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Moving beyond the eigenvalue greater than one retention criteria in pain phenotyping research

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Letter To Editor

In the recent article by Rabey and colleagues, the authors made use of a novel probabilistic approach to experimental pain phenotyping.¹⁸ The findings identified subgroups that differed importantly on clinically relevant variables, which highlights the heterogeneity of low-back pain and points to potential value of mechanism-based pain assessment in this population. The authors' use of maximum likelihood-based clustering method is a refreshing departure from the usual distance-based clustering methodology and should be implemented in future pain phenotypic work. The authors also made use of principal component analysis (PCA) for data reduction purposes because of initial difficulties in determining clear maximum likelihood estimates. As in other recent experimental^{4–7,10,13,14} and clinical pain studies,¹² the authors used the eigenvalue greater than 1 (EVG1) component retention criteria. The use of the EVG1 criterion is a practice that is deeply entrenched in many domains of behavioral research¹⁶; however, evidence from the psychometric literature and statistical simulation studies shows that it leads to overextraction and unparsimonious models.^{20–22,24} It is conceivable that overextraction could redirect attention to superfluous constructs at the expense of other major components, which could potentially distort the results and compromise their interpretation.² The use of proper retention methods is scarce within pain phenotyping research but has been successfully implemented in various clinical pain psychometric studies.^{8,9,11,19,23} Given the increasing interest in using QST for mechanism-based phenotyping,³ we recommend that investigators begin adopting these more rigorous approaches to variable reduction in experimental data as well. Some of these methods, such as parallel analysis and Velicer minimum average partial, can be painlessly implemented in SAS or SPSS.^{1,15,16} Patil and colleagues, for instance, developed an SAS-based parallel analysis engine which is available online for free and does not require one to enter any of the data set's actual data, only the number of variables in your data to be analyzed, the sample size, and a seed.¹⁷ This engine outputs the 95th percentile eigenvalues of a given number of randomly generated correlation matrices with the same number of variables to be analyzed as in one's actual data set. One can then compare this output to the

Conflict of interest statement

The authors have no conflicts of interest to declare.

eigenvalues from the real data; retaining only n -components, where the n th component of the actual data set is larger than the corresponding n th component of the randomly generated correlation matrices. Components whose eigenvalues in the real data set are smaller than the corresponding random eigenvalues are seen as sampling errors, regardless of whether they satisfy the EVG1 criteria or not. The most conservative approach to component retention is to combine parallel analysis with Velicer minimum average partial, but any one of these alone can improve confidence in the results of PCA. Rabey and colleagues' conclusions are largely in accord with previously reported pain phenotypes in samples of participants with chronic pain.^{4,5,7,14} It seems clear that researchers are detecting robust subgroup patterns in various chronic pain populations. Nonetheless, implementing established and validated PCA methods may help define clearer pain subgroups, decrease superfluous constructs, and enhance interpretability and theory building, which is crucial before moving forward to investigating the neurobiological mechanisms that underlie these phenotypic pain profiles.

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