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Provocations

Embracing Fallibility in Quantitative Research: Thoughts and Remarks on Exploratory Factor Analysis and beyond

Abarcando a Falibilidade na Pesquisa Quantitativa: Reflexões e Observações sobre a Análise Fatorial Exploratória e Além

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ABSTRACT

Objective: errors are inevitable in the scholarly pursuit of truth, yet they are often seen as flaws rather than growth opportunities. This paper examines the tension between scholars' inherent fallibility and rigorous academic research standards, particularly concerning quantitative methods such as exploratory factor analysis (EFA) and partial least squares structural equation modeling (PLS-SEM). The focus is on whether the academic community effectively balances the acceptance of errors as part of the learning process, with the relentless pursuit of truth and how this balance influences the advancement of knowledge within the context of evolving statistical tools needed to improve our understanding of complex global relationships. **Provocations:** if errors are fundamental to scientific progress, why does the academic community approach them with apprehension? This fear of mistakes may inhibit innovation, especially in fields such as quantitative methods research, where the stakes are high. Another question is whether the accessibility of user-friendly statistical software has led to a superficial understanding of complex methodologies, prioritizing convenience over depth. **Conclusions:** we advocate for a shift in how the academic community perceives errors toward viewing them as essential to the research process rather than as fatal flaws. Embracing a humble approach to pointing out mistakes and limitations, particularly with quantitative methods such as EFA and SEM, can create a more innovative and progressive research environment. We call for a cultural shift where constructive critiques are balanced with understanding our collective fallibility, with the ultimate goal of producing more impactful scholarship.

Keywords: scientific fallibility; quantitative methods; exploratory factor analysis; academic rigor; structural equation modeling (SEM).

RESUMO

Objetivo: erros são inevitáveis na busca acadêmica pela verdade, mas muitas vezes são vistos como falhas e não como oportunidades de crescimento. Este artigo examina a tensão entre a falibilidade inerente dos estudiosos e os rigorosos padrões de pesquisa acadêmica, particularmente no que diz respeito a métodos quantitativos, como análise fatorial exploratória (EFA) e modelagem de equações estruturais de mínimos quadrados parciais (PLS-SEM). O foco está em saber se a comunidade acadêmica equilibra efetivamente a aceitação de erros como parte do processo de aprendizagem, com a busca incessante da verdade e como esse equilíbrio influencia o avanço do conhecimento no contexto da evolução das ferramentas estatísticas necessárias para melhorar a nossa compreensão de questões complexas. relacionamentos globais. **Provocações:** se os erros são fundamentais para o progresso científico, por que a comunidade acadêmica os aborda com apreensão? Este medo de erros pode inibir a inovação, especialmente em domínios como a investigação de métodos quantitativos, onde os riscos são elevados. Outra questão é se a acessibilidade de software estatístico de fácil utilização levou a uma compreensão superficial de metodologias complexas, priorizando a conveniência em detrimento da profundidade. **Conclusões:** defendemos uma mudança na forma como a comunidade acadêmica percebe os erros, no sentido de os ver como essenciais ao processo de investigação e não como falhas fatais. Adotar uma abordagem humilde para apontar erros e limitações, particularmente com métodos quantitativos como EFA e SEM, pode criar um ambiente de investigação mais inovador e progressivo. Apelamos a uma mudança cultural onde as críticas construtivas sejam equilibradas com a compreensão da nossa falibilidade colectiva, com o objetivo final de produzir estudos mais impactantes.

Palavras-chave: falibilidade científica; métodos quantitativos; análise fatorial exploratória; rigor acadêmico; modelagem de equações estruturais (SEM).

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INTRODUCTION

The overall objective of this provocation is twofold: first, to reflect on our fallibility as human beings, and second, to reaffirm our commitment to the constant pursuit of truth. We have all made mistakes in life, including teaching, researching, writing reports, revising papers, analyzing data, etc. But are these mistakes made with malice or intent to deliberately harm? In most cases, the answer is 'NO.' Unfortunately, in our research field, the confrontation of ideas by meaningful replies is less common than in medicine or health sciences. Nevertheless, respecting and reflecting upon valid criticisms should be encouraged. The section 'Provocations' in the *Journal of Contemporary Administration* is an excellent example of how to conduct a high-level and robust scholarly discussion.

PHILOSOPHICAL PERSPECTIVES DIFFER — AND THAT IS GOOD

We err because we are human beings, constantly learning and, above all, embracing challenges. Consider, for example, a new theory in your area of expertise or a new approach to a well-established analytical method. Most scholars are eager to learn how theory fits into our research toolbox, but undoubtedly, all scholars will need help at some point in their careers to succeed. Unintentional failure is part of the learning curve to which scholars and many others are susceptible.

Quantitative methods have undergone a significant transformation in the last 35-40 years because books have focused on simple explanations of complex statistical concepts, user-friendly statistical software packages have been widely applied, computational capacity has increased substantially, and significantly more data is widely available and easily accessible for research scholars and practitioners.

This tectonic shift from traditional, difficult-to-apply packages to a world of unlimited possibilities with user-friendly software and open-source tools such as R, boasting over 19,000 packages, is a game changer. In short, the shift from hand-held calculators and canned packages with limited choices, to complete freedom of analytical trial, is changing how we learn, teach, and advance knowledge.

IBM SPSS and SAS have been standards in data analysis for almost 60 years, motivating many textbook authors to rely on their output to illustrate techniques, leading to substantially more opportunities for analytical errors to emerge. At the same time, the R language, when applied carefully, offers a potentially more error-proof approach. That is, it is anticipated that researchers will make fewer R mistakes since all the parameters must be clearly defined before executing the syntax. But that assumption is not always correct!

The positive side of most failures is the motivation to learn what went wrong, fix it, and try again. Conversely, most scholars avoid R and similar software because they opt for user-friendly software to prevent the challenges of the R programming task. In short, there are trade-offs in both approaches.

In our journey through the scientific landscape, we often encounter the perplexing nature of errors and overlook or minimize the never-ending reminder of an essential truth in science: progress is born from trial and error! This realization should lead us to view our failures not as setbacks but as vital steps toward meaningful discoveries. Embracing this perspective fosters resilience and cultivates a culture where learning from mistakes is anticipated, accepted, and valued.

As we delve deeper into this journey, the importance of cultivating a culture of continuous learning becomes apparent. This is a fascinating world where curiosity is the compass and where questioning is the route. This culture is one where learning is an ongoing journey, not a destination, and it nurtures intellectual growth and sparks innovation.

In a world increasingly driven by data, analytics, and more recently by artificial intelligence (AI), the importance of data analysis literacy extends beyond the confines of exact sciences. It has become a fundamental skill across various disciplines. This literacy empowers us to navigate a data-driven era with confidence and insight and extends our knowledge far beyond what was possible in the past.

Ethical considerations in research and data analysis are paramount. Researchers' moral responsibilities rise to the forefront in this realm, encompassing issues such as bias, data privacy, and integrity in publishing research results. The ethical use of data analytics and AI stands as a cornerstone in responsible scientific practice.

Finally, the power of collaboration and knowledge-sharing in science cannot be overstated. Working together is beneficial and necessary in a field with frequent rapid innovation and breakthroughs. This collaborative spirit continually pushes the boundaries of scientific knowledge, leading to deeper understandings and novel discoveries.

Embracing trial and error in scientific research enriches our understanding and leads to more robust conclusions and contributions. This approach is particularly relevant in complex analyses such as factor analysis, where multiple solutions may exist. The discrepancies in test results serve as valuable insights, prompting us to understand why different methods yield different numbers of factors as well as factor loading patterns, and how each aligns with our theoretical framework and research objectives.

FROM AN EXISTING BODY OF KNOWLEDGE AND BEYOND

Reflecting on the dynamic realms of scientific inquiry, we now focus on a recently published tutorial by Rogers (2022). That publication demonstrates the application of the Factor software for conducting EFAs. One cannot evade the fact that EFA, at least conceptually, is a 120-year-old multivariate data analysis approach (Spearman, 1904) that several researchers have perfected in the realm of this lifelong journey (Bartholomew, 1995; Cattell, 1966; Spearman, 1927), and its roots can return to Bacon or even Aristotle (Mulaik, 1987).

The importance of EFA in research can be reflected in the up-to-date literature, from Lorenzo-Seva and Ferrando (2024) on the choice of sample size for EFA, both on continuous or ordinal variables, to Cooperman and Waller (2022) on Heywood cases or even Goretzko's (2023) paper on factor rotation. EFA is alive and quite useful in today's dynamic research environment.

Rogers' tutorial expands our view of exploratory factor analysis (EFA) by providing a detailed explanation of the Factor software. And indeed, understanding and executing relevant software for conducting quantitative research is imperative today for most scholarly pursuits. Factor offers a practical entry point for EFA with its user-friendly interface. For more in-depth analyses, however, R packages such as *EFA.dimensions* (O'Connor, 2023), *EFAtools* (Steiner & Grieder, 2020), *EFAutilities* (Zhang et al., 2023), and *psych* (Revelle, 2024) offer more robust analytical features.

Moreover, with its user-friendly interface and streamlined processes, Factor offers a practical and accessible entry point for those new to EFA. It also simplifies complex statistical concepts, making it an excellent choice for educators and researchers whose objective is to become more familiar with advanced statistical methodologies.

FOOD FOR THOUGHT OR HOW TO ENHANCE THE DISCUSSION ON EFA

Our comments in this treatise are not directly related to the Factor software. Instead, the following points concern several theoretical and methodological extensions to Rogers' tutorial. To start the conversation, we present two potential perspectives regarding the nature and objectives inherent in exploratory factor analysis, followed by arguments to support further reflections and discussions.

> Perspective 1: The tutorial does not address research focused on, based on, or designed to understand causal-predictive theoretical models based on the paradigm where the aim of the study is the testing of predictive power based on a carefully crafted model grounded in theory and logic (Hair et al., 2022).

> Perspective 2: The tutorial does not mention research situations in which the objective is to assess causal-predictive theoretical models (Hair et al., 2022).

Arguments regarding aspects 1 and 2

Exploratory factor analysis (EFA) solutions are derived from common variance only. Principal components analysis (PCA) is derived from total variance and may include both common and specific variance. Both EFA and PCA are early-stage exploratory methods and can identify common dimensions of theoretical constructs when researchers develop constructs/scales. But their objective is not the final confirmation of a construct.

When the research objective is the prediction of outcome (dependent) variables/constructs, the results of common factor (CF) and PCA can be used to screen out poorly performing items but not to develop the final constructs to be included in causal-predictive theoretical models (Hair et al., 2022). For example, if an item has a low loading on a construct, e.g., lower than 0.50, then the item can be considered for removal.

Nevertheless, the individual items must be removed one at a time, starting with the item with the smallest loading (Hair, Anderson et al., 2019). After each item is removed, the EFA should be executed again since removing a single item will change the loadings of all other items (Hair, Gabriel et al., 2019).

Another methodological issue that deserves comment is the differentiation between common, specific, and error variance. This concept is essential for understanding the differences between common factor analysis (CFA) and PCA.

Retaining specific variance in PCA is essential, since variance seldom can be explained only by correlations with all other variables (common variance). However, it must also account for variance associated uniquely with a single variable (specific variance), thereby reflecting the unique characteristics of that variable apart from other variables in the analysis (Hair, Gabriel et al., 2019). In this sense, PCA with specific variance is essential in scale development when the constructs are included in a causal-predictive theoretical model, because the specific variance retained might in fact predict variance in the dependent variable(s).

Considering the pedagogical aspects of a tutorial on using a given technique or software, it is important to note that tutorial articles tend to be highly cited. Tutorial articles provide fundamental guidance for researchers in the learning process. This guidance implies accuracy, clarity, and objectivity principles, aiming to enhance researchers' analytical skills.

HOW PROPER ARE THE RULES OF THUMB THUS FAR?

Considering the abstraction level and ambiguities involved in EFA, the necessary but not always sufficient training on matrix algebra (Pedhazur & Schmelkin, 1991; Schreiber, 2021), and the need to constantly but cautiously move ahead when exploring new paradigms, the rules of thumb are valid and useful guidelines — and not outdated when PCA is used to confirm measurement models for causal-predictive theoretical models. In short, the rules are not absolute but rather a guide for consideration and decision-making, particularly for young scholars (Goretzko et al., 2021; Williams et al., 2010).

PCA and EFA, alter ego approaches

In the preface of the book celebrating 100 years of factor analysis, Cudeck and MacCallum (2007) defined PCA and EFA as alter ego approaches. With their limited statistical foundation, therefore, most novice researchers are unsure which approach to use and when. As Vogt et al. (2014) noted, both approaches yield parallel solutions when the number of variables is large, but the statistical 'direction' of each one is different.

In PCA, the variables are the IVs, and the resulting components are the DVs (formative measurement model). Conversely, in EFA, the factors are the IVs and the variables are the DVs (reflective measurement model). Nunnally and Bernstein (1994) recommended that PCA should first be employed in an exploratory study to expedite a solution, and that EFA is more appropriate for a confirmatory study. These guidelines are appropriate when there is "no guarantee that a solution can be obtained" (Nunnally & Bernstein, 1994, p. 515).

Scholars and researchers should remember that one objective of PCA is identifying common dimensions of multi-item constructs and reducing the multiple items into a smaller number of meaningful components. Following EFA, researchers should apply the causal-predictive PLS-SEM method (Hair et al., 2022; Hair et al., 2024) and the confirmatory composite analysis (CCA) procedure to confirm measurement models/constructs (Hair et al., 2020).

On the other hand, the ultimate objective of many EFA applications is to develop and confirm constructs/composites to subsequently include in causal-predictive models since the PC (principal components) method accurately calculates the factor loadings when total variance is the starting point for the analysis. Recent substantive developments in SEM methodologies, specifically PLS-SEM and common factor analysis (CFA) (Latan et al., 2023), have played essential roles as emerging analytical tools. But so do PCA and the CCA procedures for developing composites via PLS-SEM (Hair et al., 2020).

Oblique or orthogonal rotation

Despite some claims that oblique rotation is better than orthogonal rotation, orthogonal varimax rotation can be helpful and essential when multicollinearity is an issue. Both orthogonal and oblique rotations play important roles in scholarly empirical research. However, prediction via theoretical structural models is a fundamental objective of scholarly research in business and many social sciences. Thus, CFA, CCC, and PCA are only preliminary steps in assessing prediction, and more recent procedures extend the capabilities of PLS-SEM to also explore out-of-sample prediction (Shmueli et al., 2019).

CONCLUDING OBSERVATIONS

Returning to the foundational principles of humility, learning, and meaningful progress in scientific inquiry, we conclude this analytical exploration with our final observations. The journey through the complex terrain of exploratory factor analysis, marked by the diverse outcomes of various statistical methods, is a potent reminder of the inherent uncertainties and challenges in scientific research. This journey underscores the need for a humble approach, recognizing our findings' limitations and provisional nature and always focusing on advancing science to benefit all, particularly young scholars.

Rogers' (2022) critique of previous works highlights an essential aspect of scientific discourse: the balance between constructive criticism and acknowledging human fallibility. While critical evaluation is a vital part of scientific progress, it must be tempered with the understanding that all research, including our own, is part of a larger, evolving knowledge landscape. Each study, with its unique contributions and limitations, adds to the collective understanding of a field.

While providing insights to reflect on and learn from, Rogers' approach also reminds us of the delicate nature of critique in academic work. In addition, we must recognize the importance of acknowledging our flaws and limitations as researchers and the opportunities and insights scholarly research provides. As scientists, our work advances knowledge in our field. It also fosters a collaborative and respectful environment where ideas can be exchanged and debated without losing sight of our common goal: the pursuit of truth and understanding.

History provides us with two meaningful examples of respect and firmness: Galileo and Voltaire. After his trial, the first confirmed his theory by whispering, "*E pur si muove*."

The latter allegedly said, "I disapprove of what you say, but I will defend your right to say it to the death." In this sense, Rogers' (2022) alleged failures do not change the original paper's meaning: a useful educational tool and a humble piece of research.

In conclusion, our present commentary advocates a humble and respectful attitude in scientific endeavors. Such humility is not about diminishing the value of scholarly work from others but embracing scientific inquiry's complexity and collaborative nature. In this spirit, we advocate moving forward in our scientific journeys, not as isolated experts but as members of a vast, interconnected, and humble community of learners, scholars, and discoverers.

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