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COMMENTARY

What about Figure 1? Presenting descriptive figures to facilitate the interpretation of longitudinal research

Jenna A. Van Fossen

Michigan State University
*Corresponding author. Email: vanfos10@msu.edu

Murphy (2021) contends that the analytic methods that are used in organizational research have become more complex. This in of itself should not be surprising, because once constructs are proposed and nomological networks have been established scholars can begin to ask more complex questions about the boundary conditions for the effects and processes that underlie relationships. Scholars will also consider how relationships develop and change over time, necessitating longitudinal research.

Yet Murphy (2021) argues that the findings from more complex analyses are more difficult to interpret and that this may exacerbate the gap between scientists and practitioners. Murphy presents a commonsensical call for greater attention to be given to descriptive results to help increase understanding of complex analyses. However, the recommendations that he provides are mainly geared toward judging whether a complex analysis is appropriate rather than attempting to convey complex findings more clearly. Given the increasing complexity of analytic methods that are used, more should—and can—be done to promote interpretability in the results section as one means of bridging the scientist–practitioner gap.

Intensive longitudinal data and the science-practice gap

There has been a rapid proliferation in longitudinal research designs with multiple time points (Gabriel et al., 2019). Moreover, given that scholars advocate for experience sampling methods (ESM) to study how dynamic processes unfold (e.g., Can, 2020), intensive longitudinal designs with a large sample size and large number of time points are likely to continue to become more prevalent. Yet whereas many undergraduate students in psychology are exposed to the concepts of moderation and mediation, this is not the case for complex analyses such as multilevel or dynamic structural equation modeling.

An important issue is that, as noted by Murphy (2021), the increasing popularity of complex analyses may function to widen the gap between scientists and practitioners. This is a concern because the most interesting findings about within-person phenomena may be useful only in so far as they affect practices within organizations, and because practitioners can provide useful insight to challenge and spur new research questions on within-person processes. Given the ubiquity of ESM research, concern over the scientist–practitioner gap (Rynes, 2012), and the importance of translating scientific findings to the public, it is valuable to implement strategies to promote greater understanding of results from longitudinal data.

Presenting figures for descriptive results with longitudinal data

Descriptive results are often presented in the first table (i.e., Table 1). By extension, one step to facilitate the interpretation of intensive longitudinal can be to present descriptive results in an early figure (i.e., Figure 1). (Recall the adage: "a picture is worth 1,000 words, or four pages double spaced"). There is some support that using graphics to display levels of variables in longitudinal data may aid in interpretation both for academics and the public (Francis et al., 2014). Scholars have also voiced that greater use of graphs in psychology can reduce overreliance on significance testing in the interpretation of results and increase communication and understanding between different disciplines (Smith et al., 2002). Indeed, psychology as a field has been criticized for failing to draw from graphs appropriately, perhaps due to a Western "logocentric bias" for tables and words over visuals (Smith et al., 2002).

At a minimum, researchers can designate Figure 1 to show plots of the average levels of study variables over time. Researchers who collect longitudinal data typically do not include a line graph that plots the levels of the variables over time if they are not attempting to display a trend in the data. Such a figure may not necessarily aid in the understanding of the hypothesized analyses; however, it can serve a valuable role. Graphing the levels of the study variables over time may help grant understanding of (a) the degree of fluctuation in variables in a way that is more intuitive compared with presenting the standard deviation alone and (b) a basic sense of how variables covary over time. Such graphs can more clearly convey abstract ideas, such as the intervals of measurement that were used in collecting intensive longitudinal data and within-person relationships between variables (Chance et al., 2007). For instance, plotting focal within-person predictor, mediator, and outcome variables over time may grant an intuitive sense of how they fluctuatein relation to one another.

There is also an opportunity for figures to illustrate slightly more complex findings. For example, a figure can depict the magnitude of the average correlation between two variables across multiple time points to illustrate the variability in their relationship. Figures can also be used to convey some basic insight into results, including between-person differences in within-person processes. For instance, line plots can depict the magnitude of the correlation between two variables over time for subgroups of participants selected for their standing on a third variable to facilitate greater understanding of cross-level moderation effects. Finally, depending on the research design and questions, there are many alternatives to line graphs that can be used to display longitudinal data (e.g., lasagna and spaghetti plots, Weissgerber et al., 2019).

Including graphs to visually represent data does ask for additional time and effort on the part of a research team—but not that much more time and effort, especially considering the opportunity to facilitate understanding of within-person relationships and variability for a wider audience. There are online resources that are readily available to assist in creating interactive line graphs and other visual displays (Weissgerber et al., 2019). A further direction is for researchers to experiment with how to present longitudinal data in graphs other than line charts (e.g., circular spider plots, Francis et al., 2014) and study how different presentation formats may influence interpretation.

Conclusion

As analyses in organizational research grow more complex, greater training is needed to interpret results, and this carries a risk of increasing the divide between science and practice. As one means of enhancing the interpretability of findings from intensive longitudinal research, researchers can designate Figure 1 to show the fluctuations and relationships between variables in an intuitive manner to help readers grasp the dynamic nature of the data.

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