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Big Data in Educational Science II: The story of meta-analysis

Big data is a current hot topic not only in educational science but in science more generally.

Recently, meta-analysis was mentioned as "the grandmother of the 'big data' and 'open science' movements" (Gurevitch, Koricheva, Nakagawa & Stewart, 2018). Hence, we see the need to introduce the story of meta-analysis – to understand in detail the relevance of meta-analysis in relation to big data.

To present the complete story of meta-analysis and to understand the value and challenges of meta-analysis in the context of big data, we introduce first the origin of meta-analysis and then its spread in educational science. Finally, we lay out the pros and cons of meta-analysis and link it in our summary and outlook to future big data analysis.

Historical Introduction to Classical Meta-Analysis within Educational Psychology

Starting Point

Classical meta-analysis originated in the field of medicine but soon appeared in the field of education (Lipsey & Wilson, 1993; for an overview of the spread of meta-analysis in different areas, see Shadish, 2015). The starting point of meta-analysis within the educational field was Glass's (1976) presidential address to the American Educational Research Association, in which Glass introduced the key term "meta-analysis" for analyzing summary statistics from studies and, hence, for viewing study-level data as the unit of analysis to reach more power and reduce uncertainty. At that time, nonquantitative narrative reviews were often used to report the state of research within educational science. Facing similar challenges, different research teams have since developed different meta-analysis approaches (see Ioannidis, 2010; Rosenthal & DiMatteo, 2001; Schmidt & Hunter, 2014; Shadish, 2015). The three classical meta-analysis approaches were developed by three research groups, which were interested in whether selection test validities were generalizable (Schmidt & Hunter, 2014), whether psychotherapy was effective (Glass, 1976), and whether interpersonal expectations influenced behavior (Rosenthal & DiMatteo, 2001). Each group became aware of the rapidly growing research literature after the Second World War and saw that traditional narrative review methods were inadequate to summarize the knowledge. Hence, the three resulting classical meta-analysis approaches can be seen as a first attempt to handle large data corpora efficiently.

The Spread of Meta-Analysis within the Educational Field

All three approaches led to a fruitful spread of meta-analysis, resulting in mega meta-analyses. A mega meta-analysis is a meta-analysis on meta-analyses; Lipsey and Wilson (1993) or Hattie (2009) are examples in the education sciences.

Due to the success of meta-analysis, area-specific societies were founded, such as the Campbell Collaboration in 1999 for the social sciences and the What Works Clearinghouse in

2002 for specific educational studies and reviews (managed by the Institute of Education Sciences on behalf of the U.S. Department of Education). The aim of these societies is to register in a database all studies within an area, making them available for meta-analyses; the studies are thus readily found, and possible publication bias is reduced. Publication bias can lead to wrong conclusions based on meta-analysis data due to missing studies. (For a discussion on publication bias, see Rothstein, 2008, p. 78.) Additionally, a Special Interest Group, Systematic Reviews and Meta-Analysis, was formed within the American Educational Research Association to promote meta-analysis within educational science.

After introducing a short story on meta-analysis, we refer the interested reader to Shadish (2015) and highlight in the following the weaknesses of meta-analysis and how to overcome them.

The Weaknesses of Meta-Analysis and How to Overcome Them

Although meta-analysis is highly appreciated by researchers, some disadvantages should be acknowledged. In the following, five main disadvantages with recommendations for how to control them will be presented (see also Eysenck, 1994, and Table 1).

Publication bias

Publication bias, or the "File-Drawer Problem," is defined as a bias towards studies with significant results; they are more likely to be accepted. For example, it could be that studies with positive correlations are more likely to be accepted for publication than studies with a negative correlation. This fact could be pose a considerable threat to the representativeness of meta-analysis samples. In addition, one could assume that studies showing unexpected results—for example, that experts are not as accurate in their judgments as students—may have problems getting published. To prevent any publication bias influencing the interpretation of meta-analysis, the following strategies are initiated:

a. Using a comprehensive literature-search strategy to decrease the possibility of overlooking studies.

b. Checking the possibility of publication bias by means of graphics, so-called funnel plots (see Duval & Tweedie, 2000). The following figure shows a typical funnel plot (see Kaufmann, 2010). All studies that are included in a meta-analysis are highlighted by blue circles. In addition, this figure also shows the number of missing studies (publication bias) and highlights them in red (triangles).

c. Estimating the publication bias with different estimators to find out how many studies are needed to change the actual results.

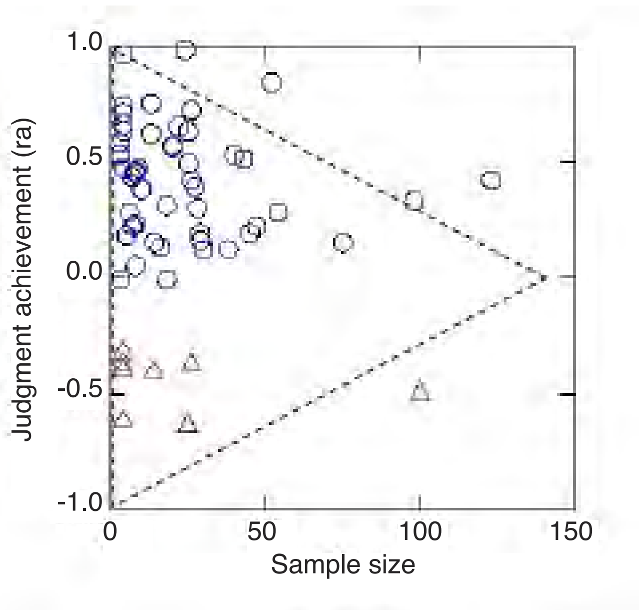

Figure 1. Funnel plot (see Kaufmann, 2010).

Table 1. Summary of disadvantages of classical meta-analysis and our suggested solutions	
Publication bias	- Comprehensive literature search - Funnel plots
“Apples and oranges” problem	- Coding - Robustness analysis
Quantitative aspects	- Evidence synthesis approach
Garbage in–garbage out	- Coding - Inclusion criteria - Robustness analysis
Ecological fallacy	- IPD meta-analysis

“Apples and oranges” problem

The “apples and oranges” problem represents the fact that, in meta-analysis, studies that do not really deal with the same constructs and relationships are often integrated and summarized.

Consequently, meta-analysis must be carefully coded to reveal any uniformity problems. Additionally, so-called robustness analysis, in which first “apples” and then only “oranges” and, finally, their combination is considered, should be conducted. By an analysis check, any differences between “apples and oranges” will then be revealed.

“Focusing on quantitative approaches only” problem

The focus on the quantitative approach may lead to neglect of the qualitative approach of the reviews. To not overlook the quality of the included studies, we recommend Slavins’ (1986) best-evidence synthesis, an attempt to combine qualitative and quantitative reviewing techniques in the same research review and not only focus on one of them.

“Garbage in–garbage out” problem

The “Garbage in–garbage out” problem represents the inclusion of studies of different methodological quality. To overcome this problem, Slavin (1986) suggests defining very strict methodological criteria for inclusion so the meta-analyst has assurance that the synthesis is based on only the “best” evidence. Hence, meta-analysts must carefully check the inclusion criteria and consider this fact in coding studies and also check this in different analysis-robustness analysis if some difference in coding also leads to differences in the results.

“Ecological fallacy” problem

Like other multilevel analysis, meta-analysis is also prone to bias by data aggregation. Ecological fallacy (Robinson, 1950) is one such possible aggregation bias. For example, the meaning of aggregated data in different levels may represent contradicting results. To overcome this ecological fallacy, individual participant data (IPD) meta-analysis is recommended. This type of meta-analysis is based on individual data instead of study aggregated data like in classical meta-analysis.

Summary

We presented different problems when conducting a classical meta-analysis and also show how to overcome these problems. A summary of our meta-analysis problems is given in table 1. Please consider that there are additional problems that are not mentioned, and we refer to it (e.g., Kaufmann et al., 2016).

Outlook for Big Data Analysis

Due to the development of meta-analysis from the starting point to recent developments, meta-analysis is also ready for today's big data challenges. We now see more and more data coming from different sources; moreover, individual data are accumulating. Hence, we see IPD meta-analysis as a grandchild of classical meta-analysis—with which it is possible to check for any aggregation bias—and IPD meta-analysis might also be an analyses tool for big data.

We see considerable potential in transferring the aggregation unit from the study unit to the individual level. However, we note that, in future, comparisons of different aggregation units will be required to increase the accuracy of data aggregation. Moreover, research into how professionals, e.g., teachers, consider (meta-analysis) advice is also included in the scope of our research.

If you are interested in our research, as a teacher, politician, or researcher, we welcome your emails with additional specific information. Please consider also our previous article on meta-analysis, see: Kaufmann, E., & Maag Merki, K. (2017). Big data in educational science: Meta-analysis as an analyze tool.

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