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Letter to the editor

Re-evaluating structural equation modelling in nursing research: Insights from compassion fatigue and empowerment in Chinese intensive care units

The recent paper by Zhou, C et al., examining effects of compassion fatigue, structural empowerment, and psychological empowerment on Chinese intensive care unit nurses' caring behaviours, uses structural equation modelling (SEM).[1] This choice raises significant theoretical and empirical concerns, primarily due to SEM's inherently linear and parametric nature. Although SEM is a powerful tool, its foundational assumptions demand careful scrutiny, particularly with nuanced biological or psychological data.

The core assumptions of SEM are its linear and parametric nature, relying on concepts like linear relationships and multivariate normality.[2–5] Though somewhat robust to certain assumption violations, significant deviations compromise parameter estimation and model fit. Independent observations, random and normally distributed measurement error, correct model specification, and adequate sample size are essential. In studies like Zhou et al.'s, biological or psychological data often inherently exhibit nonlinear characteristics, frequently conflicting with the strict requirements of SEM. Such data commonly present challenges like nonconstant variance and non-normal distributions. Applying SEM without accounting for these complexities risks misinterpreting results and undermining analysis reliability. This limitation is well established in over 300 prior studies, highlighting how such data characteristics can bias the interpretation of feature importance, a critical concern when assessing true drivers.[6–11] More details and supporting references are in the supplementary material.

To overcome these limitations, a robust analytical framework is vital. It must critically assess data and rigorously validate findings. Given prevalent nonlinearity challenges even within SEM, it should prioritise nonparametric methods, which are less constrained by standard assumptions, for exploring complex associations. Instead of exclusively relying on SEM, a synergistic methodological approach is advocated, one championing impartial, assumption-resilient techniques. This involves prioritising nonparametric methodologies capable of robustly capturing nonlinear relationships. For instance, nonparametric correlation measures like Spearman's rho and Kendall's tau excel for characterising monotonic relationships.[12,13] For more intricate, general nonlinear dependencies, mutual information and total correlation offer valuable insights.[14–16] Combining these principles with domain expertise and judicious SEM application will significantly fortify interpretations concerning complex behavioural outcomes.

While Zhou et al.'s study offers valuable insights, interpreting its quantitative SEM results, especially the estimated strength and direction of influence, requires caution. SEM's reliance on linearity can lead to biased or misleading assessments of true influence or “importance” if underlying relationships are nonlinear. To enhance the trustworthiness of findings, adopting a broader analytical framework integrating SEM with complementary methods less sensitive to these linearity assumptions is advisable.

CRediT authorship contribution statement

Mana Egawa: writing – original draft and investigation. Souichi Oka: writing – review and editing and conceptualisation. Yoshiyasu Takefuji: supervision and project administration.

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Declaration of competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Supplementary Data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.aucc.2025.101292.

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