How Cognitive Biases Influence Problematic Research Methods Practices

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Abstract: A growing body of academic research addresses issues related to questionable choices and errors in the use of research methods in published business research. These problematic research method practices (PRMPs) may be purposeful or unconscious, but they reduce the rigor of academic research and can harm the accumulation of scientific knowledge. Yet, absent from much of this literature is a theoretically grounded approach to understanding why these problematic practices occur. Prior scholars have summarized specific types of PRMPs, but attributions about their causes are primarily limited to research lack of motivation or poor doctoral education. While these may certainly be at play, the current manuscript proposes that the deeper psychological phenomenon of cognitive bias is a likely explanation. Cognitive biases occur when human cognition produces an outcome that is systematically distorted from objective reality (Haselton, Nettle, and Murray, 2016). More colloquially, cognitive biases are systematic errors that humans make when they are faced with perceiving, remembering, and understanding information. These unintentional biases are particularly likely when that information is voluminous and ambiguous. Cognitive biases are explained by two theories—heuristic theory and fuzzy trace theory. Heuristic theory suggests that humans default to using mental shortcuts as a means to make decisions more efficiently (Chaiken and Ledgerwood, 2012). Further, fuzzy trace theory explains how memory and reasoning can be flawed (Reyna and Brainerd, 1995). Because of the limitations of the human mind, heuristic theory and fuzzy trace theory act to create unintentional cognitive biases. The current manuscript argues that the cognitive biases of source confusion, gist memory, repetition effects, bandwagon effects, and confirmation bias are mostly subconscious means by which researchers make errors in research methods use. We argue that these biases are not a useful part of the didactic approach to research, but are rather mental shortcuts that can limit researcher effectiveness. Next, specific PRMPs are addressed: reliance on methodological myths and urban legends, errors in citations, use of questionable research practices, and inappropriate use of artificial intelligence (AI) tools and technology in research. Finally, there are a number of insights and recommendations derived from research on cognitive biases to assist scholars in promoting research methods best practices. In particular, researchers can combat cognitive biases by recognizing what they are and by providing more transparency about research methods use in their articles. Incentives for authors and reviewers may reduce the impact of cognitive biases on PRMPs. Editors should create and share clear guidelines on the use of AI in research. In summary, this manuscript addresses those critical issues, fills a gap in current research regarding why PRMPs occur, and provides researchers with key insights to effectively combat cognitive biases.

Keywords: Cognitive biases, Citation, Research methods, Artificial intelligence (AI), ChatGPT

1. Introduction

Given the increasing emphasis on the adoption of and reliance upon robust research methods in business research, it is no surprise that researchers often struggle to understand and correctly apply advanced techniques. The quality of business research depends on the rigor of the research methods selected and applied by researchers (Scandura and Williams, 2000), so business scholars must continue upholding high ethical research standards and implement research methods that are sound, fully understood, and appropriately used when producing novel academic research. Several incidents have shaken the confidence of scholars in social sciences (Banks et al., 2016b) and in the process depicted a concerning picture of rigor on which academic research. For instance, Diederik Stapel, a well-known Dutch social psychologist, admitted to large-scale research fraud (Stroebe, Postmes, and Spears, 2012). There were several high-profile retractions in

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Management due to data analysis improprieties (Retraction Watch, 2014). Banks et al.'s (2016) surveys of Management scholars found that 11% of researchers reported advantageously rounding off *p* values and 29% engaged in post hoc data exclusion. In response, reviewers and editors have implemented countermeasures to combat such practices, and greater transparency is now required from the scientific community (Finkel, Eastwick, and Reis, 2015; Miguel et al., 2014).

With the increasing rates of retraction of published research articles (Brainard and You, 2018), scholars, reviewers, and editors are now more vigilant regarding use of various problematic research methods practices (PRMPs). Statistical misconceptions have been argued to harm learning, hinder academic research, and compromise decision-making (Bezzina and Saunders, 2015). Those practices are perpetuated by widespread reliance upon methodological myths and urban legends (UL; Lance and Vandenberg, 2009) plaguing journals in a variety of fields. Kreamer et al. (2021) found that for all articles published that cite either or several of three seminal works published in *Organizational Research Methods* (ORM) in the past ten years, 17.4% referenced accurately, 47.7% referenced with minor inaccuracies, and 34.5% miscited. Over time, those misinterpretations and misuses persist in business research and snowball into an increased number of published papers.

Scholars have highlighted best practices aimed at effectively addressing PRMPs (Harzing, 2002; Kreamer et al., 2021). Yet, a major gap in the literature exists, because almost no business articles have attempted to provide insights into why such practices occur. To address this research gap, the current manuscript aims to apply theory and logic that provides new insights into the psychological mechanisms that underly PRMPs in business research, specifically cognitive biases. Research methods represent powerful tools that evolve rapidly to assist researchers better and consistently over time (Venable and Baskerville, 2012), and the recent emergence of artificial intelligence (AI) technology and tools poses serious concerns regarding the potential disruption of the way researchers produce unique scientific contributions. Thus, addressing PRMPs now is more critical than ever. Further, emergent moral dilemmas and concerns linked to AI (Coeckelbergh, 2020; Stahl, 2021) may not only worsen existing PRMPs but also open new avenues for scholars to potentially engage in new ones.

In this paper, we argue that researchers are faced with voluminous information and numerous decisions when crafting, conducting, and interpreting research. Because of this, they are likely to rely on heuristics, or everyday decision rules (Chaiken and Ledgerwood, 2012). Heurestic theory suggests that humans default to using mental shortcuts as a means to make decisions more efficiently. Further, fuzzy trace theory (FTT) explains how memory and reasoning can be flawed (Reyna and Brainerd, 1995). These theories posit that humans are subject to cognitive biases. We argue that these cognitive biases, rather than researcher carelessness, are the primary drivers of PRMPs.

We describe heuristic theory and FTT and how they create cognitive biases. We then provide a comprehensive review of the cognitive biases most likely to affect research methods in business research and link them to the most prevalent PRMPs. Finally, scholars are given theory-driven guidelines to build a framework of best practices aimed at tackling current and potential new PRMPs.

2. Literature Review

2.1 Heuristic and Fuzzy Trace Theory

Human beings have limited capabilities in their memory and decision-making, and even academic researchers who are trained in scientific inquiry are subject to the constraints of the human mind. In this article, we argue that some of the commonly identified problematic research methods practices (PRMPs) in business research may be due to the reasoning and information processing errors that are explained in heuristic theory and fuzzy trace theory (FTT). More specifically, these theories propose a number of cognitive biases, which, as argued here, may lead to decision-making and judgment errors.

Heuristic theory explores how humans perceive and interpret information for judgments or decision making through two opposing mechanisms. Systematic processing occurs when the person gives careful attention to the information and engages in deep thinking and intensive reasoning (Chaiken and Ledgerwood, 2012). While this is an ideal approach to decision-making, it requires a great deal of cognitive engagement and motivation. Thus, most people are likely to default to the use of heuristics, or mental shortcuts, when faced with complex problems (Tversky and Kahneman, 1974), conflicting information, and ambiguous goals (see Dale, 2015). There is the argument that the use of heuristics, rather than representing a flaw in human cognition, provides an evolutionary benefit (Haselton, Nettle, and Murray, 2015). A distinct, but related, theory is that of fuzzy trace theory (FTT). While heuristic theory primarily addresses perception and decision-making, FTT explains why the human memory is imperfect. According to the theory, there are two types of memory processes—verbatim and gist (Reyna, 2012). Verbatim memory allows a person to recall events accurately by mentally reinstating all of the features of the past event, which leads to accurate recall. However, verbatim memory is often difficult, and gist recall is more likely. Gist memory relies on remembering semantic features, and thus, people are less likely to recall details accurately.

Business scholars are trained in a systematic approach to scientific inquiry, yet they are not immune to the limitations of the human mind. Heuristic and FTT provide a framework to understand how researchers may misremember, misinterpret, and misapply information related to approach research methods applications. Today's researchers must seek, read, interpret, and apply a great deal of past literature and ever-changing information in relation to the research methods that they use. They do this under increasing pressure in a publish-or-perish field (Wright, 2016). We argue that it is not, therefore, laziness, carelessness, or unethical behavior that drives the use of PRMPs, but instead the cognitive biases that can be explained through heuristic and fuzzy trace theory.

2.2 Cognitive Biases

Cognitive biases can be described as "a systematic error in thinking that occurs when people are processing and interpreting information…" that "…affects the decisions and judgments that they make" (Cherry, 2022). At their core, cognitive biases lie in researchers' reliance on heuristics to make decisions. Heuristics are mental shortcuts used conscientiously or non-conscientiously to process information while ignoring critical parts of such information (Gigerenzer and Gaissmaier, 2011). Cognitive biases differ from occasional random errors (Caverni, Fabre, and Gonzalez, 1990); rather, they are typically due to the limitations of human memory and attention (Cherry, 2022).

Heuristics are useful and necessary when conducting research, as scholars' ability to identify the source of information is critical for many cognitive tasks (Johnson, Hashtroudi, and Lindsay, 1993). However, these heuristics might lead to critical errors throughout the research process (Tversky and Kahneman, 1974) as a result of suboptimal deviations from rational or normative approaches (Wickens et al., 2004). The cognitive biases that can emerge from heuristics relate to the psychological mechanisms experienced throughout the research and writing process that may result in the misinterpretation, and then, misuse of other scholars' work (e.g., negligent citation, meaning change due to miscomprehension, lack of authors' motivation to carefully review information source, or wrong contextual use of cited arguments). To this end, prominent cognitive biases are identified and explicitly linked to PRMP occurrence in research.

Cognitive biases have been studied in various business subdisciplines such as Strategic Management (Barnes, 1984; Tetlock, 2000), Psychology (Haselton, Nettle, and Andrews, 2015; Hilbert, 2012), and Information Systems (Godefroid et al., 2021). In addition, cognitive biases found an audience in non-business, but related disciplines such as Human Engineering (e.g., Baybutt, 2018). Cognitive biases include source confusion, gist memory, and repetition effect. While source confusion and gist memory are frequent error instances resulting from a researcher's inability to accurately remember the source of one (or more) scholarly arguments used to produce their research, repetition effects lead to increased belief in the information repeatedly carried over and encountered through miscitations in subsequent works (Dechêne et al., 2010). The perspective of the current paper is that these errors are inadvertent and that scholars have read the original works but unintentionally fail to cite them appropriately (Ioannidis, 2018). Other cognitive biases include bandwagon effects and confirmation biases. Bandwagon effect refers to an individual's propensity to join the majority and adopt their point of view even when the individual disagrees (Bindra et al., 2022; Shaikh et al., 2017). Confirmation bias, on the other hand, refers to scholars' propensity to remember and favor information that is in line with their beliefs (Oswald and Grosjean, 2004). Each of these cognitive biases is detailed below in the context of the behaviors of academic researchers.

Source confusion arises when a scholar fails to recall or misaligns information necessary to draw accurate conclusions. The effects of source confusion may be exacerbated when people who must make decisions are confronted with too much information as it creates an "information overload" (Malhotra, 1982). Further, there is evidence that source confusion arises more frequently when the perceptual similarity between memories from internal and external sources is higher (e.g., Johnson, Foley, and Leach, 1988). Johnson (1992) posed that source confusion may be the result of an ambiguous information retrieval process and/or imperfect processes responsible for attributing information to sources.

Gist memory results from the researcher's remembrance of abstract information at the expense of critical details pertaining to some phenomena, and takes the form of episodic interpretation of concepts such as relations or patterns (Brainerd and Reyna, 2002). Studies of psychological distance under the construal level theory (CLT; Trope and Liberman, 2003) showed that when people are induced with psychological distance, they interpret actions of a scene into fewer and broader units of actions (Henderson et al., 2006; Wakslak et al., 2006). Westerman (2008) found evidence that this discrepancy-attribution phenomenon generalizes to information or memory recognition. In sum, the "chunking feature" involved in information retention (Miller, 1956), while aiding scholars to categorize information segments (Fukukura, Ferguson, and Fujita, 2013), might be limiting their ability to accurately retain all relevant details pertaining to the original information. For instance, if a scholar can recall the topic of an article that he or she has read, but not the conclusions drawn, this could represent gist memory.

Repetition effects are defined as the phenomenon in which an original argument is distorted and then, carried over with a lack of accuracy. Inaccurate citations of literature may occur due to repetition effects if a repeated pattern of miscitations eventually leads to broad acceptance of some phenomena (de Lacey, Record, and Wade, 1985; Harzing, 2002). Dechêne et al. (2010) posed that this "truth effect" helps explain why people's trust in statements' truth may affect the behavior of others with respect to these statements. Repetition effects phenomena include the "whisper-down-the-lane" effect (Kreamer et al., 2021) in which misinformation is amplified in subsequent works. Kreamer et al. (2021) emphasized the potential damage done to science, specifically when misinformation concerns research methodology. Another methodology-related issue is the "cascading of adaptations" for scales (Heggestad et al., 2019), in which authors would adapt an original scale and subsequent works would cite the adapted scale as opposed to the original scale.

Bandwagon effect was coined by Leibenstein (1950) and refers to people's tendency to adopt the ideas or opinions of the majority regardless of their own views (Bindra et al., 2022). Bandwagon effects have been investigated at both the micro and macro levels in business research. Consumer research has studied bandwagon effects as a mechanism through which consumers adopt brands in order to obtain memberships in highly-prized social groups (Barrera and Ponce, 2021). Under this lens, individuals are prone to bandwagon effects because they want to present themselves favorably compared to others (Myers, Wojcicki, and Aardema, 1977), and as such, becoming a follower might constitute a way to avoid exclusion from social networks. Bandwagon effects have also been studied in the Strategic Management literature to examine the actions of firms facing bandwagon pressures to undertake strategic actions such as launching new products, innovating, or performing firm acquisitions (McNamara, Haleblian, and Dykes, 2008). Thus, firms may be pressured by competitors to avoid suffering from losses due to refusing to become an adopter. Under both lenses, the tenet of a bandwagon effect relies on voluntary or involuntary behavioral adoption of some belief or action in order to potentially achieve personal gains and/or avoid detrimental outcomes. In academic research, because of peer review, there is pressure on researchers to adopt the ideas and opinions of thought leaders in order to maximize their chances of having their work published.

Confirmation bias refers to seeking or interpreting evidence while prioritizing one's pre-existing beliefs, expectations, or hypotheses (Nickerson, 1998). Confirmation bias has often been viewed as a pernicious tendency as it impedes well-founded beliefs through reasoning distortion while ignoring potentially available contrary evidence (Steel, 2018). Nickerson (1998) noted that this process may be voluntary ("motivated confirmation biases") or involuntary ("unmotivated confirmation biases"). Confirmation bias may occur as a means to avoid discomfort (cognitive dissonance) experienced when engaging with others whose beliefs differ (Festinger, 1957). A major issue with confirmation bias is the potential emergence of unethical gatekeeping in research, in which, scholars might ignore evidenced theories and/or results because they go against their own. Confirmation biases have been widely studied in the Information Systems (IS) literature. Modgil et al. (2021) found evidence that confirmation biases have spread through the increased popularization of social media, leading to polarization as people rely on social media platforms to access information that confirms their views or beliefs (Arnott, 2006). Applied to research contexts, confirmation biases might, therefore, lead to the dismissal of one's work on the basis of disagreement or disbelief, regardless of the quality and/or soundness of the arguments and methodology used.

It is important to consider the "publish or perish" paradigm surrounding academic business research (Denning, 1997) as a motivating factor for reliance on cognitive biases. Publish or perish refers to the pressure experienced by tenure-track academics to consistently publish throughout their pre-tenure career, and often beyond (De Rond and Miller, 2015). Scholars who do not publish risk job loss—a powerfully motivating force. Despite repeated scholarly efforts aimed at tackling PRMPs (e.g., Harzing, 2002), the occurrence of PRMPs remains high in business research as the publish or perish paradigm often rewards quantity over quality at the expense of innovation, which ultimately hinders scientific progress (Bouchikhi and Kimberly, 2001). This continuous struggle to produce scientific works can create an environment in which cognitive biases are likely to flourish. Cognitive biases can be useful shortcuts in many areas of life, but they may also lead to more frequent PRMPs in business research. For instance, rather than verifying citations, a researcher might write their article quickly and fall prey to source confusion or gist memory in citing work. A scholar could be influenced to use an ineffective statistical test because of the bandwagon effect (others using it) rather than determining if the test is efficacious.

An additional pressure that may exacerbate the role of cognitive biases is the lack of incentive given to reviewers of academic papers. Reviewers should be gatekeepers who are able to identify possible PRMPs in research. Yet, they too are subject to cognitive biases which are more likely to occur when the review process becomes onerous. For many, reviewing is a task that is an obligation with little credit for the degree to which it is conducted ethically, carefully, and thoroughly. Further, with the rapid emergence of AI-based technology used in academic settings, two major issues could potentially worsen those practices and penalize science- the use of PRMPs might be increased and AI might lead to the development of new PRMPs. Finally, the current volume of information needed to navigate today's breadth of relevant literature and research methods when reviewing manuscripts may further hinder the efficient elimination of PRMPs. In the following sections, the types of PRMPs in business research are detailed and linked to the cognitive biases that likely influence their adoption.

2.3 Problematic Research Methods Practices

PRMPs encompass a variety of actions undertaken conscientiously or non-conscientiously by scholars when writing academic papers and/or reporting results as part of their methodology. PRMPs include methodological myths (Lance and Vandenberg, 2009), citation errors, questionable research practices (QRPs), and potential misconduct linked to using artificial intelligence (AI), each of which is reviewed below. As noted previously, we contend that these PRMPs are driven primarily by cognitive biases, rather than researchers' laziness or lack of ethicality. Further, as argued below, cognitive biases may be more prevalent and impactful in the current context in which most academics work.

2.3.1 Methodological myths and urban legends

Methodological myths and urban legends refer to widespread misinterpretations and common misuses of research methods (Lance and Vandenberg, 2009). Some of the specific myths and urban legends are widely accepted, yet erroneous (e.g., thresholds or cutoff values, beliefs about data quality from particular types of surveys and samples, and "best" analytic techniques). While many of those methodological myths are supported by some kernel of truth, the errors inherent in them are repeated over time, which leads to distortion, oversimplification, and exaggeration of research conclusions (Spector, 2006; Lance and Vandenberg, 2009). Particularly problematic is that practices based on myth and legend often gain popularity due to apparent, but not actual, veracity (Lance, 2011), typically because they appear repeatedly in high-quality journals.

Scholars have called for a more rigorous effort to increasingly limit the spread of methodological myths (i.e., Harzing, 2002; Lance, Butts, and Michels, 2006), yet methodological myths are still plaguing business research as reviewers continue to follow these pseudo-rules and enable them to retain their golden standard status (Li et al., 2019). We argue that a number of different cognitive biases are likely to be a primary driver of these urban myths and legends. The first is the repetition effect, in which information appears accurate because it is so often repeated. Add to that the bandwagon effect, in which prominent authors or journals use a particular practice, which then appears to be valid. Finally, an author who wants to use a particular cutoff or analysis might read in the research literature that other authors have used these approaches, and their confirmation bias stops them from questioning whether those are good choices.

Lance (2011) argues that scholars too often mention a study sample's characteristics as a potentially limiting factor to their results' generalizability. Although empirical evidence in behavioral sciences indicates that the sample used is unlikely to compromise generalizability (Highhouse and Gillespie, 2010), authors persist in naming this a limitation in research. This may indicate the bandwagon effect; if researchers read this claim in many different articles, they may feel compelled to repeat it. Another common myth in business research is the use of listwise deletion to address missing data, which has been shown to be an easy, yet suboptimal practice (e.g., Newman, 2014). Yet, a researcher who has always used listwise deletion may be unlikely to read and acknowledge research that indicates its flaws, perhaps due to confirmation bias that their commonly used technique is fine because it is widely applied by other researchers

2.3.2 Citation errors

Citation errors refer to scholars' failure to cite previous works accurately to craft their arguments. Citation problems may be minor, such as misspelling an author's name or misreporting a page number, or they may be more severe, such as misquoting the original author, using an original author's work to falsely support a claim, or citing a reference that cannot be found (Awrey et al., 2011). Citation errors in business research have been detailed by multiple authors. Harzing (2002) believed that copying references in literature about expatriate failure rates led to a misinterpretation of this literature. Lance, Butts, and Michels (2006) argue that several different statistical cutoff scores and their supporting citations are inaccurate and perpetuated through citation errors. And, Kreamer et al. (2021) found 34.5% of articles in a sample of research methods articles had major citation errors.

Almost all prior research on citation errors has attributed them to scholars' laziness ("lazy author syndrome"; Gavras, 2002) and the large number of manuscript citations that may limit authors' ability to carefully scrutinize cited works (Eichorn and Yankauer, 1987). Such mistakes might result from individual-level factors such as "shallow citing," which is when authors copy citations from another or several other articles, without prior verification of the actual content of the refereed article(s) (Awrey et al., 2011, de Lacey et al., 1985; Harzing, 2002). Yet, cognitive biases may be a more reasonable explanation than lack of motivation alone. Source confusion may occur when a researcher has read a large number of articles on a topic and later misaligns information from an article with what he or she reports in the paper. Similarly, gist memory causes problems when a researcher attempts to recall a paper to cite for their use of a particular method. If the memory is incomplete or imperfect, then the researcher may recall the paper using the gist and either fill in the detail from another paper (as in source confusion) or from a false memory. This notion is similar to arguments made by Vicente (2000), who identified miscitation as a result of "reconstructive remembering," in which researchers have a general impression (or schema) regarding information on a topic, which is then applied to new information in such a way that may distort it. And, as detailed in the prior section, the repetition effect may lead a researcher to believe that the information cited is accurate if so many others have used it in published work.

2.3.3 Questionable research practices

Questionable research practices (QRPs) encompass several behaviors performed to increase the likelihood of publishing a manuscript in a targeted journal. QRPs have been commonly employed to overcome publication bias, which occurs when the probability that a result is reported depends on statistical significance (Franco, Malhotra, and Simonovits, 2014; Simonsohn, Simmons, and Nelson, 2015; Sutton, 2009). Engagement in such tactics is problematic as it produces false positives, errors that are costly in science (Simmons, Nelson, and Simonsohn, 2011). QRPs include p-hacking, HARKing, and selective reporting of results. P-hacking consists of making decisions during data analysis that lead to the reduction of the *p-value* (Friese and Frankenbach, 2020), thus inflating the significance of the results. P-hacking strategies include deleting outliers, collecting additional data without controlling for inflated error rates, or controlling selectively for covariates (John, Loewenstein, and Prelec, 2012). HARKing refers to hypothesizing after the results are known (HARKing; Kerr, 1998) and may occur when authors seek to increase the quality of their dissertation to secure a publication (Kepes et al., 2022). Similarly, selective reporting refers to "cherry-picking" studies that worked in order to virtually increase the chances of securing a publication. Considering the validity of the findings depends on whether a study's results represent the full scope of relevant evidence (Rodgers and Pustejovsky, 2021), QRPs imply omitting critical information and may result in misinformation carried over in subsequent works.

While the use of QRPs may be intentional, it is possible that cognitive biases may lead researchers to believe that these are legitimate courses of action. Confirmation bias is likely, particularly for p-hacking. If a researcher has a strong belief about a phenomenon under study, then actions taken to find results that provide statistical support for that belief may be more attractive.

2.3.4 Artificial Intelligence

The rapid emergence of AI technologies, such as OpenAI's ChatGPT, has garnered the attention of academics for both teaching and research. In a recent *Academy of Management Journal* (AMJ) editorial, von Krogh, Roberson, and Gruber (2023) posed that AI has the potential to transform the Management field and offers researchers the unique opportunity of widening the breadth of their skillsets by learning innovative research methods and managing various, large amounts of data. In addition, subsets of AI such as machine learning (ML) allow efficient decision-making through powerful prediction capabilities based on patterns identified in big databases (George, Haas, and Pentland, 2014; Hannah, Tidhar, and Eisenhardt, 2021). Therefore, AI-reliant tools would enable further and faster production of cutting-edge business research, yet they also pose concerns regarding potential unethical or abusive use of the technology. Among these is the ability to partially or fully generate an academic research manuscript (Aghemo, Fomer, and Valenti, 2023), which is problematic for two reasons. First, an AI-generated manuscript is not original work and may indicate plagiarism, and second, the accuracy of the content is questionable. OpenAI's official website states: "ChatGPT sometimes writes plausible-sounding but incorrect or nonsensical answers" (Thorp, 2023). Finally, overreliance on such technology might result in exacerbating the publish-or-perish paradigm because scholars might be tempted to abuse the tools' innovative capabilities to serve self-interested motives.

When considering heuristic theory, a researcher's use of AI pushes them more toward a heuristic model of processing rather than systematic processing. That is, rather than the scholar engaging in literature search, reading and reviewing all papers, and making their own interpretations in a systematic fashion, the researcher relies on AI to do this work, thus reducing mental load. While the outcome could be correct, there are widespread concerns about the accuracy of information provided by AI (Nussberger et al., 2022). Thus, we apply both heuristic and FTT to the use of AI by researchers to explore how cognitive biases may have an influence.

The use of AI might seem to be an intentional, controllable activity, yet it, too, may be affected by cognitive biases. Perspectives on how academics might use AI in research indicate that culling through abstracts quickly to identify relevant research and "searching and summarizing papers" is seen as viable for some (Chubb, Cowling, and Reed, 2022). If AI is used for these purposes, then confirmation bias may arise such that a belief that a researcher has which is erroneous is also identified through an AI prompt. Additionally, AI may capitalize on repetition and bandwagon effects. For instance, Lance et al. (2006) identified a methodological myth—that Nunnally (1978) argued that a scale reliability of .70 was acceptable, when in fact, Nunnally more precisely describes .70 as being minimally acceptable for research in the early stages of use. Yet, using a popular AI tool, ChatGPT, a prompt of "What does Nunnally say about a survey scale that has a reliability of .70?" conducted by the authors on July 19, 2023, produced this response: "A reliability of .70, commonly expressed as a Cronbach's alpha coefficient of 0.70, is often considered an acceptable level of internal consistency for a survey scale. Nunnally generally advocated for a minimum acceptable reliability threshold of 0.70 for research purposes." This result from ChatGPT follows the methodological myth that was likely driven by repetition and bandwagon effects.

3. Combatting Cognitive Biases

Prior literature examining PRMPs has made assumptions about researcher behavior, without reliance on theory. For instance, citation errors are believed to be caused by laziness (Gavras, 2002) and reliance on methodological myths has been blamed on insufficient doctoral education (Vandenberg, 2006). In their review of QRPs, guest editors of the Journal of Management relied solely on conscious, intentional motives for the use of these problematic practices (Banks et al., 2016b). None of the prior literature on the use of PRMPs acknowledges that they may be driven by problems in cognition or judgment that are common to the human condition. Thus, we argue that an overlooked approach to reducing PRMPs is to understand theories of cognition and address the cognitive biases that they propose.

An ideal approach to managing PRMPs would be to engage in more accurate perception and recall as a means to avoid cognitive biases that improperly influence research. Yet, heuristic theory and FTT recognize the limitations of the human mind and propose that humans are constrained in their ability to perceive, recall, and interpret information. Research in psychology has shown that recent occurrences of arguments used in the literature are likely to be more easily remembered than earlier encounters (Tversky and Kahneman, 1974). Yet, those recent remembrances may come from sources that, while widely cited, may also be subject to cognitive biases resulting from researchers' misunderstanding and/or misuse of previous works. Altogether, those biases make academic work more difficult, as scholars cannot always know what information is accurate and what is based on errors due to cognitive biases. While the challenges presented by such biases could be complex and the list provided in this article may be non-exhaustive, there are specific steps that can be derived from heuristic theory and FTT that scholars could undertake to effectively limit the impact and spread of the effects of these biases. These recommendations constitute a practical toolbox for authors, reviewers, and journal editors.

It is important to note that there is a difference between a research method choice made under the influence of cognitive biases versus one that is made with systematic processing as a means to contribute to the dialectic nature of research. As described by Popper (1940), appropriate research processes are dialectic, meaning that they begin with a thesis, an antithesis, and then a synthesis. It is not unusual for researchers to propose the use a particular research method in a submitted paper, then through the review process, adopt or apply a new or different method. As many research methods have flaws or limitations, the application of a different method is often a trade-off of benefits and drawbacks. The dialectic process may include cognitive bias (e.g., a researcher mis-cites an article and is corrected by a reviewer; or a reviewer requests their preferred analysis, and the authors respond as to why a different analysis is more appropriate). Yet, good faith disagreements regarding use of different research methods (e.g., the best approach to including or excluding control variables), if properly perceived and interpreted, are not representative of the influence of cognitive biases. These latter circumstances advance science, and therefore are not addressed in the recommendations that follow.

3.1 Emphasizing Best Practices and Transparency

As argued throughout this manuscript, PRMPs use may be primarily unconscious, driven by cognitive biases rather than a lack of motivation on the part of researchers. If researchers can move beyond the use of heuristics to engage in more systematic processing, they may overcome many of these biases. Systematic processing should begin with knowledge of research methods best practices. Many national and regional academic conferences offer research methods workshops for participants to attend. The Consortium for the Advancement of Research Methods and Analysis (CARMA) offers live courses regarding the application of advanced qualitative and quantitative research methods to Management scholars. Similar initiatives could be undertaken to promote the reliance upon ethical guidelines to spread knowledge about best research practices in a variety of disciplines.

Journal reviewers and editors should be gatekeepers who discourage PRMPs, and thus, these parties should emphasize relevant sources as part of their reviewing and publishing guidelines. This is rather important as methodological precedence may have been driven by what theorists have done rather than what has been determined statistically sound and robust (Li et al., 2019). Providing reviewers with comprehensive guidelines and resources could generate a gatekeeping mechanism enabling efficient detection and prevention of PRMPs observed in business research. In other words, journals should provide authors and reviewers with information that gives researchers the ability to perceive and recall accurate information (i.e., increasing verbatim memory). Yet, it is incumbent upon journal editors to be sure that any best practices that they promote are truly supported by research evidence. One way in which some journals are enacting stronger reviewing is by assigning a specific methods reviewer to each empirical manuscript submitted. This may reduce the possibility that a reviewer with only a passing knowledge of a method (perhaps borne out by gist memory) recommends its use when it is not an appropriate tool. These reviewers are likely to approach research methods knowledge through systematic processing because it is their primary focus, rather than other reviewers who have expertise elsewhere and are more likely to rely on heuristics when reviewing research methods practices.

Adjacent to the issue of relying on best practices is the need for methodological transparency throughout each stage of the research process, which can enhance PRMP detection. For example, when authors provide general statements regarding outlier deletion in methodology sections without appropriate justification as to why such decisions were made (Aguinis, Ramani, and Alabduljader, 2018), a reviewer cannot know if proper methods were used or not.

3.2 Providing Incentives to Authors and Reviewers

As mentioned previously, the publish-or-perish model of many academic institutions can promote the reliance on cognitive biases as a means to accelerate research. Heuristic theory indicates that people rely on these cognitive shortcuts more often when they do not have the ability or motivation to take a more systematic approach (Dale, 2015). Research indicates that abnormally high stress levels or sleep deprivation increase the risks of experiencing cognitive biases encompassing degraded psychological functioning and higher perceived stress (Gobin et al., 2015). While those aggravating health- and psychology-related factors are beyond the scope of the present study, taking a more holistic look at how to reduce stress in academic publishing may diminish the role that cognitive biases play in the use of PRMPs.

Recent trends in academic publishing are aimed at reducing stress in the publication process. First, because the availability of reviewers is essential to the speed and quality of the publication process, there has been increased attention to the problems associated with this role being primarily volunteer. Some scholars have advocated the controversial idea of paying reviewers who review for for-profit journals (Cheah and Piasecki, 2022; Flaherty, 2022), in the hopes that this could recruit more reviewers and lead to higher-quality reviews. Additionally, colleges and universities can update faculty performance metrics to attach more value to the role or reviewer. Finally, as a means to reduce pressure on both authors and reviewers, the *Journal of the Association for Information Systems* (JAIS) implemented the "JAIS Promise" in 2020, which offers a conditional acceptance or rejection decision after the first round of reviews (Pritchett, 2020). This system speeds up the review process, which can reduce stress for authors.

3.3 Recommendations for Artificial Intelligence (AI) Tools

For problematic cases of AI-based plagiarism, we pose that the issuing of an initial warning for users violating ethical and legal guidelines could be helpful in limiting the further spread of related issues. Yet, questions remain as to how AI might be used ethically and in a way that does not increase reliance on cognitive biases. Much work is needed to address all the challenges posed by this seemingly limitless technology. At a minimum, journals should write and disseminate comprehensive policies aimed at AI use and what is considered ethical or not. More importantly, there should be additional guidance from policies and standards for a clearly defined, ethical use of AI technology in research (Dwivedi et al., 2021).

4. Discussion

There are many recommendations aimed at identifying and addressing PRMPs (Banks et al., 2016a), but little effort has been aimed at investigating psychological mechanisms that may explain why such PRMPs plague business research. In a recent article, Aguinis, Archibold, and Rice (2022) coined the "*irresponsible research perfect storm*" and highlighted a lack of replicability or usefulness due to widespread QRP occurrence in Management research. Despite this attention, the increasing amount of information researchers must digest in order to conduct research means that rigor will be difficult to uphold without a more comprehensive understanding of why such practices occur. Indeed, PRMP occurrence could potentially worsen in light of AI capabilities in academic research settings.

Overall, after providing a comprehensive review of the different cognitive biases and PRMPs, we fill here a critical gap in current research and discuss how addressing cognitive biases may contribute to reducing the occurrence of PRMPs in business research. It is possible that researchers may also not necessarily realize the extent to which their data analytic practices increase false-positive rates (Simmons et al., 2011). Because of this possibility, this paper offers a broader understanding of those psychological mechanisms that potentially hinder the efficient combatting of cognitive biases. Adjacent to this phenomenon, the unique pressures that entice scholars to produce quickly and consistently in order to secure publication in peer-reviewed journals (Kepes et al., 2022) further add to the publish-or-perish paradigm.

Future research should empirically investigate the role of cognitive biases in PRMPs. Further, more work aimed at quantifying PRMPs across various research disciplines (Kepes et al., 2022) and crafting effective strategies to educate scholars in these areas should be conducted. In addition, the different cognitive biases studied here might imply other adjacent issues linked to misuse of theory, such as when scholars borrow theory from other disciplines but omit critical information in the cited work(s) that would otherwise partially or completely invalidate the researchers' arguments. There are also risks that could further compromise the integrity of research, as AI use might lead to PRMPs spreading or producing new PRMPs, which should spur further research.

Academic business research methods are evolving in sophistication. In order to continue to use them ethically and effectively, researchers, reviewers, and editors must understand the influences on researchers and the cognitive biases on which they may rely. Thus, understanding these different cognitive biases and how they may lead to PRMPs can benefit scientific inquiry.

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