Misinformation Risks through Cognitive Biases Perpetuation in Generative Artificial Intelligence Tools: A Practical Examination Using Simulations

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Overview

We use simulations to test whether using generative artificial intelligence (GAI) tools leads to cognitive bias perpetuation (Andrieux et al., in press) using the common method variance (CMV) literature and offer recommendations for the use of GAI in academic research. Our results across three separate simulations suggest that caution should be used when looking at information generated and that researchers should not simply rely on initial or refined results.

Questions

1. Should GAI tools be trusted when conducting academic research?
2. What potential cognitive biases may affect the results generated by GAI tools?
3. Based on the capabilities of GAI for academic research, what are potential recommendations for researchers?

Methods

1. Three separate simulations in three generative artificial intelligence tools using the common method variance (CMV) academic literature.
   - Simulation 1 was performed in OpenAI's ChatGPT
   - Simulation 2 was performed in Google's Bard
   - Simulation 3 was performed in Microsoft's Copilot
2. An initial prompt was used in all three GAI tools
3. A follow-up prompt was then used in all three GAI tools
4. A comparison of the generated results and actual research was performed
5. A list of recommendations was created

Results

1. Initial prompt: Using an academic research writing style, generate a summary of the best research methods and practices in business research to deal with issues linked to common method variance.

Simulation 1: ChatGPT	Simulation 2: Bard	Simulation 3: Copilot
Including control variables and employing statistical techniques like Harman's single-factor test or orthogonalization can aid in identifying and controlling for CMV.	Harman One-Factor Test: This statistical test identifies whether a single unobserved factor explains a large portion of the variance in the data, suggesting potential CMV inflation.	A post hoc Harman one-factor analysis is often used to check whether variance in the data can be largely attributed to a single factor.

2. Follow-up prompt: Please elaborate on the soundness of the Harman One-Factor Test common method variance (CMV) issues. Use as many references as possible, include a bibliography using APA style, and provide a nuanced overview of the extent to which it works.

Simulation 1: ChatGPT	Simulation 2: Bard	Simulation 3: Copilot
Some scholars have criticized its oversimplification of the issue, highlighting that the presence of a single dominant factor does not unequivocally imply CMV. Several alternative explanations can result in a single-factor solution, such as a methodological artifact or the nature of the constructs being measured (Malhotra, Kim, & Patil, 2006).	The HOFT suffers from low sensitivity. It often fails to detect CMV unless method bias is exceptionally strong, potentially leading to false negatives and overlooking the presence of subtle but influential CMV effects (Lindell & Whitney, 2001).	Baumgartner et al. (2021) demonstrated that the Harman One-Factor Test is deficient in detecting CMV and that both beliefs that the biasing effect of CMV is of greater theoretical than practical importance and that if CMV is a potential problem, it can be easily identified with the Harman One-Factor Test are ill-founded and need correction.

Discussion

- Our results suggest that GAI tools can spread misinformation and miscitations.
- Harman's One-Factor Test has since been shown to be unreliable in detecting CMV issues through simulations (Fuller et al., 2016).
- This is the result of a *bandwagon effect*, which, in our context, refers to a high number of scholars relying on the same technique because the majority also does it, thereby attempting to ensure in-group acceptance (Barrera & Ponce, 2021; Kessous & Valette-Florence, 2019).
- Researchers should use GAI as "augmentation": Close collaboration with artificial intelligence or machines to perform tasks, which differs from automation, implying completely letting the technology or machine replace human tasks (Raisch & Krakowski, 2021).
- We suggest: (1) checking the results generated by GAI, (2) prompting further to "purify" results, (3) requesting in-text citations and bibliography, and (4) reading the original sources (De Lacey, Record, & Wade, 1985).

Limitations and future research

- Despite converging results across all three GAI tools, the simulations used in this small-scale project may not completely capture the detrimental results of AI-generated results.
- Some research fields may yield more reliable and less biased results compared to the CMV literature.
- The findings obtained here may not stand the "test of time" as GAI algorithms evolve continuously.

Conclusion

While we acknowledge that the results obtained from GAI tools contain some value for novice users seeking to learn about research methods, the results generated are flawed with mistakes resulting from cognitive bias and/or false assertions. We argue that GAI should not be trusted blindly by users. We urge scholars to rely on our guidelines to collectively work on progressively eliminating cognitive biases plaguing the research methods field. To maintain rigor in academia, we should ensure that future publications remain free of bias and adopt reliable methods while abandoning others that yield unsatisfactory results. Ultimately, it seems apparent that GAI will not fully substitute for academic expertise and augmentation seems to be the best possible use of such tools.

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