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EDITORIAL

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Introduction

A pressing issue facing health psychology research, and science in general, is ensuring precision and confidence in findings of empirical studies. With concerns surrounding the replicability of findings in psychology more broadly (namely, the 'replication crisis'; Maxwell, Lau, & Howard, 2015; Pashler & Wagenmakers, 2012), questions and criticisms have been raised over the way researchers conduct and analyse studies. In response, researchers need to make substantial changes to the way studies are conducted to ensure research integrity (Asendorpf et al., 2013; Cumming, 2014; Munafò et al., 2017) and that findings stand up to replication (Earp & Trafimow, 2015). Researchers must use the best methods and data analytic practices feasible to conduct tests of research questions that stand up to scientific scrutiny and the rigours of replication. Applying contemporary statistical methods to analyse data is paramount to ensure rigour and confidence in the findings of research in health psychology (Cumming, 2014). Researchers therefore have a responsibility and an obligation to draw on advances and progress in statistical methods when analysing data and drawing inferences, and need to avail themselves of the emerging advanced statistical tools to avoid selection and other inappropriate data analytic practices.

Given the pace of improvements in statistics and methods, it is understandable when researchers express feelings of uncertainty or fear and lack sufficient self-efficacy to fulfil such demands, especially for those who are not methodologists or do not consider themselves experts in statistical analytic methods. As a result, researchers may choose to fall back on their tried-and-tested, but dated and potentially inadequate, statistical methods, perpetuating further criticism of findings within the discipline or preventing researchers from making more creative advances. To address this issue, we suggest that researchers should seek out expert opinion and keep up-to-date on advances in analytic techniques so that they may select the most appropriate methods when analysing their data.

The latter suggestion motivated the inception of the current Special Issue on advanced analytic and statistical methods in health psychology. The aim of the issue is to provide researchers in health psychology with a compendium of advances on selected analytic techniques that are increasingly being applied in health psychology and related research. Specifically, the Special Issue showcases six articles that provide diverse and stimulating perspectives on innovative, alternative, and/or increasingly popular statistical methods. Each article outlines the relevance of the statistical method to health psychology and provides examples of how to use the statistical method in health psychology research. Moreover, each article demonstrates how to apply the statistical method, providing resources and key practical points on how to implement the analyses. Each article can be considered a tutorial aimed at increasing knowledge on the statistical method and used as a template to engage in these advanced approaches in the future.

Highlights of the Special Issue

Three key themes unify the current collection of articles. First, the collection highlights study methods such as N-of-1 and ecological momentary assessment (EMA) that can take advantage of increasingly sophisticated methods to collect time-series data with a high number of observations for each individual and model that data over time. Second, alternative and more comprehensive statistical approaches that can stimulate advances in the quality of primary-level research are presented,

such as advances in assessment of scale quality using omega and alternatives to the traditional frequentist statistical analysis approach using Bayesian methods. Finally, with the expanding literature on primary research in health psychology, the articles outline advances in methods of meta-analysis that can help to provide more rigorous syntheses of existing research findings, methods such as meta-analytic structural equation modelling (MASEM) and spatiotemporal meta-analysis.

Focusing on the first theme of analysing time-series data with a large number of data points, Vieira, McDonald, Araújo-Soares, Sniehotta, and Henderson (2017) discuss N-of-1 studies. N-of-1 studies offer an opportunity to explore within-person variability over time for a single person, or series of persons, to accommodate periodicity effects (repeating patterns) as well as social–ecological factors (e.g., interactions with other people, traumatic events, extreme weather). As variance associated with a set of predictors and response to treatment is calculated for the one person, individualised health psychology interventions and making treatment recommendations for individual patients can be developed (Gabler, Duan, Vohra, & Kravitz, 2011). Despite the potential strengths of N-of-1 studies, a key barrier in the use of these designs is the complexity and uncertainty around its statistical analysis. The authors have tackled this issue by recommending the use of dynamic regression modelling as a robust method to analyse time-series data, a suggestion Davidson and Cheung (2017) make in their commentary on this article, and provide an illustrative example of its use in physical activity. Although the authors chose to use physical activity as an example, N-of-1 studies are useful for many health behaviours and chronic conditions when tracking change over time provides a more nuanced picture of change within individuals, rather than such a specific use (Gabler et al., 2011). To date, the use of N-of-1 studies has not been fully exploited. Although important assumptions must be considered when using dynamic modelling and there remain other issues inherent in using N-of-1 studies that need addressing, the authors have brought us a step closer to making the use of such designs more accessible to researchers. In moving this field forward, an avenue for future research is to use meta-analytic procedures to synthesise results from independent N-of-1 studies that examine the same phenomena and procedures with studies examining the same phenomena in $N > 1$ samples (Vieira et al., 2017).

Continuing this theme, Richardson, Fuller-Tyszkiewicz, O'Donnell, Ling, and Staiger (2017) discuss an increasingly popular method of intensive longitudinal data collection in health psychology: EMA. EMA studies offer an opportunity to capture repeated, state-based assessments of individuals' health behaviours, experiences, and emotions using data collection tools such as daily diaries or smartphones. Although these methods provide exciting opportunities to collect real-time data, similar to N-of-1 studies, statistical analysis of these kinds of data presents some challenges. To encourage researchers to take advantage of EMA designs, the authors recommend the use of regression tree modelling (RTM), suggesting it to be a useful alternative to multilevel modelling (MLM) for investigating the association between a set of explanatory variables and a continues outcome. Using an example of an analysis undertaken to assess the relationship between intentions to use alcohol, level of stress, and planned to be at home that evening, the authors illustrate and compare the application of RTM and MLM. They conclude that although both approaches model the data equally well, RTM offers more advantages and flexibility over MLM to analyse data collected using EMA. As with all methods, the authors highlight some of the limitations of using RTM, and these caveats are nicely outlined by Modecki and Mazza (2017) in their commentary of this article. Both Richardson et al. and Modecki and Mazza recommend that future health psychology research needs to consider the diverse repertoire of potential methods when analysing EMA data, and applying a range of models rather than exclusively relying on regression approaches.

In addressing the second theme of using alternative and more comprehensive statistical approaches that can stimulate advances in the quality of primary-level research, Crutzen and Peters (2017) provide a solid argument for abandoning the use of the alpha coefficient (Cronbach, 1951) as an indicator of the internal consistency of a scale. The authors argue that although alpha continues to be a popular technique used to assess scale quality in health psychology, it is unrelated to a scale's internal structure. Instead, the authors recommend a shift to an alternative coefficient,

leave significant heterogeneity unexplained. The authors then outline an innovative spatiotemporal strategy to meta-analysis to enable analysts to incorporate such factors. Johnson et al. outline the uses and methods of spatiotemporal meta-analysis, and offer detailed advice on coding the location and time of studies, often labelled *geocoding*. By taking into account community contextual factors and the spatial distribution of studies included in meta-analyses, these can guide not only analyses – explaining some portion of heterogeneity in results that study-level moderators do not – but also decisions on where additional studies and health interventions are needed. The authors also identify challenges in applying such an approach, such as how to treat missing or approximate spatiotemporal information. Card (2017) agreed and expanded upon the challenges that need to be addressed in advancing this approach; particularly important is the ability to identify at what level spatiotemporal factors operate (e.g., individual vs. site vs. community levels). Both Johnson et al. and Card advocate the use of spatiotemporal strategies when examining health psychology phenomena that theoretically are influenced by social networks linked to study participants and that comprise relatively large research literatures. Of course, this recommendation to incorporate community-level factors applies not only to meta-analytic approaches but also to primary-level studies that examine phenomena with sufficient variability over time and/or space, and that identify important spatial information (e.g., place of residence or work).

Conclusions

The six contributions in this Special Issue on advanced analytic and statistical methods in health psychology reflect diverse and stimulating perspectives on a range of statistical approaches that can be applied to the discipline. The collection of articles, which were written by leading international researchers at the forefront of the development and application of statistical methodology to health psychology research, is intended to be used as a guide to assist researchers to use these advanced approaches in their future studies. This, in turn, will provide greater confidence in the findings presented in the empirical literature; logically, it should also generate more comprehensive and creative science related to health psychology. More broadly, incorporating higher quality methods or using a broader spectrum of methods may help to illuminate why there are sometimes poor levels of replicability between studies.

Nonetheless, researchers must also be aware of the challenges inherent when applying advanced statistical methods and should be warned against selecting approaches naïvely or with insufficient background knowledge. Of course, adopting topical analytic strategies do not, in themselves, lend a solution to the replicability issue currently facing psychological research, but will contribute to providing greater precision in findings and, thus, greater confidence in findings. Statistical methods will continue to advance along with the technology and software designed to enable their use by researchers. The onus is on health psychology researchers to keep up-to-date on advances in these and other analytic techniques as well as a need for appropriate training and expertise in the use of advanced analyses as health psychologists are not specialist statisticians. It is our hope that this Special Issue will help to catalyse further debate on the use of statistical methods to health psychology research.

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