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Why the Veracity of Data Matters in Health Care Research

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Why the Veracity of Data Matters in Health Care Research

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Credentials Display

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My mom will occasionally express her frustration with the outcomes of scientific findings. She will exclaim, for example, that one day fish is good for you and the next day it isn't; they just can't make up their minds. As the health professions have pushed for evidence-based practice (EBP), many clinicians have expressed similar frustrations with the research on which they are supposed to base their practice. The same treatment that is found to be effective in one study will be not effective according to another study. My students recently completed a case study for which they had to provide a research article to support their treatment plans. One student used a study that found eye exercises were just as effective if done in the home or in the practitioner's office while another student used a study that found that eye exercises were only effective if done in the practitioner's office. Why did these studies have different findings? How could one study find a treatment to be effective while another study did not? How can fish be good for you one day and not good for you the next? The answers, of course, are in the data.

The veracity of data is simply the truthfulness of the data. The data should be accurate, reliable, and trustworthy. Does the answer provided by the data tell the truth? The data may have problems because they are imprecisely collected or misinterpreted. As the health professions have come to rely on data to drive EBP, it is imperative that we consider the veracity of the data. This letter from the editor will discuss veracity related to big data, small data, and statistical significance.

Big Data Problems

The promotion of systematic reviews and meta-analysis for EBP along with the prevalence of electronic health records has created the advent of big data. Although there does not seem to be a definitive definition of big data, it is generally described as large, aggregate data sets typically created from data mining of public records or electronic medical charts (Raghupathi & Raghupathi, 2014; Rothstein, 2015). Big data sets can have problems that affect veracity. Because clinical practice generally does not provide researchers with large data sets, big data sets are obtained via chart review or shared data. These data sets may lack consistency, and the data collection procedures may be less controlled than in small clinical trials. The "who, what, where, when, and why" of the data and data collection are much more variable and sometimes difficult to ascertain. The general assumption about conclusions drawn from health research is that the data are "certain, clean, and precise" (Raghupathi & Raghupathi, 2014, p. 4). With big data, however, researchers draw conclusions about the effectiveness of treatments based on data that may not reflect the same people, treatments, environments, time-frame, or purpose. As stated by Lukoianova and Rubin (2014), "This is an important limitation of current big data research and practice, since without identifying big data veracity big data-driven discoveries are questionable" (p. 5).

In addition to the data collection issues that surround big data, the interpretation of statistical findings is an issue. Big data may be too big to fail. With high levels of power, statistical significance

may be easily found, yielding some unusual results and conflicts in data interpretation. Type I errors, in which statistical significance is found but a true difference does not exist, lead to misinterpretations of data. Therefore, one study may find a relationship between a treatment and improved function, while another one may not, and therapists are left puzzled by the implications of the results related to EBP.

Small Data Problems

In the occupational therapy profession, as in most health professions, there are fewer big data problems. The evidence on which we base our practice is typically derived from small data gathered through clinical trials with a uniform and discrete sample with specific problems. These data, however, have a different set of potential problems. While big data may be too big to fail, small data may be too small to succeed. The lack of power to find statistical differences may lead to Type II errors, in which there is a real difference but a statistical difference is not found. So, one type of treatment may be more effective than another type of treatment for improving function, but the data do not indicate a difference.

While big data have more consistency and control issues, small data, both quantitative and qualitative, have more issues with objectivity. Small, clinical research lends itself to higher involvement and investment from the researcher, which may make it difficult to delineate the differing roles of the therapist researcher (Hinojosa, 2003). Confounding variables, such as the relationships between the therapist or researcher and

(Davies & Dodd, 2002). A treatment may be effective when used by one therapist but not effective when used by another. The researcher, especially the one who collects data on his or her own treatment sessions, as is often the case in clinical research, may have difficulty not only carrying out the treatment according to the standard procedure outlined in a research protocol but also remaining objective in the interpretation of the data.

The Significance of Significance

Further contributing to the problem is the preferential publication of research that is statistically significant or novel over that which has veracity (Ware & Munafò, 2014). If statistical significance is found, the research article, regardless of the size of the data, is more likely to be published. The publication of research solely based on the significance of findings may inhibit the veracity of the presentation of the data and promote misinterpretation of findings. Findings that are not statistically significant, however, also have implications for clinical practice. A study that finds that a treatment is not effective is ultimately important for decision making regarding treatment choices.

In addition, if one treatment is not found to be significantly better than the other, that is useful information for a clinician who is making daily client-centered clinical decisions. If one treatment is preferred over another by the client, and there is not a statistically significant difference in the effectiveness of those treatments, the therapist could provide the client both treatment options, as the evidence supports them both. For example, many years ago, I co-wrote an article that examined the

differences between a remedial versus a compensatory treatment for attention and processing postacquired brain injury (Dirette, Hinojosa, & Carnevale, 1999). The participants in both groups improved significantly from pretest to posttest, but there was no statistical difference between the groups on the level of improvement. One reviewer commented that it was “too bad” that there was no evidence found to support the compensatory treatment over the remedial treatment. That comment always stayed with me. Why was it “too bad” that I did not find a statistical difference between the treatments? Both groups improved significantly from pretest to posttest. The fact that the clients who developed their own strategies during the remedial intervention did as well on the blinded posttests as the clients who were taught compensatory strategies is as interesting and useful as one treatment being significantly better than the other. Unexpected outcomes and gray areas are interesting. This is where we learn the subtle differences in the options for our clients and find our clinical judgment to be useful.

Strategies for Clinical Research

To improve the veracity of your data, focus on three sections of your study: the method, the results, and the discussion. Consider how bias and misinterpretation could affect each area. Keep asking if the data are objective, accurate, reliable, and trustworthy, and keep revisiting these questions during the planning, data collection, analysis, and interpretation of the study.

For the method of the research, consider how the veracity of the data will be impacted by the sampling, data collection procedures, validity of the

instruments, and data analyses. Detailed methods that are approved by a human subjects internal review board can help with this process, but the review board’s main purpose is the protection of the participants. Consulting with other researchers with specific questions that help ensure veracity of the data before beginning the research project is recommended. Have the consultants generate ideas about potential problems, such as sampling and procedural variability, instrument issues, confounding variables, and faulty analysis plans that might be too weak or too powerful and likely to result in errors.

To ensure that the results section is accurate, examine the source and variability of the data. At least one author from the study should have full access to the data, especially if it is a big data source (Deangelis & Fontanarosa, 2010). Before the data are analyzed, reflect on your expected outcome. When analyzing the results, let the data surprise you and even contradict your former assumptions and preconceptions. In addition, consider having an independent analysis carried out by a statistician to review and verify your results (Deangelis & Fontanarosa, 2010). When reporting the data, focus on the facts that are in the data and do not attempt to interpret or explain the data.

The discussion section is the chance for you to reflect on the results of the research. Question the results and do not judge them as obvious (Malterud, 2001). Look at the context of the study and possible bias. Generate alternate explanations for the results to ensure possible confounding factors have been considered. Then, consult again with other sources, such as the literature, expert

opinions, and participants, to confirm or counter your interpretation of the data.

Conclusion

So, is fish good for you or not good for you? Do you need to have clients do eye exercises in the clinic or can they do them as a home program? The answers are in the data. Differing results may indicate that the veracity of the data is lacking, that there may be an error in the data analyses, or that the researchers may be misinterpreting the data. Whether you are conducting a study with big data or small data, using steps to foster the veracity of the data is important to ensure that clinical practice is accurately informed. Let the data lead you where they may, even if they counter your assumptions and expectations. With improved veracity in the data, we can ensure better evidence on which to base our practice.

Diane Powers Dirette, Ph.D., OTL, FAOTA is the cofounder of OJOT and has served as Editor-in-Chief since the first issue was published in the fall of 2012. She is a professor in the Department of Occupational Therapy at Western Michigan University and was inducted into the American Occupational Therapy Association Roster of Fellows in 2016. Her areas of research include self awareness after acquired brain injury, evidenced-based practice, visual disorders, and cognitive rehab. She has extensive experience with scholarly writing, editing, and publishing.

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