus, in this editorial, we will describe how meta-generative thinking can be both maximized and optimized with respect to quantitative research data/findings. This enhanced promotion of meta-generative thinking can occur via the use of *Bayesian methodology*.

Frequentist-Based Null Hypothesis Significance Testing

Several authors (e.g., Kruschke, 2015) have pointed out the fallacies of frequentist-based null hypothesis significance testing (NHST). Because of these fallacies, in their 2015 editorial, the editors of the *Journal of Basic and Applied Social Psychology* banned NHST in general and *p* values and confidence intervals in particular from their journal (Trafimow & Marks, 2015).

A concern that seems to be ignored in introductory statistics classes is the fact that in research, we are mostly concerned with the probability that the research (i.e., alternate) hypothesis is true. Instead, in NHST, we focus on finding evidence to reject the null hypothesis (i.e., frequentist approach). Although we might be able to reject the null hypothesis, we never know the probability of the alternate hypothesis. Other concerns include the following:

- NHSTs cannot provide information about the probability of the null hypothesis being true given the observed data, that is, $P(H_0|D)$—which *is* of interest to analysts. They rather provide information about the probability of the observing data as extreme as the current data (D) given the assumption that the null hypothesis is true, that is, $P(D|H_0)$ and usually conclude this as the probability that the null is true given the data. Two problems exist here. These conditional probabilities are neither interchangeable nor equal. Moreover, $P(D|H_0)$ is *not* of interest to analysts.
- NHSTs are mostly irrelevant because researchers representing the field of social sciences—including the field of education—rarely work with complete random samples from a known population.
- NHSTs are based on the standard error for the sampling distribution of the population, which will never be known in reality, and the inaccuracy in estimating it from one sample can make NHST inferences misleading.

- The incorrect reliance on the results of NHST as having replicability has led to what is referred to as the *replicability crisis* (Ioannidis, 2005).

Despite these serious flaws, the use of NHST has prevailed since the first one third of the 20th century, when Sir Ronald Fisher (1890–1962), an English statistician and biologist, popularized *significance testing* (cf. Fisher, 1925), and Jerzy Neyman (1894–1981), a Polish mathematician and statistician, and Egon Sharpe Pearson (1895–1980), an English statistician, popularized *hypothesis testing* (cf. Neyman & Pearson, 1933). This dominance in NHST use has occurred even though statisticians have had access to an alternative statistical paradigm, namely, Bayesian statistics. Created in the 18th century by Thomas Bayes (1701–1761), an English mathematician, statistician, philosopher, and Presbyterian minister, and after a period of relative obscurity, it was used successfully in several high-profile projects during the first half of the 20th century, such as cracking the Enigma Code in World War II. However, in recent years, there have been renewed calls for the use of Bayesian statistics as a viable alternative to using NHST (e.g., Kruschke, 2015).

Bayesian Estimation

Bayesian methods estimate the probability distribution of the parameter (posterior) as a function of the product of the information contained in the data (likelihood) and the information known about the parameter from previous research (prior). This relationship forms the basis of Bayes's theorem and is commonly denoted in Proposition 1 as:

$$posterior \propto prior \times likelihood. \tag{1}$$

Therefore, each parameter has a range of possible values and each possible value is associated with a probability. There are several advantages to using Bayesian estimation compared to NHST. To appreciate some of these advantages, it is important to understand that researchers relying on NHST make decisions based on the sum of: (a) the conditional probabilities of the observed data and (b) more extreme, unobserved data given that the null hypothesis is true, which is given in Proposition 2 as:

$$P(D|H_0) + P(more\ extreme\ data|H_0). \qquad (2)$$

As noted in the prior section of this editorial, researchers tend to interpret inaccurately the *p* value as the probability that the null is true given the observed data (Cohen, 1994). On the contrary, the probability that is obtained in Bayesian statistics is $P(H_0|D)$. Rather than the point estimates that are accompanied by a standard error estimate in frequentist methods, Bayesian methods provide the joint posterior density distribution of the parameters. The use of posterior probability distribution has two advantages: (a) researchers have more information about all possible values of the parameters along with their respective probabilities, and (b) it yields credibility intervals that have probability distribution shapes. This means the probability that the true parameter value is found in a 95% credibility interval is 0.95. This straightforward interpretation of credibility intervals is often misapplied to confidence intervals. In particular, a probabilistic statement about a single confidence interval's chances of capturing the true value cannot be made because confidence intervals are based on hypothetical resampling and do not have a shape representing probabilities of parameter values.

Furthermore, recall that NHST's entail making a dichotomous decision (i.e., reject the null hypothesis vs. do not reject the null hypothesis) based on continuous p values. In contrast, Bayesians make probabilistic statements using posterior density distributions (Gill, 2015). The Bayesian posterior region of practical equivalence (ROPE; Kruschke, 2015) provides more information about statistical significance and effect sizes than does NHST. This is because Bayesian results yield probability distributions for parameters and effect sizes. This makes the decision of statistical significance to be based on a range of values with associated probabilities. A key implication for working with a range of values with associated probabilities is that researchers using Bayesian methods can “accept the null hypothesis,” whereas the best that NHST results can suggest is “do not reject the null hypothesis.” Another implication is that Bayesian approaches can promote clearer thinking around the idea that the absence of evidence is not evidence of absence (Altman & Bland, 1995). That is, a statistically non-significant result in NHST for a small sample case might reflect merely the lack of power to detect a statistically significant result. This does not mean that there is no evidence of a meaningful result, but rather that we might not have adequate power to detect an effect even if it exists. Conversely, a statistically significant result might be merely a function of a large sample size. In summary, results of Bayesian application are more meaningful to interpret when compared to NHST.

Bayesian methods also can yield informative results in situations where the assumptions of NHST simply cannot be met, such as with small sample cases and autocorrelated errors (e.g., Natesan & Hedges, 2017). For instance, Bayesian ANOVA still yields reasonable estimates when group sizes are unequal and lack homogeneity of variance (Kruschke, 2015). These are conditions under which traditional (frequentist) ANOVA performs non-optimally. Additionally, loss in statistical power while performing post-hoc comparisons is not a concern in Bayesian ANOVA. For instance, Type I error rate or Type II error rate differ from the nominal value under heterogeneity of the variances and the inequality of sample sizes (Maxwell & Delaney, 2003).[1] Yet, frequentist methods continue to be used even though the validity of the results of such analyses is limited. This need not be the case however, especially since Bayesian methods allow for greater modeling flexibility (e.g., Natesan & Hedges, 2017; Natesan Batley, Minka, &

Hedges, 2020; Natesan Batley, Shukla Mehta, & Hitchcock, in press; Natesan Batley, Contractor, & Caldas, 2020).

Bayesian Priors: In Bayesian methodology, the prior is specified by the researcher. Specification of the prior distribution by the researcher can be a point of contention for those who believe that NHST provides objective results (see Berger & Berry [1988]). Although the subjectivity of using priors is seen as a drawback by some frequentists, the use of priors should be seen as a systematic way to incorporate findings of previous research studies into the analysis stage of research, rather than ignoring them (Gill, 2015). Prior specification allows for the coherent merging of information from multiple sources, quantitative and qualitative alike (Newman, Onwuegbuzie, & Hitchcock, 2014) and supports meta-analytic thinking (Onwuegbuzie, Hitchcock, Natesan, & Newman, 2018). A naive criticism of the potentially subjective nature of the prior should not be used to disregard Bayesian methodology both for statistical and philosophical reasons. What makes this criticism naïve is that priors can range from completely non-informative to informative to anywhere in between. Therefore, priors are beneficial rather than troubling, although they must be carefully chosen. Improper priors might after all lead to inaccurate estimates (e.g., Natesan, Nandakumar, Minka, & Rubright, 2016). Fortunately, there is much research surrounding sensitivity of the estimates to prior specification that can be used to investigate the impact of priors on the estimates (Gelman, et al, 2002). Given that Bayesian analysis involves statistical simulation, an understanding of statistical simulation can be very helpful to the reader (e.g. Natesan, 2019a). To summarize this section of this editorial, a comparison of classical null hypothesis significance testing and Bayesian testing for a simple independent samples *t* test is given in Table A of supplementary material (SM).

Examining the Landscape of Bayesian Meta-Generative Thinking

According to Onwuegbuzie and Frels (2016), there are 12 components of a research study and all 12 components of a research study should be informed by a comprehensive literature review process (Figure 1). These 12 components are problem statement, literature review, theoretical/conceptual framework, research question(s), hypotheses, participants, instruments, procedures, analyses, interpretation of the findings, directions for future research, and implications for the field. Although the literature review process has been applied to 11 of these 12 components to varying degrees, the one component of the research process that, until now, has not been informed (fully) by the extant literature is the *analysis*. In other words, researchers use results from previous studies to inform the introduction or background to the study, the literature review, the methods, and the discussion phases of the study. Thus, every step of the research process, except the analysis stage, is contextualized and situated within the existing body of research, as shown in Table B of SM. In fact, by ignoring the findings of previous studies in the analysis stage, researchers acontextualize the data as though they exist in a vacuum. With the exception of statistical assumptions and corrections, researchers do not consider the sample data as being a representation of a population, although the assumption behind NHSTs is that the sample represents the population adequately well. Thus, the analysis stage tends to ignore the additive nature of research in the classical framework, thereby yielding a lack of meta-generative thinking.

In contrast, considering the results of previous studies and including them in a systematic manner in the form of priors promote fully meta-generative thinking. Consider a continuum of evidence with p values in NHST at one end of the spectrum, which represents minimal evidence for meta-analysis. As we proceed away from this end, one could consider confidence intervals and effect sizes as medium evidence for meta-analysis. Fully Bayesian integrated meta-analysis—a mixed methods-based, meta-generative concept advanced by Onwuegbuzie et al. (2018)—is at the end of this spectrum[1]. By incorporating the information attained from previous studies into the specification of a new study's prior, the resulting posterior is the *consolidated information of many studies* and not the findings from a single sample. In this manner, a single study itself becomes partially meta-generative via the integration of prior and present information, which represents a multimethod. In a fully meta-generative approach, information via the extant literature will contribute to the likelihood, as shown in Proposition 3. In the case of a single study being at least partially meta-generative in nature, the evidence or information from the literature is incorporated in the form of a prior, as given in Proposition 4.

Fully meta-generative approach:

$$posterior \propto prior \times \underset{\substack{\uparrow \\ \boxed{\text{Evidence from literature}}}}{likelihood} \tag{3}$$

Single study as partial meta-generative approach

$$posterior \propto \underset{\substack{\uparrow \\ \boxed{\text{Evidence from literature}}}}{prior} \times likelihood \tag{4}$$

For those readers who are new to Bayesian methods, we appreciate that their adoption in standard analytic practice can be a challenges. Indeed, Bayesian methods were sparsely used until a few decades ago due to problems with intractable integrals even in slightly complex models and the lack of software programs to fit such models. However, modern sampling

[1] Note however that we hope that this end of the spectrum will grow as our collective understanding of meta-generative thinking advances.

methods and software programs have made Bayesian methods more accessible. Bayesian methods also have been made more accessible to applied researchers via several textbook authors (e.g., Gelman et al., 2013; Gill, 2015; Kruschke, 2015).

We argue that adaptation of Bayesian approaches and co-occurring meta-generative thinking is worthwhile. Consider that within the field of medicine, virology researchers have displayed some meta-generative thinking that is extremely relevant for this COVID-19 era. In particular, this field has seen the use of a Bayesian framework to estimate the basic reproductive number (R_0) and the distribution of the serial interval (SI), which are often used to quantify transmission during an infectious disease outbreak. Specifically, Moser, Gupta, Archer, and White (2015) used an expansion of the Bayesian framework to provide estimates of R_0 and SI from the 2003 SARS outbreak in Hong Kong and Singapore, and the 2009 pandemic influenza A(H1N1) outbreak in South Africa. This expanded framework involved the incorporation, through prior distributions, of additional information, such as contact tracing and household data. As another example, Bettencourt and Ribeiro (2008) developed a Bayesian scheme for real time estimation of the probability distribution of the effective R_0 and demonstrated “how to use such inferences to formulate significance tests on future epidemiological observations” (¶ 2). Such real-time estimation of R_0 and SI using Bayesian techniques is a particularly compelling example of meta-generative thinking.

The developments in Bayesian methods have prompted many theoretical and simulation Bayesian studies in educational research. Yet, despite this increase in studies (Hamaker & Klugkist, 2011), there is disconnect between practice and theory (i.e., *theory-to-practice gap*). That is, practitioners still do not use Bayesian estimation when it is most appropriate to use such estimation. As such, to date, meta-generative thinking, for the most part, has eluded the field of educational research. This leads to missed opportunities when it comes to using real time estimation in ways that are similar to the above example from medicine. Consider the speed by which the post-truth and COVID-19 era can complicate problems in education research. As an example, there are unprecedented changes to school closures, use of on-line learning, and later there will be deeply altered social ecologies in primary, secondary and university settings. So can policymakers benefit from real time estimation of the probability distribution of the dropout rate of at-risk high school students in settings with a new emphasis of on-line learning? Will school leaders use real time estimation and meta-generative thinking as researchers develop expanded frameworks to understand phenomena like school violence in a post-truth era?

These examples raise the broader question: where are the gaps between theory and practice in the social and behavioral science field in general and in the field of education in particular? To begin addressing this question, we identified publication standards and the organizations that establish these publication standards, such as the American Psychological Association (APA), the American Educational Research Association (AERA), and editorials, as one group of influences on the use of certain methodologies in publications. The ban on NHST by the *Journal of Basic and Applied Social Psychology*—as mentioned previously—is one such example (Trafimow & Marks, 2015). The fifth, sixth, and the very recent seventh editions of the APA Publication Manual emphasized that statistical analyses should report effect sizes, supplemented by confidence intervals where possible (Wilkinson & the Task Force on Statistical Inference, 1999). This is because the task force recognized that reporting statistical significance was inadequate and that the magnitude of the difference or phenomenon was necessary to gauge the complete nature of the results. Although they mentioned the use of Bayesian posterior distributions for Rubin's causal models, it did not further elaborate on the advantages of Bayesian estimation.

AERA's (2006) standards for reporting on empirical social science were written from a frequentist inferential perspective. These standards correctly emphasize the use of confidence intervals and effect sizes when using inferential tests. However, they ignore the drawbacks of NHST and its basic logical fallacy. In fact, neither the 2006 standards nor the sixth edition of the APA Publication Manual contain a single mention of the term *Bayesian methodology*. For example, although editors of the *American Educational Research Journal* (AERJ), one of AERA's flagship journals, state that AERJ "publishes original peer-reviewed analyses that span the field of education research across all subfields and disciplines and all levels of analysis" (AERJ, 2020a), they recommend that "Researchers submitting manuscripts should consult the Standards for Research Conduct in AERA Publications and the AERA Code of Ethics"; AERJ, 2020b)—standards that omit any discussion of Bayesian methods! Similarly, with the exception of specifying that the abbreviation for "Bayesian information criterion" is "BIC" (p. 119) and the non-descriptive mention of "credibility intervals" in the standards for reporting meta-analysis results (p. 252), the authors of the sixth edition of the Publication Manual (APA, 2010) refer to Bayesian methods only on one occasion, where, on pages 251-252, they reproduce Table 4 from the APA Publications and Communications Board Working Group on Journal Article Reporting Standards (2008)—namely, a table entitled, "Meta-Analysis Reporting Standards (MARS): Information Recommended for Inclusion in Manuscripts Reporting Meta-Analyses"—that includes the statement: "How effect size credibility intervals were calculated, if used" (p. 252), although no definition or explanation of credibility intervals is provided in the APA Publication

Manual. Authors of the latest (i.e., seventh) edition of the Publication Manual (APA, 2020) refer to Bayesian methods only on one occasion, on page 93, where they state the following:

> *Bayesian techniques* are inferential statistical procedures in which researchers estimate parameters of an underlying distribution on the basis of the observed distribution. These standards are complex and address the needs of this analytic approach, including how to specify the model, describe and plot the distributions, describe the computation of the model, report any Bayes factors, and report Bayesian model averaging. (p. 93) [emphasis in original]

Although the authors of APA (2020) should be applauded for referring to the journal article reporting standards for quantitative research in psychology of the 2018 APA Publications and Communications Board task force report, authored by Appelbaum et al. (2018), which contained a single table (i.e., Table 8) entitled "Reporting Standards for Studies Using Bayesian Techniques," as can be seen from this quotation, the use of Bayesian techniques was not endorsed by the authors of APA (2020). Unfortunately, this rampant lack of encouragement by publishing gatekeepers representing the field of education and beyond for authors to use Bayesian methods maintains the frequentist status quo. This in turn can discourage the kind of meta-generative thinking that we believe can help transform research in the social sciences.

In sum, the gatekeepers of research such as authors of publishing standards acknowledge the problems in NHST but offer only patchwork solutions such as confidence intervals and effect sizes, rather than actively encouraging alternative frameworks. These solutions are still steeped in the NHST logic. This practice—which is the equivalent of "kicking the can down the road" or "passing the buck"—is dangerous because it encourages current and future generations to continue to train in NHST methods rather than actively investigating alternative solutions such as Bayesian methodology that can in turn facilitate meta-generative thinking.

Universities and departments, colleges, schools of education, and the like, that train future educational researchers are another group of influences. For instance, a course on NHST is required in most educational doctoral programs (Capraro & Thompson, 2008). As the pipeline for producing educational researchers, the graduate curriculum plays an important role in determining the statistical methods that are employed in the literature. Given the utility of Bayesian methods, the question that arises is: are education graduate students given the opportunity to learn Bayesian as an alternative to NHST in their graduate curricula?

The third set of influence on the use of methodologies consists of policymakers and funding agencies that support educational research. For instance, what types of research are funded by agencies such as the Department of Education and the Institute for Education Sciences (IES)? Since 2004, 11 out of 62 grants (approximately 17.7%) for statistical and research methodology in education that have been funded by IES use Bayesian methodology. However, only 25 of 1,516 grants (approximately 1.6%) funded under all programs of the IES use Bayesian methodology. Given the disparity between the percentages of statistical and research methodology grants and all grants that involve the use of Bayesian methodology, an investigation is warranted to determine the degree to which Bayesian methods remain used only by methodologists and not by substantive researchers.

Examining Pathways for Bayesian Meta-Generative Thinking

Research Questions

To address the concerns raised earlier, we examined publication trends and types for Bayesian methodology in educational research, the authors who publish them, and the curricula at the universities where the authors are employed. Specifically, we sought to answer the following research questions: What is the frequency of Bayesian articles published in education research? What types of articles are these? To what degree do graduate curricula include a course in Bayesian methodology? and To what degree do the authors who published articles using Bayesian methods formally have the opportunity to train students at their institutions in Bayesian methods, equipping a pipeline of scholars with methodologies that are superior to NHST?

Study 1: Publishing Trends

Method

In order to understand how frequently Bayesian methodology is used in education research publications, Natesan, Boedeker, and Onwuegbuzie (2017) reviewed all articles published from the years 2005 to 2015 in the following four AERA journals: *Educational Researcher*, *American Educational Research Journal*, *Educational Evaluation and Policy Analysis*, and the *Journal of Educational and Behavioral Statistics*. The keywords that they used for the search were: "Bayes," "Bayesian," "Markov Chain Monte Carlo," "posterior," and "prior." These authors documented that of the 1,248 articles reviewed, a total of 111 studies employed Bayesian methods. Of these, 56 utilized empirical Bayes methods (Table 1) whereas 55 used fully Bayesian methods (Table 2). Thus, only 8.9% of all articles published in these four journals during this 11-year period involved the use of Bayesian methods. Bayesian methods were used in less than one third of these studies to answer applied research questions, which might indicate that Bayesian methods have not been broadly employed by the applied research community.

Insert Tables 1-2 about here

Study 2: Graduate Training for Doctorates in Education

In order to identify additional gaps between theory and practice, Natesan et al. (2017) emailed 32 U.S.-based Bayesian scholars, of which 16 scholars (i.e., 50%) responded. Also, they identified the top 11 graduate school programs in Educational Psychology with a concentration in quantitative methods based on the U.S. News and World Report (2015) publication of the 2016 Best Graduate Schools of Education. They reviewed degree plans and graduate school course catalogs for each program to determine which Bayesian courses, if any, were required or elective and in which department the courses were offered.

Six of the scholars who responded taught Bayesian courses in the colleges of education, whereas one taught outside the college. None of these institutions required their students, who were pursuing a doctorate in education, to enroll in a Bayesian course; however, all of them required a classical (i.e., frequentist) statistics course covering content such as NHST. Of these, one institution (University of Maryland) required its students completing a Ph.D. in quantitative methods to enroll in its Bayesian course. Five other universities had a Bayesian course listed as an elective in the doctoral degree plan. Of these, only three were taught within the college. These programs represent some of the best in the nation in quantitative methods training; yet, they do not uniformly require a Bayesian course. Without such training in graduate school, educational researchers are hard pressed to learn Bayesian methods on their own. This difficulty is compounded by the need to publish, often in journals that rarely publish articles in which Bayesian methods are used, and the lack of training opportunities at national conferences. For instance, the most recent annual meeting did not have any Bayesian methodology training course offerings (cf. AERA, 2019).

Recommendations

Some researchers have placed emphasis on the use of valid statistical methods and moving away from depending on a single index as a substitute for academic reasoning (Wasserstein & Lazar, 2016). This speaks directly to the alignment of Bayesian methodology with meta-generative thinking. Considering this and the statistical advantages of Bayesian methodology, the following recommendations are made to improve quantitative research in education:

Editorial Policy

There is an immediate need for journal editors to review their publication requirements. Given the importance of publication for scholars in general, changes in editorial policies could have a large impact on the use of Bayesian methods in educational research. Editors unable to ban the use of *p* values should at the least include the use of Bayesian methods as a favorable approach, explicitly named in publication guidelines. To introduce a skeptical readership to the utility of Bayesian methods, authors should be encouraged to present results of the same study conducted using Bayesian *and* frequentist methods, promoting the use of multiple methods research! Juxtaposing the findings and highlighting the Bayesian interpretation of results would make the findings more understandable for research consumers. (For an example of the benefit of using both Bayesian and frequentist methods in randomized controlled trials, see Wijeysundera, Austin, Hux, Beattie, and Laupacis [2009].) APA journals now require translational abstracts because their editors recognize the need for research to become more accessible to a wider audience. Similarly, publication efforts to make more appropriate statistical methods such as Bayesian methodology more accessible to a wider audience should be encouraged (e.g., Kruschke, 2015; Natesan, 2019b; Natesan, Onwuegbuzie, Hitchcock, &

Newman, 2019), as well as the framing of Bayesian methodology as a mixed methods (Natesan Batley, in press; Onwuegbuzie et al., 2018) and multiple methods research approach.

Graduate Training

The graduate training of quantitative researchers in education should include at least one Bayesian methods course. Considering that Bayesian methods likely are unfamiliar to many graduate students in education, a first course in which students are taught Bayesian methods in a focused manner is recommended. Beyond that, more advanced courses that currently exist in the graduate curriculum can be modified to include Bayesian applications.

Accessibility

Until a few years ago, only programming-savvy individuals could conduct Bayesian analyses. However, with the advent of programs such as BUGS, JAGS, STAN, and R (MPlus and SPSS now have Bayesian options), Bayesian analysis is becoming more accessible. There is a learning curve associated with programming in these languages. However, learning to write the program for conducting ANOVA should be favored over using a graphical user interface (GUI) while ignoring all other aspects of data analysis. Indeed, writing a program necessitates a more thorough understanding of the analysis and the results. Instead of the GUI results pointing the researcher to identify and to interpret a statistically significant p value or a substantially high effect size, the researcher has to think about what particular results are important, why they are so, and what this means to replicability of the analysis.

In the recent years, the call for proposals from the Institute of Education Sciences (IES) for statistical and research methodology in education (CFDA 84.305D; IES, 2018) specifically states that the institute is interested in products, “that can be used by most education researchers (rather than only by statisticians and researchers with highly sophisticated statistical skills) to improve the designs of their studies, analyses of their data, and interpretations of their findings." As stated previously, the institute has funded several Bayesian proposals such as development of Bayesian software that is accessible to other researchers (e.g., Stan software developed by Andrew Gelman and colleagues). This is an encouraging step in the right direction.

Our study indicates that there are pockets of Bayesian efforts both in the form of training and research. However, the review of education research literature and IES funded grants show that there is a big chasm between Bayesian methodologists and substantive researchers. It seems that most educational researchers and agencies recognize the issues with NHST but perhaps are not fully convinced that Bayesian methodology is a superior alternative. Yet there are many publications that can convince a reader of this superiority. Of course, there are many quantitative researchers who recognize the advantages of Bayesian methodology, but our work shows that the efforts to making these methods accessible are few and far in between. In any case, without the ability to utilize Bayesian methodology, it will be difficult for quantitative researchers representing the field of education and beyond to adopt a multiple method-based, meta-generative thinking.

In conclusion, to maximize and to optimize the conduct of both analyses *of* policy (i.e., analyses that are analytical and descriptive and that represent attempts to explain policies and their development) and analyses *for* policy (i.e., analyses that are prescriptive and that represent attempts to create policies and proposals), researchers should incorporate findings from the extant literature into their existing analyses to the greatest extent possible in order to ensure that past and present findings are connected via a cumulative, multimethod approach to conducting research. And as we have outlined in this editorial, quantitative researchers can accomplish this by adopting meta-generative thinking via the use of Bayesian methodology. We contend that

Bayesian meta-generative thinking is essential, given the potential for divisiveness and far-reaching sociopolitical, educational, and health policy implications of findings that lack generativity in a post-truth and Covid-19 era. It is only by holding the conduct of quantitative research to such high standards that researchers can hope to maximize their opportunities to effect policy in a post-truth and Covid-19 era and beyond.

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Table 1

AERA Journal Review, 2005-2015, Empirical Bayes

Journal	Total Articles Reviewed	Articles that Used Bayesian	Classification	Articles by Classification*	Model: Regression	HLM	SEM	Psychometrics	Multivariate
Educational Researcher	378	4	Empirical/Applied	4		3	1		
			Simulation/Theoretical	0					
			Empirical/Theoretical	0					
			Sim&Emp/Theoretical	0					
American Educational Research Journal	370	10	Empirical/Applied	10		8		3	
			Simulation/Theoretical	0					
			Empirical/Theoretical	0					
			Sim&Emp/Theoretical	0					
Educational Evaluation and Policy Analysis	242	17	Empirical/Applied	17		16		1	
			Simulation/Theoretical	0					
			Empirical/Theoretical	0					
			Sim&Emp/Theoretical	0					
Journal of Educational and Behavioral Statistics	258	25	Empirical/Applied	0					
			Simulation/Theoretical	3		1		2	
			Empirical/Theoretical	9		6		2	1
			Sim&Emp/Theoretical	13	1	7		6	
Totals	1248	56			1	41	1	14	1

*Some articles contained more than one model. Therefore the sum of numbers across the model columns may add to more than their corresponding articles by classification value.

Table 2

AERA Journal Review, 2005-2015, Fully Bayesian

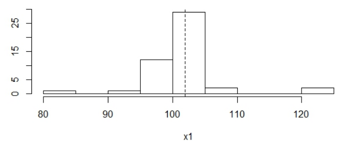
Journal	Total Articles Reviewed	Articles that Used Bayesian	Classification	Articles by Classification*	Model: Regression	Model: HLM	Model: SEM	Model: Psychometrics	Model: Multivariate
Educational Researcher	378	0	Empirical/Applied	0					
			Simulation/Theoretical	0					
			Empirical/Theoretical	0					
			Sim&Emp/Theoretical	0					
American Educational Research Journal	370	0	Empirical/Applied	0					
			Simulation/Theoretical	0					
			Empirical/Theoretical	0					
			Sim&Emp/Theoretical	0					
Educational Evaluation and Policy Analysis	242	3	Empirical/Applied	3		3			1
			Simulation/Theoretical	0					
			Empirical/Theoretical	0					
			Sim&Emp/Theoretical	0					
Journal of Educational and Behavioral Statistics	258	52	Empirical/Applied	0					
			Simulation/Theoretical	4		1		3	
			Empirical/Theoretical	14	3	8	2	4	
			Sim&Emp/Theoretical	34		17	1	21	1
Totals	1248	55			3	29	3	28	2

*Some articles contained more than one model. Therefore the sum of numbers across the model columns may add to more than their corresponding articles by classification value.

Electronic Supplementary Material

Table A

Comparison of classical and Bayesian t-tests for a heuristic data

<table>
<tr><th>Step</th><th>Traditional</th><th>Bayesian</th></tr>
<tr><td>Given the data
$\overline{x_1} = 101.92;\ \overline{x_2} = 100.35$
$s_1 = 6.02; s_2 = 2.51$
$n_1 = 47, n_2 = 42$


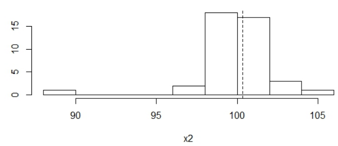
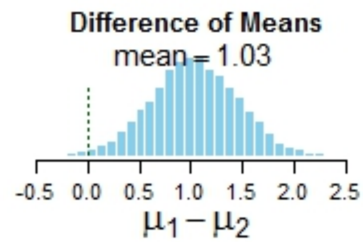
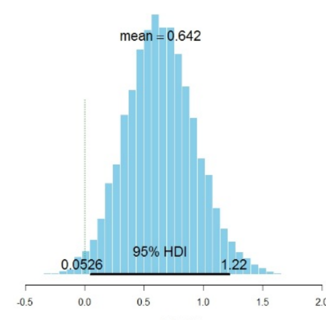

</td><td>Is $P(Data|H_0)$ so small that the null hypothesis can be rejected?</td><td>What is $P(H_0|Data)$ or what is $P(H_{alternative}|Data)$ so that the null or the alternative hypotheses can be accepted/rejected?</td></tr>
<tr><td>Hypothesis: Null</td><td>$p_{calc} = 0.1$. Reject H_0</td><td>The posterior of the mean difference for the distributions from which x1 and x2 are drawn (i.e. $\mu_1 and\ \mu_2$,respectively) does not contain 0.

</td></tr>
<tr><td>Cohen's d and 95% interval</td><td>$d = 0.335\ [-0.63, 1.30]$</td><td>Cohen's d Posterior distribution

</td></tr>
<tr><td>Interpretation</td><td>This 95% CI contains d = 0</td><td>The probability of $0.05 \leq d \leq 1.22$ is 0.95</td></tr>
</table>

Table B

Stages of the Research Process and their Contextualization Via the Extant Literature

Stages of the Research Process	Role of the Extant Literature	Outcome
Introduction	Sets up background to the study, states the existing open problems and why they are a problem	Convinces the reader of the impetus for the study
Literature Review	All relevant arguments and findings for, against, and surrounding the current topic	Identifies the gaps in the literature
Method	Research designs, instruments (e.g., surveys), data (e.g., secondary data), types of analyses.	Informs the researcher of some appropriate methods and analyses. What method worked and what did not.
Analysis	No context. Previous findings are ignored, data are acontextualized and treated as a standalone entity instead of as representation of the population	Standalone analysis that ignores the findings of previous studies
Discussion/conclusion	How the results of the present study resonate, confirm, add to, or contradict existing research	Informs the reader as to how the study contributes to the body of knowledge and fills an existing gap

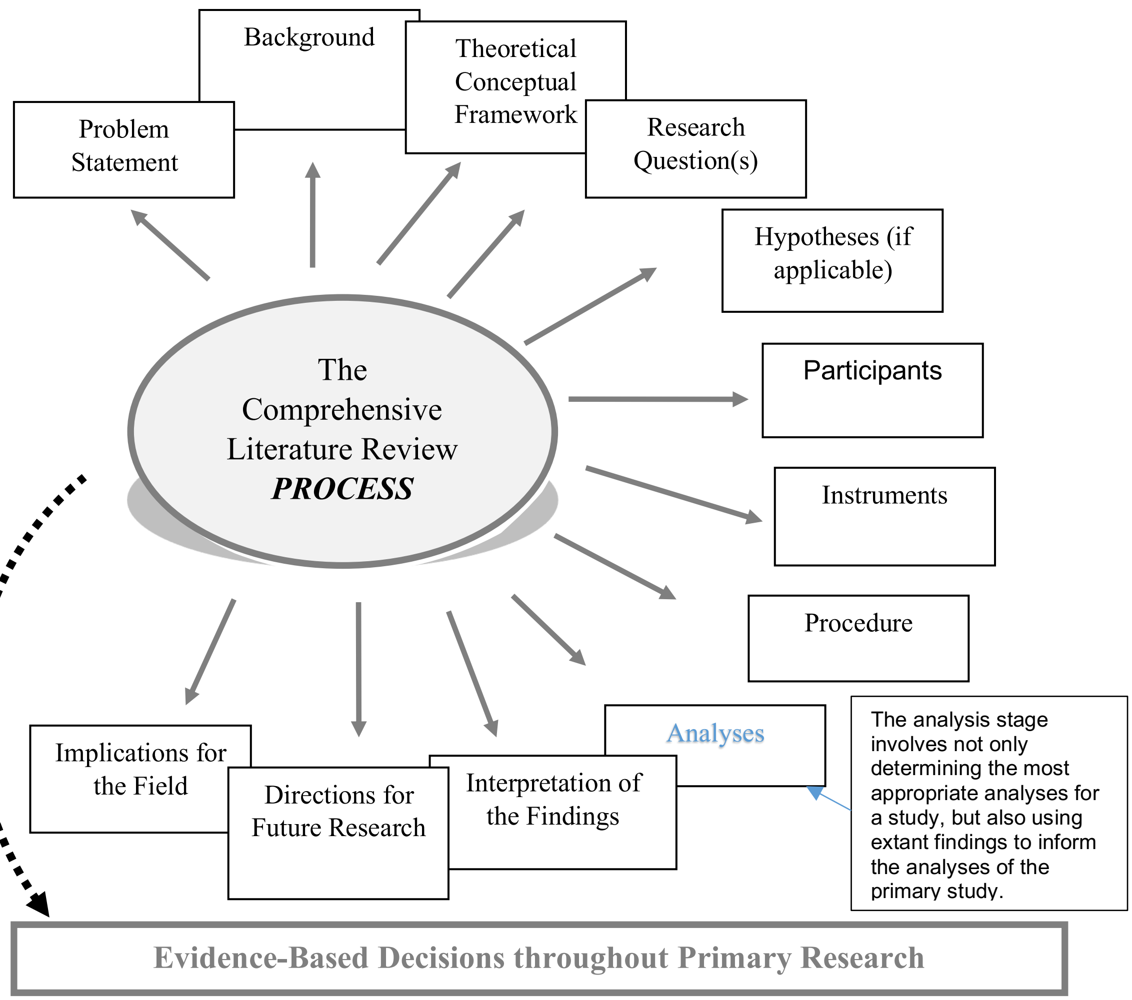


Figure 1. The Comprehensive Literature Review process as it informs the various components of a primary research report.

Adapted from "Seven steps to a comprehensive literature review: A multimodal and cultural approach," by A. J. Onwuegbuzie and R. K. Frels, 2016, p. 59. Copyright 2016 by Sage Publications.