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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

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). Heuristic 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; Waksalak 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 (Kremer et al., 2021) in which misinformation is amplified in subsequent works. Kremer 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 (Heggstad 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, Halebian, 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* (Friesse 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 of 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 of 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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Statistically Validating a Theory Represented by a Venn Diagram

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Abstract: To date, there has been no proposed method to statistically validate Venn diagrams. We seek to correct this shortcoming. This paper is a review of a proposed method that offers the possibility of statistically validating Venn diagrams through the lens of the management vs. leadership debate in business. Through this research, we demonstrate a way to statistically validate Venn diagrams by using a modified method of exploratory factor analysis (EFA). First, when performing EFA to validate a Venn, we suggest the scree plot of eigenvalues will indicate how many circles should be in the diagram. Additionally, when normally conducting EFA, cross-loaded items are removed. However, when using EFA to validate a Venn, we propose items that cross load should be retained and placed in the corresponding intersection of the two (or more) circles of the diagram. Applying this method to a sample of 431 (n=431) employees aged 25 years or older, we created a statistically validated Venn diagram that identifies those skills that are uniquely management, uniquely leadership, and the overlap as reported by employees. As a result, this research provides scholars with the opportunity to classify actions as leadership or management based on their placement within the statistically validated Venn diagram of management skills and leadership skills. Importantly, through the application of this new research method, we bring the possibility of statistical confirmation to many of our social science theories that are represented by Venn diagrams. In the Discussion section, we offer a critique of possible limitations of the method and mistakes that researchers can make when applying this method.

Keywords: Validation, Venn diagrams, Management vs. leadership, Skills based, Exploratory factor analysis

1. Introduction

Venn diagrams illustrate sets of information, their intersections, and their differences (Moktefi and Lemanski, 2022). They serve the purpose of giving a picture to an idea. However, to date, Venn diagrams have simply been pictorial representations of ideas without determining their validity or if items placed within the Venn are in the correct locations. We propose that a modified version of exploratory factor analysis (EFA) could be utilized to statistically validate Venn diagrams based on data. The purpose of this study is to determine if a modified method of exploratory factor analysis could offer a way to statistically validate Venn diagrams.

By using this proposed method, we can use statistical analysis to confirm the placement of each item within a Venn, thus validating the content of the Venn diagram. The proposed method offers a solution to the current shortcomings of Venn diagrams and provides social scientists with a tool to move their ideas from theory into something more concrete and data-driven.

As a demonstration of this method, we statistically validated a proposed Venn diagram that illustrates the differences and overlaps between management skills and leadership skills. By doing so, we made two main contributions; to the field of leadership, we offer statistical backing for the differences and overlap between management skills and leadership skills. However, more importantly, we offer a new method that allows statistical confirmation of many social science theories represented by Venn diagrams.

This paper's organization is deliberate. In the next section, we explain Venn diagrams and briefly explore the concept of EFA cross-loadings as they relate to and differ between traditional EFA applications and the validation of Venn diagrams. This introduction aims to establish a shared understanding of their definitions and terminology. Then, we provide the context of the management vs leadership theory debate. Owing to that debate, an unvalidated model, attributed to Jamieson and Donald (2020), emerged as a response to the theoretical debate. Using that unvalidated Venn diagram as our case study, we demonstrate how application of our proposed method can statistically validate or correct item placements within a proposed Venn diagram, thus providing data backed evidence into a mostly, to this point, theoretical debate.

One of our goals is to provide a step-by-step walkthrough that can be replicated. This is accomplished in our method section. Our new method seeks to ensure that each item within the Venn diagram is positioned based on empirical data rather than solely relying on existing literature. After confirming item placement based on mathematics, we consult the literature to assess whether there is support for these newly established positions. Lastly, we offer a critique of this newly proposed method by highlighting some shortcomings and possible misapplications in our discussion. We undertake this structured exploration in service of our research question:

Can a modified method of exploratory factor analysis be applied to create and/or validate Venn diagrams and their overlapping segments?

2. Overview of Venn Diagrams

Venn diagrams represent a relationship model using integrating ideas demonstrated by overlapping circles or patterns. Venn diagrams were created by John Venn sometime in the late 1800s to expand diagrammatic reasoning. Though originally applied to deliberating logic, they are more likely to be seen today as presenting a discernable method of understanding the relationships and connectivity of various societal elements (Moktefi and Lemanski, 2022). They serve to compare as well as sort and classify. Venn diagrams can be used in almost any discipline and are thoroughly customizable (Gilbert, Winters and Kimmins, 2019).

Venn diagrams can have an unlimited number of circles but the complexity of it sometimes renders the visual to be just as confusing as the original problem one sets out to explain once more than three circles are represented. For more entangled ideas, computer software has been written to aid in their interpretation. The circles of Venn diagrams demonstrate where elements stand alone and then overlap and/or integrate. The parts of the diagram are labeled as unions, sets, and integrations.

To identify the terminology, the union of the circles is all the data in however many circles are shown. The intersection contains all the data points that pertain to both. The intersection or that part of the visual where the circles overlap represents a comparison of the information. As Venn diagrams have evolved, their usefulness and benefits have become interdisciplinary to sort and classify as well as compare ideas and concepts that may or may not be statistical or mathematical in nature (Houser, 2020).

2.1 Overview of Exploratory Factor Analysis Cross Loadings

Spearman (1904) was first to use exploratory factor analysis (EFA). Since that time, it has become a commonly used tool that is shared across multiple disciplines (Bartholomew, 1995). "Factor analysis is a hybrid of social and statistical science" (Fricker, Kulzy and Appleget, 2012, p. 30). Specifically,

"Exploratory factor analysis (EFA) is one of a family of multivariate statistical methods that attempts to identify the smallest number of hypothetical constructs (also known as factors, dimensions, latent variables, synthetic variables, or internal attributes) that can parsimoniously explain the covariation observed among a set of measured variables (also called observed variables, manifest variables, effect indicators, reflective indicators, or surface attributes). That is, to identify the common factors that explain the order and structure among measured variables...." (Watkins, 2018, p 1).

We propose the identified factors from factor analysis would be equivalent to the sets (circles) in a Venn diagram.

EFA seeks to identify unique variables to identify a factor. Variables that provide information on multiple factors, known as cross-loadings, are often culled from the variable list (Costello and Osborne, 2005). For example, figure 1 shows two distinct factors with no overlap.

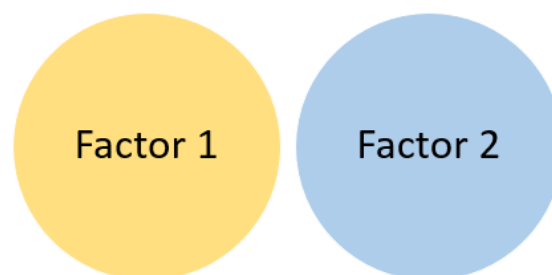


Figure 1: Showing two distinct factors with no overlap

Removing items with overlap (cross loaded items) is standard procedure owing to the EFA goal of data reduction or trying to reduce the number of variables. What if, however, we wanted information about the overlap in a Venn diagram? Cross loadings contain information about the overlap, or intersection, between sets as represented in figure 2.

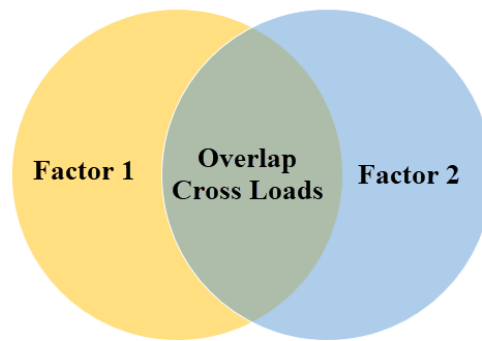


Figure 2: Showing two factors with overlap in the middle (a two-circle Venn diagram)

Keeping cross-loadings in the model would give us statistical information on the validity of the proposed overlap.

Therefore, we ask:

Research Question: can a modified method of exploratory factor analysis be applied to create and/or validate Venn diagrams and their overlapping segments?

*Please note that a detailed critique of EFA steps and challenges is provided in the discussion section of this paper.

To test our research question, we apply this proposed method to the case study of the management vs. leadership debate.

2.2 Case Study: Management VS Leadership Debate

Questions regarding the similarities, differences, and interactions between management and leadership are a recurring subject in business literature (Hunter, Bedell-Avers and Mumford, 2007; Kotter, 1990; Simonet and Tett, 2013; Yukl and Lepsinger, 2005). Yukl and Lepsinger (2005) observed that the debate has gone on so long because we narrowly define the roles in a way that prevents us from understanding how these two concepts work together to affect outcomes and how they integrate with one another.

One proposed reason for this shortcoming is the lack of operationalization and justification as outlined by Hunter, Bedell-Avers, and Mumford (2007):

To begin to address the problems arising from potentially false assumptions when conducting a typical leadership study, researchers must first be more explicit in their operationalizations and justification for what a leader is and why, precisely, a given sample represents “leaders”. For example, in many cases managers may in actuality be acting as leaders. However, without addressing the operationalization issue directly, we may be drawing false conclusions about leadership and leadership behaviors. (p. 438).

Taking a skills-based approach can allow us to correct for the issue highlighted by Hunter, Bedell, and Mumford and we can better conceptualize leadership and management and how they interact. Importantly, if researchers had agreed upon skills that are uniquely management and others that are uniquely leadership, we could identify when someone is acting in a leadership capacity or in a management capacity based on the primary skill being used.

Consider the Venn diagram in figure 3. This Venn is based on the research of Jamieson and Donald (2020) regarding the overlap between management skills and leadership skills:



Figure 3: Jamieson and Donald’s Venn Diagram Showing the Overlaps and Distinctions Between Management and Leadership

If accurate, this Venn diagram offers a categorization of leadership skills and management skills and could address the shortcomings of researchers not having a list of skills exclusively management and exclusively leadership. However, this Venn is based on leadership theory and a known weakness in leadership research is that debates have been largely theoretical without data and statistics to support them. Tourish (2015) laments how many of our leadership publications are a simple selection of a well-known leader that discusses their practices in specific situations. The generalization of these case studies is dubious at best and lacks data to demonstrate their soundness. Additionally, sometimes a manager may be acting in a leadership capacity (Hunter, Bedell-Avers and Mumford, 2007). Thus, categorizing based on “who” performed the action instead of the action itself is problematic at best.

Jamieson and Donald (2020) sought to provide a contextual framework to integrate leadership and management skills within a discipline’s curriculum. To accomplish this, leadership theory was examined including historical leadership and transformational leadership. However, skills-based leadership, and the capability model of leadership proved most useful because it could be applied. From this, they created the Leadership-Management Development Matrix (LMDM). At length, the Jamieson and Donald (2020) model amplifies the differences between management and leadership by distinguishing an individual’s contribution to a work system to that of the skills needed to accomplish leadership of others in that same system. To illustrate their research and the scaffolding and skills-based progression of leadership and management skills, Jamieson and Donald proposed the Venn diagram found in Figure 3. Consequently, while Jamieson and Donald’s model could offer a solution and allow us to conceptualize leadership and management through their operationalizations and skills-based tasks, no data is present to support the correctness of this model. This reality holds true for other theories represented by Venn diagrams. Therefore, we propose that by using a modified factor analysis, statistical validation can be provided to substantiate or refute this proposed model, which will be used as our case study.

3. Methods

3.1 Method Overview

The goal of this research was to determine if a modified method of EFA could be employed to statistically validate Venn diagrams (including their overlapping segments). To accomplish this, we first employed a customized approach to exploratory factor analysis to ascertain the accurate placement of each item within the unvalidated sample model that grew from the management vs leadership theory debate. To achieve this, data collection was conducted as the initial step. During this process, survey participants were shown each item listed in the proposed Venn diagram and asked to select (using a Likert scale) how much the task was a management task or a leadership task. Following data collection, a scree plot was created and utilized to determine the appropriate number of circles to comprise the new Venn diagram. Subsequently, exploratory factor analysis was conducted, ensuring that cross-loads were appropriately assigned and placed in their corresponding overlaps within the Venn diagram.

After the statistically created Venn diagram was completed and all items were categorized by their placement owing to the modified exploratory factor analysis, a literature review was conducted to ensure that there is theoretical backing for the placement of each item (that the Venn diagram made through statistics also makes sense to scholars). To date, this is the first application of this proposed method to validate a proposed Venn

diagram. Therefore, to aid in replication and understanding, we supplied all our code and datasets so others could replicate our results.

3.2 Data Collection

In determining the appropriate survey participants, consideration was given to demographic and ideology diversity. The goal of this research was to secure comments from employees within the general population. It was acknowledged that a sample that overrepresented education and business expertise would result if researchers created a survey and sent it to their networks with a request to share. The goal was to determine what employees view as leadership and management skills. Fortunately, a solution was presented in the use of Amazon's Mechanical Turk (MTurk). MTurk is a labor market or online pool of participants that will take surveys for a small fee.

MTurk has become a widely accepted sampling platform in academic research and its samples are valid (Hauser and Schwarz, 2015; Smith, et al., 2016). Additionally, MTurk is a commonly used platform for sampling by researchers who publish in the top leadership journals (Archer and Kam 2022; Can, 2020; Kuhn and Maleki, 2017; Cheung, Sinclair and Sliter, 2017; Giacomini, Tskhay and Rule, 2021; Marasi, Wall and Brewer, 2019; Wall, et al., 2022).

For this study, 435 participants were recruited and received nominal compensation of \$0.50. The survey was created in Qualtrics and an advertisement and link were listed on MTurk. Questions were presented using a 5-point Likert scale asking, "Are the following skills more important for successful managers or for organizational leaders?" with a list of the skills provided. Answers ranged from 1 to 5, with 1 being "Most Important to Managers", 3 being "Equally Important to Both" and 5 being "Most Important to Leaders".

In addition to the 24 skills questions and demographic questions, the survey offered one attention check. The attention check consisted of the question "Please click 'Most Important to Managers' to show you are reading the questions." Three participants were removed for failure to respond appropriately. Thus, the final data set was comprised of 432 respondents.

3.3 Survey Participants

When setting the parameters for survey inclusion, it was delineated within the MTurk system that the survey should only be made available to those who reside within the United States. Additionally, the parameter of age being 18-24 was set at false with the goal of securing a sample with several years of work experience. This decision was made based on data from the department of labor that shows the average 25-year-old has had 6.3 jobs (U.S. Bureau of Labor Statistics, 2022). We thought it was important for our participants to have had a variety of work experiences to inform their opinions.

All survey participants resided in the United States and were 25 years or older. Age distributions were as follows: 39% were 25-34, 38% were 35-44, 10% were 45-54, 8% were 55-64 and 3% were over 64. Females represented 40% of participants, 58% of participants were male, and the rest preferred to not identify. Education levels were also secured. Most reported having a bachelor's degree (58%) while 12% had advanced degrees, 18% had associate degrees or some college, and the remainder had high school diplomas or preferred not to reply. Individuals who identified as White/Caucasian were 82%, Black/African American 8%, Asian 6%, Others 3%, and the remainder preferred not to say. When asked, "What best describes your employment status over the last 3 months?", 86% reported working full-time, 6% working part-time, 4% retired, 3% unemployed but looking, and the remainder (1%) were other.

3.4 Sample Size

The first step in the analysis was to determine if our sample size was appropriate for our goals. When using EFA, there are two methods for determining the appropriateness of sample size.

Sample size Method 1: Item Ratio

The first method is to use item ratio. This is calculated as the number of subjects per item. "Gorsuch (1983, p.332) and Hatcher (1994, p. 73) recommend a minimum subject-to-item ratio of at least 5:1" (Osborne and Costello, 2014, p 2). Therefore, to accomplish this suggested minimum with our 24-question survey, we needed $n = 124$ participants, which was surpassed with our sample size of 432. Additionally, Costello and Osborne, (2005) note, "Strict rules regarding sample size for exploratory factor analysis have mostly disappeared" (p4). They go on to share results that demonstrate 62.9% of academic publications that use factor analysis had ratios of 10:1 or less and almost 1/6 had ratios of 2:1 or less. Only 15.4% of published research had ratios that represented

>10:1, ≤ 20:1. Thus, cumulatively 78.6% of papers have ratios less than or equal to this range. Since our ratio is 18:1 we have clearly surpassed the ratio sample size requirement.

Sample size Method 2: Sample Size (n)

Sample size (n) is the other method used for determining the appropriateness of dataset size, and some argue this is a more important consideration. Comfrey and Lee (1992) offer the following “The adequacy of sample size might be evaluated very roughly on the following scale: 50 – very poor; 100 – poor; 200 – fair; 300 – good; 500 – very good; 1000 or more – excellent” (p. 217). Our sample size was 432, which is 44% higher than what is required to reach the “good” threshold. Therefore, we have clearly surpassed the sample size (n) threshold. Once it was determined that our sample size was adequate for our research purpose, we moved forward with our first test of validation for the Venn diagram.

3.5 Correlation Matrix

It is important to note that viewing the correlation matrix would be an important step in traditional EFA and in creating a Venn diagram from a dataset. However, we tested a Venn diagram that had already been created based on theory. Therefore, we did not remove items because our goal was to statistically confirm the placement of each item within the Venn diagram segments.

3.6 Scree Plot: First test of Venn Diagram Validation

The first check of validity for the proposed Venn diagram comes with the scree plot test. The scree plot tells us how many factors are present within the data. Since the model is represented by the Venn diagram, and the Venn is comprised of two overlapping circles, the scree plot test should support a two-factor model if the two-circle Venn is to be validated.

To accomplish this, the following code was run in the Stata Statistical Software Package:

```
pca planning controlling coordinating allocating scheduling organizing managingplan goaloriented  
solvingproblems engaging accountability makingdecisions responsible integrity honesty socialcultural vision  
influencing motivatingandinspiringothers alignment context thinktransform modelvalues executeplan  
screeplot
```

The results of the scree plot are as presented in figure 4:

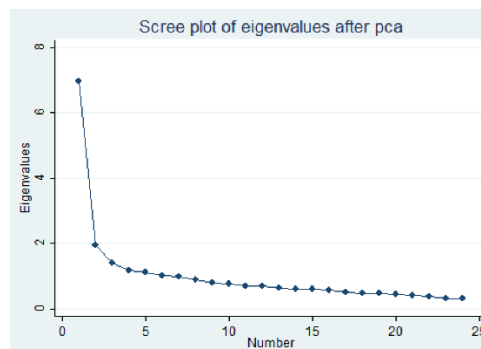


Figure 4: Scree Plot of Leadership and Management Data

The scree plot of eigenvalues does not contradict the two-factor model (thus, the two-circle Venn diagram). Therefore, we moved forward with the next step in the validation process.

3.7 Exploratory Factor Analysis

Next, to conduct an exploratory factor analysis, the following code for exploratory factor analysis was input into the Stata Statistical Software Package.

```
*factor loadings, communalities (1-uniqueness), and proportion of variance
```

```
set more off
```

```
factor planning controlling coordinating allocating scheduling organizing managingplan goaloriented  
solvingproblems engaging accountability makingdecisions responsible integrity honesty socialcultural vision
```

influencing motivatingandinspiringothers alignment context thinktransform modelvalues executeplan , pcf factors (2)

After determining the factors unrotated, we tested to see which rotation we should use. We input the code:
estat common

The output is a table that reveals the correlation between the factors. If the correlation between factors is less than 0.3, the varimax rotation should be used. If the correlation between factors is more than 0.3, promax is the more appropriate rotation.

Our results indicated a correlation of less than 0.3 (results = 0). Thus, we proceed with inputting the following code into Stata to use varimax rotation on our data.

Rotate, blanks(.3)

Below is the code, in its entirety, employed to produce the results we used to build our Venn diagram.

**factor loadings, communalities (1-uniqueness), and proportion of variance*

set more off

factor planning controlling coordinating allocating scheduling organizing managingplan goaloriented solvingproblems engaging accountability makingdecisions responsible integrity honesty socialcultural vision influencing motivatingandinspiringothers alignment context thinktransform modelvalues executeplan , pcf factors (2)

rotate, blanks(.3)

The results are presented in Table 1.

4. Results

Table 1: Results of Exploratory Factor Analysis Showing Management Skills, Leadership Skills, and the Overlap

Item	Differences	Management	Overlap	Leadership
Planning		.5477		
Controlling		.4143		
Coordinating		.7172		
Allocating Resources	Was Mgt. should be Lead			.3254
Scheduling		.7576		
Organizing		.7019		
Managing a Plan		.5662		
Goal Oriented			.3656, .4152	
Solving Problems	Was Both should be Mgt.	.5760		
Engaging			.3971, .4250	
Accountability	Was Both should be Lead			.4725
Making Decisions	Was Both should be Lead			.4424
Being Responsible			.5028, .3560	
Integrity			.4555, .4396	
Honesty			.4900, .4583	
Social and Cultural Intelligence			.4062, .5060	
Creating a Vision				.7034
Influencing				.6982
Motivating and Inspiring				.5733

Item	Differences	Management	Overlap	Leadership
Creating alignment	Was Lead should be Both		.3651, .3357	
Understanding Context	Was Lead should be Mgt	.5616		
Thinking and transforming				.5219
Modeling Values				.5530
Executing the Plan	Was Lead Should be Mgt	.6051		
Portion of the Variance		.2081		.1623
Total Variance .3704				
Scale Reliability Coefficient (Cronbach's alpha) .8876				
Chi2 (276) =3213.81				
Prob >Chi2 = 0.000				
Observations: 432				

When performing traditional EFA, item reduction owing to low loads and cross loads would follow. However, the goal of this modified method is not to reduce items but to categorize those that load in a single factor (circle of the Venn diagram) and those that cross-load across factors (fall with the intersects). Thus, the next step was to plot the items of the Venn diagram.

Plotting resulted in the statistically validated Venn diagram provided in figure 5.

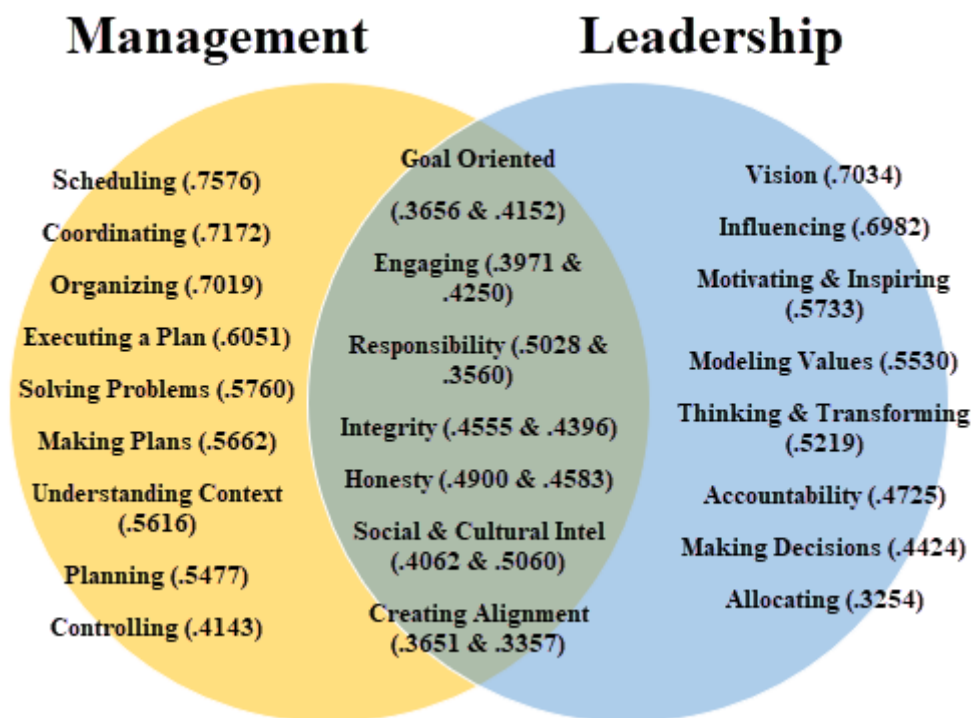


Figure 5: Statistically Validated Venn Diagram Showing Management Skills and Leadership Skills

After the creation of the statistically validated Venn diagram, it was important for authors to conduct a literature review. This review served the dual purpose of confirming the theoretical basis for the positioning of each element and ensuring that the mathematical construction of the Venn diagram resonated with scholarly principles. In the next sections, the differences between the originally proposed Venn diagram and the mathematically crated Venn are explored. To ensure the data-based placement of these differences had theoretical justification, it was appropriate to conduct a literature review after the creation of the model.

4.1 Difference Between Proposed and Validated Venn Diagram.

Notably, there are some differences between the theory and the data-supported results, and those differences are highlighted in column 2 of Table 1. However, researchers would first like to focus on the similarities. Jamieson and Donald (2020) proposed 24 skills and their placement between management and leadership. Considering their original Venn diagram, data supports that they were correct over 70% of the time. It is also important to note they created the original Venn without the aid of a statistical method to test Venn diagrams because that method is only now being presented here.

4.2 Allocating Resources Falls Within the Leadership Sphere

Jamieson and Donald's (2020) original model classified allocating resources as a management skill. Yet, results indicate it is a leadership skill. Placing allocating resources within the leadership sphere does have theoretical backing. Survey participants likely saw this as helping to ensure that others have the needed resources to accomplish their goals. This fits within the framework of path-goal leadership. Where, "...leaders can help followers along the path to their goals by selecting specific behaviors that are best suited to the follower's needs and to the situation in which followers are working" (Northouse, 2015, p. 116). Often, followers view resources as necessary and a lack of resources as something that can prevent them from succeeding. Thus, ensuring followers have the needed resources to succeed falls under the obligation of the leader.

4.3 Solving Problems Falls Within the Management Sphere

At first, we were surprised that solving problems, which had been in the intersect of the original model, fell within the management domain when validated. However, we were reminded by Hunter, Bedell-Avers, and Mumford (2007) that managers and leaders may flow between these spheres and sometimes a leader may act as a manager because that is what is needed. Yet it is important to realize that data suggests this is viewed as management by followers.

The notion that solving problems is in the management domain is backed by literature. Zaleznik (1981) confirms that the essence of a manager is that of a problem solver who ponders the problems that need to be solved and the best way to achieve results. Schwarzmuller, et al. (2018) advocated that being a problem solver is a core competency for an effective manager. Typically, managers are expected to be acute problem solvers. Managers are typically in a position to see the problems because they tend to reside in the thick of their active business. Braudis (2018) postulates that managers solve problems they see while leaders are held to a standard of seeing problems before they develop.

4.4 Accountability and Making Decisions Are in the Leadership Sphere.

Jamieson and Donald's (2020) original model placed both accountability and making decisions in the intersect of management and leadership. However, data supports the placement of these two items in the leadership sphere. Making responsible decisions precedes measuring the outcomes and professing one's place in the process as well as its results. Some researchers put forward that managers are in a unique position to make decisions for which they may or may not be held accountable (Lerner and Tetlock, 1999), thus implying that the leader is ultimately held accountable. This would coincide with whether one is accountable during the process or accountable post-process (Patil, Vieider and Tetlock, 2014). This supports the idea that the person standing before the authority (the leader) will ultimately be held accountable for what happens as a result of the processes the entity utilizes (Frederick, et al., 2016). Furthermore, this aligns with the findings of Phillips and Phillips (2020) who succinctly spotlight the courageous leaders who hold themselves accountable for all levels of decisions and outcomes despite uncertainties.

4.5 Executing a Plan and Understanding Context Fall Within the Management Sphere

Although originally placed in the leadership section, data shows that executing a plan and understanding context fall within the management sphere.

Context evolves and adaptability is crucial. Kotter (2000) described managers as grappling with complexity. Managers work within an organizational structure they must create and sustain. Consequently, they are expected to have an integral understanding of the internal and external framework necessary to achieve their goals. Included in that contextual framework are environmental factors, matters of policy and regulation, and societal and cultural challenges necessary to shape the strategies behind one's business activities (Trapp, 2014).

Similarly, executing a plan is the responsibility of the manager, as strategic plans are often global and vaguely written. Managers should clarify and add meaning to these broad expectations and "lofty strategic objectivities"

through day-to-day activities (MacLennan and Markides, 2021, p. 88). Janiesch and Kuhlencamp (2019) discussed the acumen required for the manager to execute a plan in a changing and evolving context. Such an observation addresses the successful manager's awareness of capacity specific to monitoring contextual changes for intervention and adaptation of execution.

4.6 Was Leadership but Should Be Both: Creating Alignment

Creating alignment was originally placed in the leadership sphere. However, through the validation process, it falls within the intersect, indicating that it is both a management and leadership task. This confirmation is affirmed when one considers alignment is about alliances and agreements and outcomes depend on shared intentions (Ungureanu, Bertolotti and Pilati, 2019). Though one might think aligning is the sole responsibility of leadership, it entails the establishment of goals and the building of strategies to coincide with purpose and vision; ergo, alignment is not a singular reflective task. Alignment might be inter-departmental, cross-departmental, and company-wide. Indeed, Trevor and Varco (2016) argued that leaders and managers are challenged to align teams and units, and undeniably, alignment at the enterprise level is vital for the truest connection of organizational strategy to organizational purpose.

4.7 Results Conclusion

Through our newly proposed method, we were able to find statistical justification for each item within the proposed Venn diagram. However, the data suggested that some items were misplaced (originally placed in the wrong section of the Venn diagram). Following this, we conducted a literature review to determine that theoretical justification did exist for the data-suggested placements, which indicated that data and theory matched and resulted in a Venn diagram supported by statistics and theory.

5. Discussion

5.1 Methodological Critique: Additional Questions to be Answered Regarding This New Methodology

The modified EFA method described here allows us to build and validate Venn diagrams. However, to become commonly practiced and applied with confidence, the method needs academically accepted norms and benchmarks. While we depend on many of the already established best practices of EFA, our assumptions that these practices are transferable may be faulty. Additionally, some procedures will be unique to validating a Venn diagram.

The most glaring need is to establish the proper cutoff for determining cross loads. While our example above has secondary loads of .3 or higher when cross-loaded, that may not be the case for all data. Thus, a reasonable benchmark for the cross-load inclusion in the overlapping section of the Venn needs to be determined. For example, if a primary load is .7 and a secondary cross load is 0.2, should this variable be included as part of the primary circle or the intersection?

Negative cross-loads also need to be considered. Should a variable that has a positive primary load and a negative secondary load be placed in the primary (single?) category or the intersection?

Another important statistic for EFA evaluation is the variance explained. Armstrong and Soelberg (1968) justified a benchmark of 60%. That is, to be considered strong, an EFA should account for 60% of the variance. However, this benchmark was set with the intention of data reduction as a primary goal. When performing EFA, a higher variance often can be achieved by removing low-load and cross-load items. Since the goal of this new application is not a reduction in items, we may determine that a lower benchmark cutoff is justified. Better yet, if the goal is simply to validate the distinct sections and intersections of the circles of a Venn diagram, perhaps the total variance explained should not be considered at all. In specific cases, the item placement within a Venn diagram may be enough to accomplish the researcher's goal.

Additionally, the new approach needs a standard for determining how many items define a set of the Venn diagram. When performing traditional EFA, best practice calls for a factor to be comprised of at least 3 items, but flexibility is offered for the design of the study (Tabachnick and Fidell, 2007). One can imagine a Venn diagram that resulted in a circle with one item in the main circle and 2 items in the intersect. Therefore, if trying to honor a three-item cutoff, items in the independent circle and the overlap should be considered. However, additional research should be conducted to determine if the 3-item minimum is still valid under the new framework.

5.2 Methodological Critique: Number of circles within the Venn (how many components to retain)

Finally, we must offer an honest critique of ways in which this method can be mismanaged. One possible misuse of this method can be found in the practice of using Scree plots and/or eigenvalues to determine the number of circles within the Venn diagram. Because we borrow this practice from factor analysis (determining how many factors to retain), we also inherit one of the issues of this method.

Owing to this inherited issue with factor analysis and the difficulty of determining the number of factors to include (or how many circles make up our Venn diagram), we echo the advice of Ford, MacCallum, and Tait (1986):

Since evidence suggests that it is better to overestimate rather than to underestimate the number of factors (Guertin, Guertin and Ware, 1981; Levonian and Comrey, 1966; Rummel, 1970), it is suggested that researchers examine the highest to the lowest number of factors until the most interpretable solution is found (Hakstian, Rogers and Cattell, 1982). (Ford, MacCallum and Tait, 1986, p. 294)

While we echo this advice, we openly acknowledge this method leaves interpretation up to the researcher instead of having hard cutoffs. Unlike methods like regression analysis, there is not an agreed benchmark for statistical validation. With regression, you either achieve or fail to achieve the .05/.10 level for statistical significance. The success or lack thereof is clear. However, with factor analysis, interpretation is still required and, thus, the possibility of misinterpreting must be acknowledged. Therefore, determining the number of circles that should be included within the Venn diagram can be misinterpreted.

5.3 Methodological Critique: Rotation

Again, because this method derives from factor analysis, we also inherit the critiques of that commonly accepted method. Another concern that we acknowledged is rotation. Researchers should pick their rotation method based on the project's needs. More specifically, an orthogonal rotation (often conducted through a varimax rotation) is used for simple structures while oblique rotations allow for complex structures.

In this research, we used the varimax rotation, assuming that leadership and management are simple structures. We also tested the correlation between our factors to ensure that our data met the <0.3 benchmark. Owing to the goals of this method application (validating a Venn diagram) we argue that varimax is the most appropriate rotation method because each circle of the Venn diagram is distinct and not correlated with the others. However, we would be academically dishonest if we did not also draw attention to the critique that researchers should consider alternative constructs to decrease the potential to be biased (Ford, MacCallum and Tait, 1986). This same sentiment is persuasively expressed by Sass and Schmitt (2010). We acknowledge researchers may be enamored with simple structure because it is clean and easily explained (Sass and Schmitt, 2010). The correlation of factors should be determined before opting for a rotation pattern.

5.4 Methodological Critique: Must be Grounded in Theory

Finally, we come to one of the largest weaknesses of this method, and that is an inability to mathematically guard against bad theory.

Armstrong and Soelberg (1968) demonstrated that random numbers linked to variables can be analyzed and results can be "meaningful" as they relate to factor interpretation. Therefore, being able to find meaningful results in factor analysis is dependent not only on the mathematics behind the process but also on the theory used to create the items and variables. Owing to this reality (and it is a reality that holds in most statistical methods), researchers are urged to guard against this weakness. To do so, they must ensure that variables and variable constructs are informed by a thorough review of literature and strongly linked to theory. Additionally, guarding against sampling error by ensuring a large enough sample size and an accepted ratio-to-factor must be employed whenever using this method (Cliff and Pennell, 1967). Researchers can help to strengthen the integrity of results by doing so.

6. Future Research and Conclusion

The purpose of this study was to determine if a modified method of exploratory factor analysis could offer a way to statistically validate Venn diagrams or confirm item placement within Venn diagrams. This objective was achieved. Through this study, the authors offer a significant step forward in the realm of social science research by introducing a rigorous and data-driven approach to creating and validating Venn diagrams. To date, Venn diagrams have been pictorial representations and while they could aid in understanding, they lacked statistical backing. Our newly proposed method addresses this long-standing short coming of Venn diagrams, and we

demonstrated how the application of a modified version of exploratory factor analysis (EFA) could be utilized to position items within the Venn diagram, thus creating a Venn diagram based on empirical data and enhancing its validity and credibility.

In this study, this newly proposed method was applied to the leadership vs. management theory debate. This work underlines the significance and importance of empirical evidence in validating and refining our understanding of complex concepts and relationships. While the context of this example was business, our work has established a structured framework that can be applied to a wide range of social science theories represented by Venn diagrams.

Finally, we concede that this method offers promise but still has limitations. Because this is the first application of this method, many of the best practices and benchmarks from traditional exploratory factor analysis are used. For example, the 0.3 cutoff is used for load factors as is a common practice in EFA. However, scholars have had decades to finetune the EFA process and after the same fine-tuning, academic debates, testing, and applications, it may be found that EFA for Venn validation should have different benchmarks than the traditional EFA application. We recommend that researchers conduct similar studies to determine whether modifications to the proposed method need to be implemented. Questions related to this method and debate are welcomed and needed to progress this method and deepen our understanding of leadership and the social sciences.

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Double Bias of Mistakes: Essence, Consequences, and Measurement Method

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Abstract: There is no learning without mistakes. However, there is a clash between ‘*positive attitudes and beliefs*’ regarding learning processes and the ‘*negative attitudes and beliefs*’ toward these being accompanied by mistakes. This clash exposes a cognitive bias toward mistakes that might block personal and organizational learning. This study presents an advanced measurement method to assess the bias of mistakes. The essence of it is the detection of the existing contradictions between attitude and behavior toward mistakes at the personal and organizational levels, as well as combined. This study is based on empirical evidence from a sample of 768 knowledge workers, divided into biased and non-biased subsamples following the procedure proposed in this paper. Those subsamples were next applied to the structural model, examining knowledge, learning, and collaboration cultures (the KLC approach) 's influence on organizational intelligence to validate the proposed method. Results showed that the applied method efficiently detects the DBM and exposes that in doubly mistakes-biased knowledge-driven organizations, the influence of knowledge culture on the mistakes acceptance component of learning culture is negative. So, organizations with a dominated double bias of mistakes do not accept the affirmation of learning from mistakes. Summing up, this study constitutes the Double Bias of Mistakes Theory, which states that the clash between positive attitudes and beliefs regarding learning processes and negative attitudes and beliefs toward mistakes exposed by focusing on control managers (bosses) might block organizational learning from mistakes and, as a consequence, negatively affect organizational intelligence. Without the empirical support for this theory, there was a risk that the idea of accepting mistakes as a potential source of learning would be simplified by biased minds to mistakes tolerance and rejected as ridiculous. Accepting that mistakes can be a source of precious learning does not equal mistake tolerance. On the contrary, it is the first step to managing mistakes and creating efficient error avoidance systems thanks to lessons learned from failures. This study introduces the method of measurement and detection of the Double Bias of Mistakes phenomenon, contributing to the science of organizational learning and collective intelligence-building.

Keywords: Cognitive bias of mistakes, Double bias of mistakes, Knowledge culture, Learning culture, Collaborative culture, Company culture, Organizational intelligence, Collective intelligence, Fixed mindset, Growth mindset, Change adaptability, Tacit knowledge sharing, Explicit knowledge sharing, Trust, The KLC cultures approach

1. Introduction

The bias of mistakes is rooted in the specific cognitive bias (Tversky and Kahneman, 1981) named the framing effect (Clark, 2009; Druckman, 2001a,b; Plous, 1993) and is caused by the positive claims about mistakes as a natural part of humanity and learning processes but at the same time experiencing negative consequences of the mistake event. This clash results in the negative framing effect of mistakes (experiences affect us more powerfully than statements do). The framing effect is observed if the negative or positive connotations of the particular phenomenon (here: mistakes) impact its perception and judgment. The framing bias is one of the most significant biases influencing situational judging and decision-making (Thomas and Millar, 2011). So, the negative framing effect of mistakes can be powerful in organizations and societies—it can affect situational judgment and decisions. Therefore, its detection and measurement are important in organizational studies.

There is no learning without mistakes (Argyris, 1982; Argyris and Schön, 1996; Senge, 2006). However, knowledge workers still see making mistakes as shameful. The clash between positive attitudes and beliefs regarding learning processes and negative attitudes and beliefs toward the accompanying mistakes can make personal and organizational learning problematic (Hosseini *et al.*, 2023; Samhran *et al.*, 2023; Rass *et al.*, 2023).

Furthermore, in organizations, this cognitive bias is often doubled by the other shared solid belief that “bosses never make mistakes”, or in other words, the belief that only excellent employees can be promoted and hold managerial positions. Therefore, mistakes are perceived as indicators of negligence and in strong contradiction to excellence and perfection, and thus are hidden by employees afraid to be labeled as “losers”. This situation creates an illusion of personal and organizational perfection. Self-awareness is the most important skill for intelligence-building (Gallup, 1998; Rai and Rai, 2024). Hence, maintaining this perfection illusion kills intelligence. In biased societies and organizations, people try to expose excellence and hide mistakes. Mistakes,

if ignored, diminished, and hidden, cannot be a lesson either for the mistake-maker or for the organization. In this case, personal and organizational learning is jeopardized, and the consequences of the cognitive bias of mistakes are severe. Therefore, it is important to understand the phenomenon of the cognitive bias of mistakes and its consequences. Without it, there is a risk that the entire idea of accepting mistakes as a potential source of learning will be simplified by biased minds to mistake tolerance and rejected as ridiculous. In practice, accepting that mistakes can be a source of valuable learning is not the same as being tolerant of mistakes. On the contrary, it is the first step to managing errors and creating effective systems to avoid mistakes through lessons learned.

Understanding the essence of the cognitive bias of mistakes and, even more importantly, the consequences of this phenomenon can significantly enhance mistake management and, in this way, support the avoidance of hiding mistakes in organizations. The key benefit of these efforts is organizational learning. Kucharska, Bedford, and Kopytko (2023) introduced a method for identifying and measuring the cognitive bias of mistakes, focusing mainly on the DBM. The personal bias of mistakes (PBM) and Organizational (OBM) were omitted. It is unknown if the bias of mistakes affects individuals (PBM) and organizations (OBM) synchronously or asynchronously. If so, is it frequent? What are the consequences? It is unknown whether the discrepancy exists between bosses and organizations or whether a boss's bias impacts organizational bias.

To find answers, this study aims to expand Kucharska *et al.*'s (2023) procedure to expose and compare the consequences of mistake bias at the organizational (OBM), personal (PBM), and doubled (DBM) levels. Such expansion is important for a better understanding the DBM phenomenon's impact on organizational learning and collective intelligence building. It is important to find out if the omission of personal bias of mistakes (PBM) or organizational bias of mistakes (OBM) influence organizations in the Kucharska *et al.* (2023) study modify our understanding of DBMs impact on organizations gained so far. Finally, it will be beneficial if the identification and measurement method of the DBM proposed by the Kucharska *et al.* (2023) study be simplified to make it easier to apply. This study aims to deliver this.

2. Literature Review

2.1 Learning From Mistakes

It is known that there is no learning without making mistakes. However, in most organizations, mistakes are perceived as an indicator of negligence and poor performance. Therefore, when people make mistakes, they will most likely do everything in their power to conceal them because they are ashamed (Senz, 2021). This situation pushes individuals and organizations to create an illusion of excellence that blocks organizational intelligence (Kucharska *et al.*, 2023). Feuerstein *et al.* (1979) defined intelligence as the ability to adapt to change. Following him, the organizational capacity to adapt to change is seen in this study as organizational intelligence.

For organizations to learn from mistakes, communal reflexivity is needed (Ellis *et al.*, 2014). Parker, Racz, and Palmer (2020) noted that organizational reflexivity is not exclusively the individual's action—it is a co-created practice of the whole team within a specific organizational context.

Bryans (2017) noted that 80% of employee learning occurs informally and is entirely unplanned, incidental, and mainly experiential. An example of incidental learning is, e.g., learning from mistakes. Therefore, most organizational learning is tacit. Kucharska and Bedford (2020) discovered a paradox that even if employees learn from mistakes, their companies usually do not. This is caused by company culture issues. Unfortunately, individual learning in a workplace is not equal to collective learning (Wiewiora, Smidt, and Chang, 2019). Therefore, for organizations, it is important to be aware of and manage mistakes and the bias accompanying them.

According to the Transformative Learning theory (Mezirow, 1995, 1997), which claims that adult learning happens thanks to modified interpretations of the meanings of personal experiences and frames of reference through critical reflection, where critical reflection is seen as a result of "intuitively becoming aware that something is wrong with the result of one's thought, or challenging its validity through discourse with others of differing viewpoints and arriving at the best-informed judgment" (Mezirow, 1995, p. 46), mistake reflectivity is a critical factor for learning. If mistakes are denied or ignored they cannot be a source of reflection and learning for anybody, neither the mistake-maker, nor anyone else. Hidden mistakes cause harm and are a waste of value rather than a precious learning source (Kucharska, 2021). This in line with the concept of negative resource spirals (Hobfoll *et al.*, 2018), according to which the loss of one resource (e.g., knowledge from mistakes) can generate losses of other resources. A lack of learning from experience is a waste. Mistakes are precious, common human experiences. Without accepting them, we can neither understand their meaning nor learn from them.

Exposing the cognitive bias of mistakes can help in releasing it. The lower the cognitive bias of mistakes, the better organizational learning. Without learning, neither individuals nor organizations can build intelligence and grow.

Both small mistakes and big failures can provide precious lessons and contribute to intelligence-building; the difference is that small mistakes can be hidden while big failures cannot. More precisely, the bigger the mistake and its consequence, the more problematic it is to hide the error. In extreme cases, it is downright impossible. Therefore, the "game of blame and shame" (Ferguson *et al.*, 2017; Tingle, 2022) is very common in organizations that do not see mistakes as a potential source of learning and do not manage them at all.

"Being human is that we have to understand the meaning of our experiences" (Mezirow, 1997, p.5). Mistakes are precious, common human experiences. Without accepting the fact we make them and can learn from them, we can neither understand their meaning nor learn from them. Therefore, the shift from the culture of apparent perfection (which is radical and harmful) into the authentic learning culture that constantly modifies interpretations of experiences to fully understand their meaning (mental model change), and frames reference through shared critical reflection, and creates organizational dynamic capabilities is highly desirable in a dynamically changing business environment (Béliveau and Corriveau, 2021; Kimberley, 2021; Kucharska and Bedford, 2023a-b;). It is necessary, especially since acting in hyperdynamic conditions may naturally be accompanied by mistakes.

Organizations and their leaders have been slow in adopting error management, an orientation that accepts error occurrence and focuses on correction and learning from errors (Dimitrova and Hooft, 2021; Edmondson, 2023). These authors suggest that the key problem with this concerns image and, based on their experimental and field study, Dimitrova and Hoft (2021) revealed positive outcomes of leaders' error orientation as employee-perceived leader warmth, competence, and employee job satisfaction, reduced turnover intention, greater work engagement, and better job performance. Farnese *et al.* (2019) and Farnese, Fida, and Picoco (2020) confirmed authentic leadership's positive influence on error management. Moreover, Reason (2005) classified errors into two groups: active (easy to detect) and latent (hidden). Latent errors reside in weakened organizational defenses and are related to managerial decisions regarding safety procedures, organizational structure, and cultural factors. The consequences of managerial latent errors may remain hidden for a long time, only becoming exposed when they combine with active failures and local triggering factors to breach the system's many defenses (Reason 2005, p. 58). These studies confirm that cognitive bias doubled by leaders' biases is worth studying.

Many positive examples of error management and learning from errors come from the healthcare industry (Fischer *et al.*, 2006; Van Dyck *et al.*, 2013; Waeschle *et al.*, 2015; Metcalfe, 2017; Kalender, Tozan, and Vayvay, 2020; Keith, Horvath, and Klamar, 2020). Frese and Keith (2015) and Weinzimmer and Esken (2017) studied learning from mistakes and revealed that the essence of organizational learning is to identify and modify errors. Jung *et al.* (2021), Kalender *et al.* (2020), Anderson and Abrahamson (2017), and Zhao and Olivera (2006) noted that the critical problem of organizational learning from mistakes is a lack of reporting. These authors highlighted the need for organizations to change their attitude toward errors. Based on Ferguson (2017), Zabari and Southern (2018), and Robertson and Long (2018), the reporting problem in healthcare may stem from an organizational culture of "blame and shame". To avoid blame and shame, people hide mistakes. If their mistake stays hidden, it cannot be a lesson for anybody except the person who made it. Mohsin, Ibrahim, and Levine (2019) suggest that error reporting should be a standard learned at medical schools.

Learning from the healthcare industry may help promote a similar standard of behavior more widely. A learning culture that is open to organizational learning from all available resources can significantly improve mistake reporting, management, and learning and also benefit the avoidance of mistakes in the future. Such a culture should be built with a full understanding of cognitive bias and how severe its consequences may be for individuals, organizations, and societies.

2.2 The Essence of the Cognitive Bias of Mistakes and its Consequences

The existing clash between positive attitudes and beliefs regarding learning processes and the negative attitudes and beliefs accompanying mistakes is the essence of the cognitive bias of mistakes, which can make personal and organizational learning from mistakes problematic (Hosseini, Treur, and Kucharska, 2023; Hull, 1930; Kucharska and Bedford, 2023b). Moreover, in organizations and societies, this cognitive bias is often doubled by the shared belief that those who hold managerial positions are expected to never make mistakes and should hold such a disposition to legitimize their credentials to be leaders. In other words, the belief exists that only

perfect individuals can hold power and consequently only excellent employees can be promoted to managerial positions. Therefore, mistakes are perceived as indicators of negligence and thus in strong contradiction to excellence, and thus are hidden by employees afraid to be labeled as “losers”.

This double bias leads to a chain of consequences. First, the fear of personal consequences of mistakes may lead to the cultivation of a fixed, instead of a growth mindset in society (Dweck, 2017; Athota, 2021). Mindset (mental model) is the psychological construction of an internally held structure (Vazquez, Liz, and Aracil, 1996) that shapes a particular person’s perception of things and determines their understanding of the world (Shih and Alessi, 1993; Doyle and Ford, 1998). Such personal perceptions and understanding shape attitudes and behaviors toward everything, including those important for mistakes that influence learning abilities. So, growth mindsets are learning-oriented (constant progress), while fixed mindsets are image-oriented (constant confirmation of self-perfection). As a consequence, a fixed mindset makes people non-learners in the long run (Dweck, 2017). Learning-oriented mindsets love a challenge, believe in learning effort, are resilient in the face of setbacks, and are creative (Dweck, 2017, p. 19). Fixed mindsets perceive failure as a lack of intelligence, so any validation of their own actions is risky. They often believe that avoiding any challenge that can expose setbacks and cause a social rejection as a result of revealing a lack of perfection is better than taking the risk of failure because “bosses never make mistakes”.

So, bosses avoid the risk of making mistakes for two reasons: first, to maintain their positive self-image; second, to prove to others they are fully justified in keeping their positions due to the shared belief that “bosses never make mistakes”, and therefore they are perfect. This is why we have a crisis in transformational leadership. Leaders with fixed mindsets avoid any risk of losing their image, so the fixed mindset dominates organizations, and this also affects the organization’s ability to learn and adapt to changes. The double bias of bosses’ mistakes, which act here as a trigger for a dominant collective, immediate performance orientation, is remote from long-term sustainability and is a waste of long-run learning as well as a loss of potential social growth.

The negative framing effect of mistakes is powerful in organizations and societies, as it affects situational judgment and decisions. Kucharska *et al.*’s (2023) findings revealed the severe impact that the DBM has on organizational adaptability by weakening collaboration and learning cultures and blocking tacit knowledge creation. Hosseini *et al.* (2023) and Kucharska *et al.* (2023) see the DBM as a serious impediment to collective learning and expose the negative consequences for organizational learning and intelligence-building. Therefore, methods to detect and measurement this phenomenon are essential for organizational studies. Based on the literature outlined above, Table 1 summarizes the essence of the bias of mistakes.

Table 1: The essence of the bias of mistakes

BIAS OF MISTAKES: The contradiction between the declared positive attitude toward mistakes and the exposed negative behavior detected at the personal or organizational level					
Respondents' views*	PERSONAL LEVEL				
	attitude	positive	BIAS	negative	behavior
		positive	BIAS	negative	
	ORGANIZATIONAL LEVEL				
DOUBLE BIAS OF MISTAKES: The contradiction between a declared positive attitude toward mistakes and the negative behavior DETECTED AT THE SAME TIME at the personal and organizational level					

*The respondent answers for themselves (self-view report) and about the organization or society she/he works or lives in (her/his workplace observation report).

2.3 Measurement of the Cognitive Bias of Mistakes

Kucharska *et al.*’s (2023) study introduced the method of the cognitive bias of mistakes at the personal (cognitive bias of mistakes, PBM) and organizational level (doubled cognitive bias, DBM) measurement, which is based on the detection of the contradiction between the attitude and the behavior at the personal and organizational levels at the same time. More precisely, Kucharska *et al.* (2023) focused on the DBM and its consequences for organizations and assumed that if the aim is to detect the DBM via questionnaires, this bias should be observed simultaneously for the responder and the organization the responder refers to. Based on a sample of 640 Polish knowledge workers and following this procedure they detected the DBM in 28% of their sample, and showed

51% cases of this sample were free from DBM. Next, they validated the method by comparing findings obtained for the same model (structure of variables) but developed separately for the DBM-biased sample and sample free from DBM (Table 2, Figure 1). In this way, these authors not only proved the existence of the DBM, but also exposed its negative consequences for organizational learning culture, tacit knowledge sharing, change adaptability, and innovativeness.

Following Senge (2006), learning is a matter of the company's shared mindset. Therefore, it may be the case that people with growth mindsets working in an organization where a collective mindset is a fixed one behave according to a fixed mindset because the company culture ensures this, or they stay as they are, or the converse. Hence, the bias of mistakes can affect individuals and organizations both synchronously and asynchronously. Therefore, the proposal by Kucharska *et al.* (2023) should be expanded.

The question arises regarding the 21% of their sample that is not free of the DBM but, at the same time, is not affected by the DBM. This sample probably represented respondents who are affected by the cognitive bias at a personal level (PBM), or are not, but their organizations are biased. To summarize, in this group of respondents, mistake perception is undoubtedly biased somehow, but this bias is not doubled in the case of this group of respondents. So, it is assumed that in this group, mistake bias exists at the personal (employees) or organizational y levels (organization). The method for assessing the DBM proposed by Kucharska *et al.* (2023) should be advanced by including these two additional, previously omitted situations of the existence of mistake bias that, although not doubled, still exists and may affect organizations. This study aims first to advance the existing mistake bias measurement procedure by including the options of organizational bias and personal bias and, next, to compare how frequent these options are and how the identified variants affect organizations.

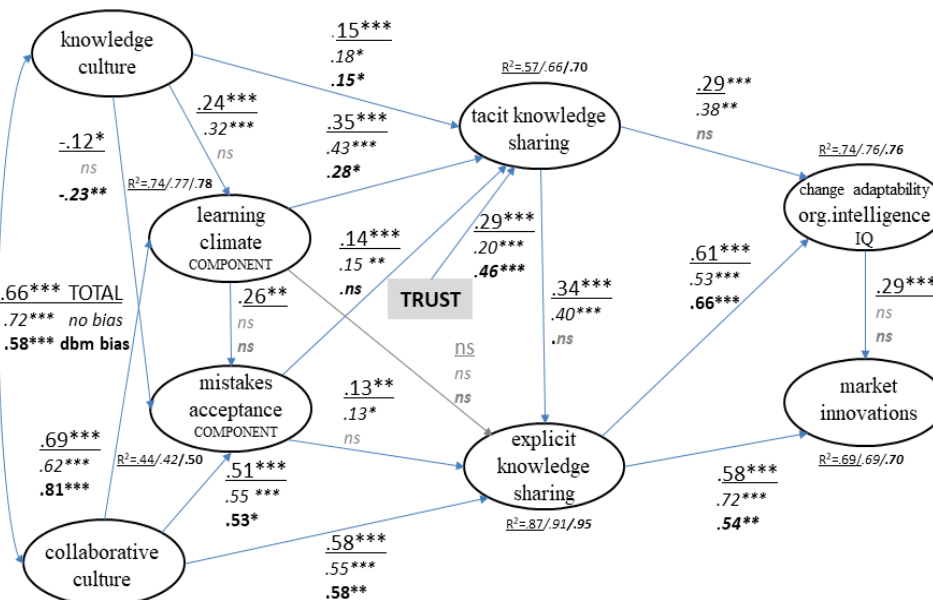


Figure 1: Consequences of DBM

Note: $n=640/n=327/n=183$ (total/no bias/DBM bias) ML; $\chi^2=1043.45(331)/700.082(305)/638.55(305)$; CFI=.941/.939/.896; TLI=.933/.930/.880; RMSEA=.059/.063/.078; Cmin/df=3.15/2.27/2.09; $p<.05$ $^{**}p<.01$ $^{***}p<.001$; ns-not significant result; DBM bias, the double bias of mistakes.

Source: Kucharska *et al.* (2023)

3. A new Approach: The DBM Identification and Measurement Method Improvement

Kucharska's *et al.* (2023) model method validation is very complex (Figure 1). The advantage of such a complex structure is that it clearly exposes the consequences of the DBM. Kucharska *et al.* (2023) proved that DBM severely affects organizations, based on 79% of their study sample ($n=640$ cases). However, 21% of their study sample was omitted because this sub-sample was not large enough (reason: Structural Equation Modeling (SEM) methodology restrictions) to validate the study model, which, in fact, should be additionally divided into biased individuals and biased organizations. As a result, the measurement and consequences of the cognitive bias of mistakes at the personal-only or organizational-only levels were omitted in Kucharska *et al.*'s (2023) study. It is unclear if 21% of the sample represents 'other options' rather than 'no bias', if the DBM is a characteristic of this

particular sample, or if it is a general pattern observed in the population. Therefore, this study focuses on expanding the procedure and validation based on all possible options: first, no bias; second, PBM; third, OBM; and last, the DBM (2023) to check the legitimacy of its omission. It might be that because of this omission, some critical knowledge about the cognitive bias of mistakes impact on organizations has been lost. The essential advantage of the proposed new approach is that it lets us identify the frequency of the omitted earlier options in a totally different sample. Next, if the frequency is reasonable, then verify how these omitted biases affect organizations and, in this way, gain a better understanding of their nature. To do so, the advanced mistake bias procedure of measurement (Table 2) and detection (Table 3) were proposed and validated based on the simplified model of Kucharska *et al.* (2023), visualized in Figure 2.

Table 2: The advanced measurement method for mistake bias

		Statements	Procedure
PERSONAL LEVEL	(E) EMPLOYEE	A. <u>ATTITUDE</u> <u>Positive</u> - Mistakes are inevitable <u>Negative</u> - I do not accept mistakes	The positive and negative statements are presented. The respondent selects the one that fits him/her best (TRUE/FALSE).
		B. <u>BEHAVIOR</u> <u>Positive</u> - I report my mistakes <u>Negative</u> - I hide my mistakes	The positive and negative statements are presented. The respondent selects the one that fits him/her best (TRUE/FALSE).
ORGANIZATIONAL LEVEL	(O) OTHER EMPLOYEE S	- ATTITUDE <u>Positive</u> - Mistakes are accepted in my organization/society as a natural part of learning and experimenting <u>Negative</u> - My organization members/society does not tolerate mistakes - Employees generally hide mistakes	The positive and negative statements regarding the shared organizational attitude are presented. The respondent selects the one that best describes his/her organization (TRUE/FALSE).
		<u>BEHAVIOR</u> <u>Positive</u> - Employees generally report and openly discuss mistakes <u>Negative</u> - Employees generally hide mistakes	The positive and negative statements regarding the most frequent organizational behavior are presented. The respondent selects the one that best describes his/her organization (TRUE/FALSE).
	(B) BOSS	A. <u>ATTITUDE</u> <u>Positive</u> - Company leaders see mistakes as part of learning and experimenting <u>Negative</u> - Company leaders do not tolerate mistakes	The positive and negative statements regarding the attitude of the leader are presented. The respondent is asked to select one statement that best describes the supervisor's declarations (TRUE/FALSE).
		B. <u>BEHAVIOR</u> <u>Positive</u> - Company leaders admit mistakes <u>Negative</u> - Company leaders must always be right (blame others for their own mistakes)	The positive and negative statements regarding the behavior of the leader are presented. The respondent is asked to select one statement that best describes the supervisor's behavior (TRUE/FALSE).

Note: To detect the bias more naturally, researchers should consider the certainty and reliability of responses. Therefore, the EMPLOYEE-BOSS-COMPANY (E_B_C) parts should be intentionally separated in a questionnaire (not displayed in a sequence one by one) to avoid blindly consequent or image-filtered answers.

Based on the literature (Schein, 1992; George, Sleeth, and Siders, 1999), we assumed that leaders shape organizations more strongly than organizations shape leaders (Schein, 1992; George *et al.*, 1999). However, both options are possible (Cogner, 2004), including the shared leadership idea that assumes shared company culture creation (Cullen *et al.*, 2012). So, bearing in mind this study's purpose, we have assumed that the boss's attitudes and behaviors toward mistakes are equal to those of the organization and that the boss's attitudes and behaviors are reflected in the organizational (employees) attitudes and behaviors. This assumption was applied to the bias mistake detection method (Table 3). However, the bias of mistakes can affect individuals and organizations synchronously or asynchronously. This study aims to determine whether the discrepancy between bosses and organizations exists and how frequent this phenomenon is.

Table 3: The bias mistake detection method

Personal	Organizational		BIAS DETECTED
E	C	B	
employee	company/employees	boss	
no bias	no bias	no bias	no bias detected (NOB)
bias	no bias	no bias	personal bias detected (PBM)
no bias	no bias	bias	organizational bias detected (OBM)
	bias	no bias	
bias	bias	bias	double bias detected (DBM)
	no bias	bias	

4. Validation of the new Method of Measurement and Identification

Kucharska *et al.* (2023) proved that if the bias of mistakes is evidenced by employees and company leaders simultaneously (is doubled), this affects organizations severely. This study aims to verify it and advance their contribution by proving that DBM and the bias of mistakes itself (not simultaneously) may jeopardize organizational learning. To do so, this study aims to describe the theoretical framework and measurement methods enabling the identification of the empirical evidence that both the bias of mistakes and the DBM are barriers to the growth of organizational intelligence. Precisely, this study aims to focus on the four possible cases: first, no bias detected in the sample (NOB); second, PBM only; third, OBM only; and fourth, the DBM, to verify if the 21% of the Kucharska *et al.* (2023) sample representing 'other options' than 'no bias' and the DBM were characteristics for this particular sample or might be that it is a general pattern observed in the Polish population. Since the validation process is based on the simplified model introduced by Kucharska *et al.* (2023) and Kucharska and Bedford (2023 a,b), this study does not repeat the justification of the hypotheses included in the theoretical model structure (Figure 2). The general idea of the simplified model is that the knowledge, learning, and collaboration cultures synergy - the KLC approach introduced by Kucharska and Bedford (2023) affects organizational intelligence (Kucharska and Bedford, 2023a,b). Feuerstein *et al.* (1979) defined intelligence as the ability to adapt to change. Following him, the organizational capacity to adapt to change is seen in this study as organizational intelligence. So, our DBM detection method is validated based on this simplified model reflecting the KLC cultures and organizational intelligence relation (Kucharska and Bedford, 2023 a,b). So, this study does not repeat the justification of the hypotheses, but for validation clarity, all are visualized in Figure 2 and listed below:

H1a: Knowledge culture positively affects the learning climate component of the learning culture.

H1b: Knowledge culture negatively affects the mistakes acceptance component of the learning culture.

H1c: The learning climate component of learning culture positively affects the mistakes acceptance component of a learning culture.

H1d: Collaborative culture positively affects the learning climate component of the learning culture.

H1e: Collaborative culture positively affects the mistakes acceptance component of the learning culture.

H1f: Knowledge culture and collaborative culture are correlated.

H2a: Knowledge culture positively affects organizational intelligence.

H2b: The learning climate component of learning culture positively affects organizational intelligence.

H2c: The mistakes acceptance component of the learning culture positively affects organizational intelligence.

H2d: Collaborative culture positively affects organizational intelligence.

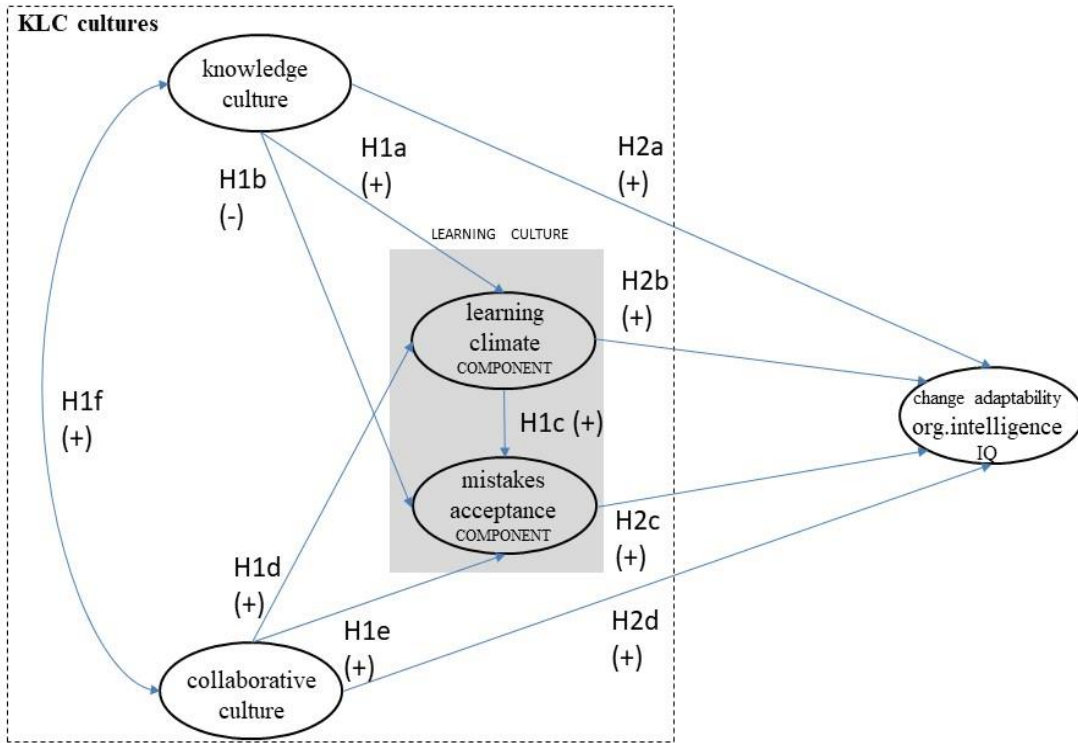


Figure 2: Validation stage: Theoretical model visualization

Source: Simplified model by Kucharska and Bedford (2023 a,b)

Below, Table 4 presents the steps of the validation of the new advanced methodological approach, from the procedure for measuring the bias of mistakes (personal, organizational, and doubled) through to the detection of the bias type, its frequency, and verification of its impact.

Table 4: Validation procedure

STEPS of the procedure		STEP	DETAILS
1.	Measurement stage		
A	Bias measurement procedure	Gather questionnaire responses	Table 2
B	Bias type detection procedure	Bias type detection in the sample No bias PBM only OBM only DBM	Table 3
2.	Validation stage		
a.	Theoretical model development	Simplification of Kucharska et al.'s 2023 model	Figure 2
b.	Empirical models development and comparison	Models run and assessed using SEM techniques	Figure 3

The statements presented in Table 2 were incorporated into the questionnaire for knowledge workers to validate the method. The sampling method and sample characteristics are presented below.

Sampling procedure and measures: This study was targeted at a convenience sample of Polish knowledge workers. The respondents included were those who declared that their work's first input and output was

knowledge. Moreover, to ensure the respondents' familiarity with their organizations' issues, we included only those who had worked for a minimum of one year for their current employer. Data were collected in October 2023 by computer-assisted web interviewing.

The respondents answered the majority of the test statements using a 7-point Likert scale, but to statements regarding the measurement of cognitive bias (Table 1), respondents answered stating whether the particular statement was TRUE=1 or FALSE=2.

The study by Kucharska and Bedford (2023 a, b) describes the construct scales and their sources. The reliabilities obtained are given in Tables 5a-e together with basic statistics and AVE root squared, and correlations between the constructs for each sub-sample creation according to the bias detected when following the procedure described are given in Table 3 (total sample, no bias sub-sample, personal bias sub-sample, organizational and double bias sub-samples). The model by Kucharska and Bedford (2023b) was simplified to enable data analysis using exact SEM.

Sample characteristics: The conceptual framework of the original model is given in Kucharska *et al.* (2023) and Kucharska and Bedford's (2023a,b) studies. However, the sample selected for the advanced method validation in this study is different. The study sample is composed of 768 cases (fully completed and valid questionnaires with SD > .4) representing Polish knowledge workers: 227 specialists and 541 managers, 389 women and 379 men working mostly in private (76%) companies in different sectors and almost equally represented by micro (3%), small (31%), medium (35%), and large companies (31%). The dominant sectors in the study sample were knowledge-intensive sectors: IT (9%), finance (7%), higher education (10%), health care (6%), trade (10%), and construction (6%), accounting for 48%. However, production (15%), other than higher education public services (12%), and other private services (23%) categories were also included. Compared to the samples from Kucharska *et al.* (2023) and Kucharska and Bedford's (2023b) studies, this sample contains more managers and a greater diversity of sectors.

Method of analysis: SEM with the use of SPSS Amos 26 software.

Sample quality: Sample quality assessment began with the Kaiser–Meyer–Olkin test to determine the suitability of the data for factor analysis. The result of KMO test, .946 was good (Hair *et al.*, 2010). The total variance extracted was 78%, while common method bias, tested using the common latent factor method, was 38%. This suggested that the sample quality is good and enabled us to proceed to the subsequent stage of the analysis.

5. Validation Results

The proposed method was aimed to be validated by a comparison of the results for the total sample (n=768) and the four identified sub-samples based on the procedure outlined in Table 2. However, the sub-samples representing 'PBM' (n=58) and 'OBM' (n=80) are too small to be included in further analysis of their impact on organizations using the SEM method. So, they were concluded as marginal and excluded from further analysis. The comparison then proceeded for the total sample, 'no bias', and the DBM subsamples. This required an assessment of the qualities of the total sample and all two sub-samples; next, empirical models for all three were formed and analyzed (Figure 3, Table 6).

The evaluation of the models' qualities was initially conducted based on construct measurement consistency tests, such as the average of variance extracted (AVE), composite reliability (CR), and Cronbach's alpha. The AVE value exceeded 0.57 for all constructs, which was acceptable (Byrne, 2016; Hair *et al.*, 2017). Cronbach's alpha test was used to confirm the consistency of the construct measurement model. The alpha coefficient was greater than 0.77 for all constructs, which was adequate (Hair *et al.* 2017, pp. 112). The CR was greater than 0.73 for all loadings, exceeding the required minimum of 0.7 (Hair *et al.*, 2017). The square root of each construct's AVE exceeded the correlations between the majority pairs of distinct constructs, but not for all. The collaborative culture and the learning climate components in the total sample and the 'no bias' sample may slightly supercharge one another. This case does not arise in the DBM sub-sample.

Table 5: Basic statistics and AVE root square and correlations between constructs

a) Total sample

	Mean	SD	AVE	CR	Cronbach's alpha	CC	KC	LCc	LCm	IQ
CC	4.2	1.86	0.60	0.82	.86	0.776				
KC	4.60	2.3	0.71	0.88	.89	0.587	0.845			
LCc	4.06	2.04	0.60	0.82	.83	0.796	0.688	0.777		
LCm	3.60	1.50	0.60	0.82	.79	0.626	0.398	0.593	0.776	
IQ	4.20	1.88	0.81	0.93	.90	0.765	0.533	0.702	0.6	0.902

Note: n=768 KC-knowledge culture, LCc-learning culture climate component, LCm-Learning culture mistakes acceptance component,

CC-collaborative culture, IQ- organizational change adaptability.

b) No bias of mistakes detected in the sample

	Mean	SD	AVE	CR	Cronbach's alpha	CC	KC	LCc	LCm	IQ
CC	3.5	2.0	0.62	0.76	.81	0.790				
KC	4.2	2.5	0.74	0.90	.89	0.587	0.862			
LCc	3.8	2.3	0.64	0.84	.79	0.796	0.698	0.800		
LCm	3.87	1.7	0.85	0.95	.94	0.626	0.398	0.593	0.923	
IQ	3.5	2.1	0.64	0.84	.86	0.765	0.533	0.702	0.6	0.797

Note: n=326 KC-knowledge culture, LCc-learning culture climate component, LCm-Learning culture mistakes acceptance component,

CC-collaborative culture, IQ- organizational change adaptability.

c) DBM detected in the sample

	Mean	SD	AVE	CR	Cronbach alpha	CC	KC	LCc	LCm	IQ
CC	4.2	1.94	0.66	0.85	.80	0.812				
KC	4.5	2.29	0.70	0.88	.89	0.596	0.839			
LCc	4.08	1.87	0.64	0.84	.79	0.737	0.545	0.798		
LCm	2.80	1.82	0.84	0.94	.88	0.614	0.256	0.571	0.919	
IQ	3.90	1.83	0.57	0.73	.77	0.785	0.451	0.616	0.62	0.755

Note: n=304 KC-knowledge culture, LCc-learning culture climate component, LCm-Learning culture mistakes acceptance component,

CC-collaborative culture, IQ- organizational change adaptability.

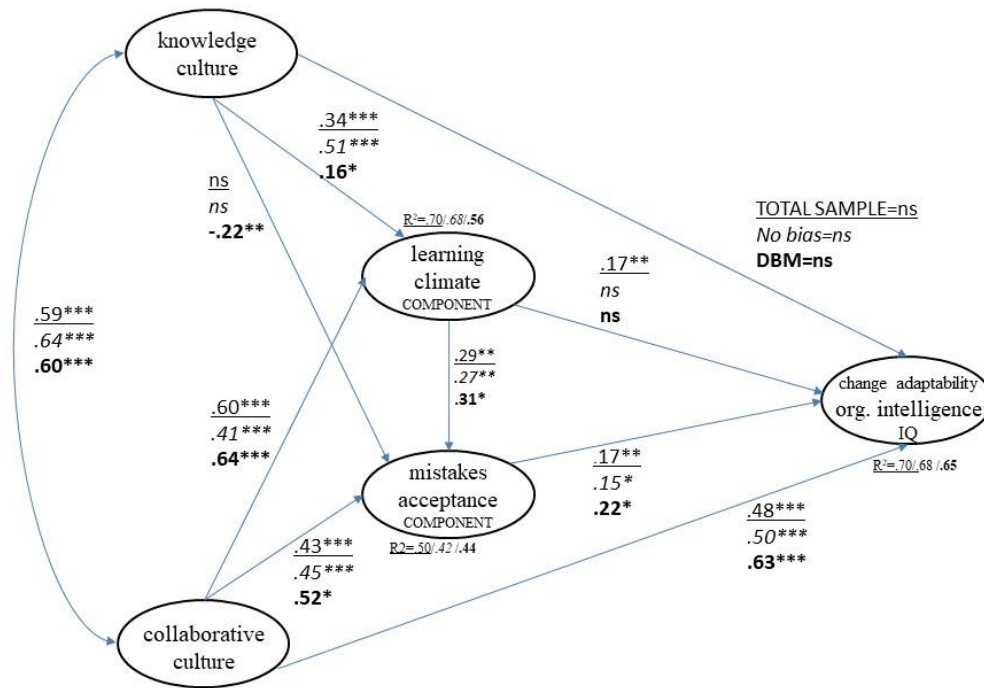


Figure 3: Validation stage: Empirical model

Note:

a) Total sample n=768 $\chi^2=204(80)$ CFI=.979 TLI=.973 RMSEA=.050 Cmin/df=2.55; $p<.05$ ** $p<.01$ *** $p<.001$; ns-not significant result; ML – maximum likelihood

b) No bias sub-sample n=326 $\chi^2=80(44)$ CFI=.987 TLI=.980 RMSEA=.050 Cmin/df=1.82; $p<.05$ ** $p<.01$ *** $p<.001$; ns-not significant result; ML – maximum likelihood

c) DBM n=304 $\chi^2=55(25)$ CFI=.981 TLI=.967 RMSEA=.064 Cmin/df=2.22; $p<.05$ ** $p<.01$ *** $p<.001$; ns-not significant result; ML – maximum likelihood

OBM sub-sample n=80 is too small size to create a SEM model

PBM-sample n=58 is too small size to create a SEM model

Table 6: Hypotheses verification

Hypothesis	Total sample n=768	No bias sub-sample n=326	Doubled bias n=304
H1a	.34***	.51***	.16*
H1b	ns	ns	-.22**
H1c	.29**	.27**	.31*
H1d	.60***	.41***	.64***
H1e	.43***	.45***	.52**
H1f	.59***	.64***	.60***
H2a	hypothesis rejected	hypothesis rejected	hypothesis rejected
H2b	.17**	hypothesis rejected	hypothesis rejected
H2c	.17**	.15*	.22**
H2d	.48***	.22*	.63***
	$\chi^2=204(80)$ CFI=.979 TLI=.973 RMSEA=.050 Cmin/df=2.55	$\chi^2=80(44)$ CFI=.987 TLI=.980 RMSEA=.050 Cmin/df=1.82	$\chi^2=55(25)$ CFI=.981 TLI=.967 RMSEA=.064 Cmin/df=2.22

Note: $p<.05$ ** $p<.01$ *** $p<.001$; ns-not significant result; ML – maximum likelihood.

This study clearly exposed that in doubly mistakes-biased knowledge-driven organizations, as reflected here by the DBM sub-sample, the influence of knowledge culture on the mistakes acceptance component of learning culture is negative. So, it confirms the risk of adverse consequences of such a situation for organizational intelligence. The empirical model (Figure 3) exposes the broader picture of the KLC culture's synergic power supporting organizational intelligence building. Therefore, it is clear that the collaborative culture and learning climate component of learning culture facilitate the negative effect of the KC impact on the LCm (H1b) observed for the DBM sub-sample. So, in mistakes-biased organizations, collaborative culture and learning climate components of the learning culture are critical to building organizational intelligence—studies by Kucharska and Bedford (2020, 2023a,b) explore the KLC approach power more in-depth.

Focusing on this study purpose, the critical finding of the DBM measurement and detection method validation stage is precisely the knowledge from comparing the H1b verification in all samples. This comparison, in the light of the entire model structure (Figure 3), exposes that DBM-biased knowledge-driven organizations cannot build their collaborative intelligence without a collaborative culture and learning climate component of a learning culture, which facilitates the negative affection of knowledge culture on the mistakes acceptance component of a learning culture.

Returning to the study's fundamental purpose, the simplified DBM measurement and detection procedure was positively validated. Moreover, the validation stage results (Figure 3; Table 6) revealed that while personal and organizational mistake-related biases exist, their frequency is marginal in this sample of knowledge workers. The dominant sub-samples in knowledge-driven organizations are no-biased and doubly-biased subsamples. Based on this, it is clear that bosses' bias impacts organizational bias. So, the omission of personal bias of mistakes (PBM) or organizational bias of mistakes (OBM) influencing organizations in the Kucharska et al. (2023) study did not modify our understanding of DBMs' impact on organizations gained so far. It confirmed our understanding because data from two different samples confirmed the general conclusion - the DBM negatively affects organizational learning through mistakes culture by annihilating the development of mistakes acceptance component of a learning culture and, consequently, jeopardizing organizational intelligence.

6. Discussion

Comparing these results to those of Kucharska *et al.* (2023), the main conclusion is that the knowledge workers group in Poland shows personal and organizational mistake-related biases. However, their frequency is marginal compared to the 'no bias' or the 'DBM' sub-samples. In light of this, the current broader study confirms the general finding of Kucharska *et al.* (2023) that DBM negatively affects learning from mistakes. The value of this confirmation is that it is made based on a different sample, and the applied new, simplified methodology proposed for DBM detection and measurement was positively validated. In other words, based on these results, from a business research perspective, the DBM detection method efficiently reveals the negative impact of the double cognitive bias of mistakes on organizations. The sample applied to this study, similar to (Kucharska *et al.*, 2023), contains more managers and a greater diversity of sectors. This might be the reason why the sample was still too small to explore the PBM and OBM in more depth. This might be that further studies should rely on the biggest samples dedicated to the particular sectors. Sample size matters to avoid potential biases rooted in methodological limitations (Andrieux *et al.*, 2024).

When assessing each hypothesis in detail, H2a, regarding the direct influence of knowledge culture on adaptability to change, was rejected for all samples. This suggests that Kucharska *et al.*'s (2023) model, presented in Figure 1, proves that the KLC approach matters for adaptability to change and, while omitted in this study's simplified model (Figure 2, 3), knowledge sharing is a very significant mediator between a knowledge culture and adaptability to change. In other words, this relation is indirect, rather than direct.

Moreover, the negative direct influence of knowledge sharing on the acceptance of mistakes (H1b) is confirmed for the DBM sub-sample. This is similar to the result obtained by Kucharska *et al.* (2023) for the total and DBM samples, but this hypothesis is not confirmed for the total and 'no bias' samples; it is confirmed only for the DBM sub-sample. The results obtained for H1c also differ from those of Kucharska *et al.* (2023). In this study, the direct, positive influence of the learning component on the acceptance of mistakes component of a learning culture is confirmed for all samples, in findings given in Figure 1 (Kucharska *et al.*, 2023) only for the total sample. Similarly, the synergy between the learning culture component of organizational climate for a learning and collaborative culture observed in the total and 'no bias' samples is also observed in Kucharska *et al.*'s (2023) study for all samples, including the DBM.

Summing up, these comparisons show that in social sciences, results based on data collected from questionnaires are not identical, even if they are repeated in the same population (Gorrell *et al.*, 2011; Kountur, 2011). However, sample size may also play a significant role here. Larger samples would allow the identification of more sensitive and weaker relations (Shi, Lee, and Maydeu-Olivares, 2019). Moreover, the models compared in this study are similar but not identical. What is essential is the fact that the general findings are confirmed. This study revealed that while personal and organizational mistake-related biases exist, their frequency is marginal in this sample of knowledge workers. The dominant sub-samples in knowledge-driven organizations are the 'no bias' or the 'DBM' groups. Thus, the omission by Kucharska *et al.* (2023) of the personal and organizational biases of mistakes samples is fully justified.

7. Practical Implications

This study confirms the DBM's negative impact on organizational learning. There are profound practical implications regarding the effect of the DBM when it is dominant in organizations. Our findings indicate that rethinking and re-framing the organizational approach to mistakes is necessary. Enterprises with zero tolerance for mistakes in divisions and areas other than in production or operations can face severe difficulty in creating a competitive advantage that comes with adaptability to change (intelligence) and innovations developed over the long run. The essence of collective intelligence, seen as a network of knowledge workers' 'brilliant minds' that collaborate smoothly, is a crucial organizational strength that needs to be activated. The DBM can severely impede achieving this due to its negative impact on collective learning.

Summing up, from the practical perspective, the fundamental starting point is to be aware that the cognitive bias of mistakes can severely affect organizations. The next step is to try to control it to secure the aptness of managerial decisions.

8. Scientific Implications

This study is the first to introduce a method enabling the identification of persons and organizations affected by the DBM to measure its influence on different aspects of human, organizational, or social life and to confirm that the DBM blocks collective intelligence. Further studies are needed to expose any other serious impacts that the DBM may cause. Furthermore, this study is based on a sample of Polish knowledge workers and is therefore highly specific. There may be numerous national or local factors that can strengthen or weaken the DBM. Similarly, the consequences of the DBM may also differ between organizations, societies, regions, and nations. Thus, further studies are worthwhile to fully understand how the DBM impacts countries, cultures, institutions, organizations, and communities and how to deal with this impact and free the collective intelligence. Another important line of research inspired by this study's findings is the question: How can organizations deal with the DBM to perform better? How should we train managers to deal with the DBM reflected in the paradox of simultaneous learning from mistakes and mistakes avoidance, which is vital for supporting employees' performance and development? Moreover, how can artificial intelligence (AI) influence an organization's collective intelligence? Furthermore, how does AI deal with human mistake bias? These exciting questions require further investigation.

9. Limitations and Further Study Ideas

This study and Kucharska *et al.*'s (2023) study are based on the Polish population and present a Polish perspective, and other nations' perspectives are needed to understand this phenomenon entirely. Moreover, the comparison of findings based on two different samples confirmed the general knowledge about the negative consequences of the DBM but also exposed another limitation: the size of the sample. The validation of the advanced method showed that further studies would probably require comparatively larger samples. This is because "mistakes" are very sensitive issues. Therefore, to detect a DBM and then examine it within complex structures and compare effects with and without a DBM being detected using, for example, SEM methods, it is recommended to employ samples of 400 or greater per cohort.

Furthermore, regarding the SEM model, the square root of each construct's AVE exceeded the correlations between the majority pairs of distinct constructs, but not for all. The collaborative culture and the learning climate components in the total sample and the 'no bias' sample may slightly supercharge one another. This case does not arise in the DBM sub-sample. This means that the collaborative culture and learning climate components of the learning culture in the double-biased sub-sample are not as expressly tied as in the 'no bias' and 'total' samples. The favorable climate for learning in organizations is created thanks to collaboration. In the DBM sub-sample, this relation is not so inherent. Kucharska *et al.* 2023 found a correlation between these two

variables in all three samples (in the DBM sub-sample, too). So, it might be that this issue is a characteristic of the Polish population. The collaboration culture in Polish organizations can be seen as an extreme motivational power and, consequently, a lack of it as a blocker. So, this issue, to formulate an unequivocal statement, requires further studies.

Moreover, this study concludes that while personal and organizational mistake-related biases exist, their frequency in organizations is marginal in the samples of knowledge workers that naturally characterize higher-level self-awareness and intelligence compared to most of society. It is highly possible that exploring DBM based on the sample representing the findings of the general society will be significantly different. The cognitive bias awareness and control depend on the personal intelligence of the particular individual. In light of this study's findings, it strongly depends on leaders' intelligence and self-awareness.

Finally, further studies based on samples that represent society can expand our knowledge regarding the cognitive bias of mistakes phenomenon. Especially when examining entire societies, we can better understand how the cognitive bias of mistakes happens. So far, we know that a significant part of society is affected by the cognitive bias of mistakes, which might block collective learning. Mindsets are shaped until early childhood. However, we do not pay enough attention to raising youths or training adults, especially managers, to prevent the double bias of mistakes. This study shows we should. So, it is another topic worth scientists' attention.

10. Conclusions

The proposed advanced method to measure the DBM was positively validated in this study. So, the presented advanced methodology for DBM detection and validation is simplified comparably to that introduced by Kucharska *et al.* (2023), which makes it easier to use. Moreover, the dominant sub-samples in knowledge-driven organizations are the 'no bias' or the 'DBM' groups. So, the omission by Kucharska *et al.* (2023) of personal and organizational biases of mistakes samples seems to be justified, and the current study confirms the findings of Kucharska *et al.* (2023) that the DBM negatively affects learning from mistakes. Moreover, this study concludes that while personal and organizational mistake-related biases exist separately, their frequency in organizations is marginal in the samples of knowledge workers that naturally characterize higher-level self-awareness and intelligence compared to most of society. On the contrary, the DBM is more frequent, and its negative impact is more straightforward to expose. Organizations affected by the DBM face troubles in collective learning from mistakes, which negatively affects their collective intelligence building. This study clearly exposed that in doubly mistakes-biased knowledge-driven organizations, the influence of knowledge culture on the mistakes acceptance component of learning culture is negative. So, this study constitutes the Double Bias of Mistakes Theory, which states that the clash between positive attitudes and beliefs regarding learning processes and negative attitudes and beliefs toward mistakes exposed by focusing on control managers (bosses) may block organizational learning from mistakes and, as a consequence, negatively affect organizational intelligence. It is highly possible to explore DBM based on the sample representing the general society, not only knowledge workers, as this study did so that the findings will be significantly different. The cognitive bias awareness and control depend on the personal intelligence of the particular individual. Knowledge workers' intelligence is above the mean society level. So, by selecting a representative for the entire society sample, we can better understand the scale of the cognitive bias of mistakes and find methods to manage and prevent its consequences. So, further studies should focus on leaders' mindset training, shaping the attitudes and behaviors that support learning from mistakes and balancing mistake avoidance simultaneously. Those two contradicting approaches - might cause some tensions. However, smooth managing paradoxes is precisely what is expected from modern leaders today. So, this direction of further studies is promising and valid in the context of organizational and societal benefits. Leaders who are free of the DBM and skilled in managing paradoxes can improve society's lives and development.

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Expanding Qualitative Research Horizons: The Development and Application of Intuitive Field Research (IFRes)

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Abstract: This article is a study introducing a new qualitative research methodology - Intuitive field research or IFRes - involving words and the narrative and relying on the experience and intuition of the [experienced practitioner] researcher (Stein, 2019). Though similar, it is different to autoethnography as the latter's focus is seen to be on culture (ethnography) whilst IFRes may focus on any aspect – including, also, machine-type interactions. IFRes is a six-step process, described herein, which seeks to take advantage of considerable previous work experience, in the field, to answer a research question posed following a literature review. It is an iterative process which seeks to perfect the knowledge produced (Baldacchino, Ucbasaran & Cabantous, 2023). Intuitive Field Research (IFRes) emerges as a pioneering qualitative research methodology that capitalizes on the nuanced intuition and rich field experiences of researchers to uncover deep insights into complex phenomena (Stein, 2019). Distinct from autoethnography, IFRes introduces a structured six-step process designed to systematically harness and refine these insights for academic and practical application. Originating at the University of Aveiro, this method represents a significant departure from conventional research methodologies by valuing experiential knowledge and intuitive understanding as critical components of the research process. In the context of business and management, IFRes holds particular promise for addressing the intricate challenges of contemporary business environments. These environments demand an agile and nuanced understanding that transcends traditional quantitative analyses, making the case for methodologies that can capture the subtleties of consumer behavior, organizational culture, and innovation dynamics. By enabling researchers and practitioners to integrate their intuitive judgments with rigorous academic inquiry, IFRes offers a unique approach to exploring and solving pressing business and academic issues. This article delineates the foundation of IFRes, its methodological underpinnings, and its potential applications within business and management, illustrating how intuitive insights can drive innovation, strategic decision-making, and transformative organizational practices. Through this expanded lens, IFRes not only contributes to academic discourse but also provides practical frameworks for businesses seeking to navigate the complexities of modern markets and organizational challenges. A practical example of applying Intuitive Field Research (IFRes) in business and management could involve a multinational corporation seeking to enhance its customer experience across diverse markets. By employing IFRes, the corporation's research team could immerse themselves in different cultural contexts, using their intuition and experience to gather nuanced insights into consumer behavior and preferences (Gorry & Westbrook, 2013). This approach would allow them to identify subtle, culturally specific factors influencing customer satisfaction that traditional surveys or data analysis might miss. These insights could then inform tailored strategies for each market, leading to improved customer engagement and loyalty. This example illustrates how IFRes' emphasis on intuitive understanding, combined with rigorous analysis, can address complex challenges in global business environments, leading to innovative solutions and competitive advantages. This article on Intuitive Field Research (IFRes) significantly impacts research by offering a novel method that blends intuitive insights with rigorous academic inquiry. It addresses the need for methodologies that go beyond traditional quantitative analysis to capture the complexities of human behavior and organizational dynamics (Ganzarain, Ruiz & Igartua, 2019). By emphasizing experiential knowledge and intuitive judgment, IFRes empowers researchers and practitioners to uncover deeper understandings of complex issues. This approach fosters innovation, enhances strategic decision-making, and facilitates transformative practices in various fields, thereby enriching academic discourse and offering practical solutions for real-world challenges.

Key words: Intuition, Field research, Qualitative research, Experience

1. Introduction

“The Wonderful Wizard of Oz believes a heart, not a brain, makes one happy” (L. Frank Baum).

This article, which presents a new qualitative research methodology and approach, IFRes – Intuitive Field Research, starts with a look at the background of how IFRes arose and was developed. IFRes was created and developed at the University of Aveiro when an academic PhD supervisor (the first author of this article) saw in

his student (the second author of this article) the possibility of solid knowledge acquired over the years as an operative and manager - solid, objective, and scientific knowledge. This student was in stark contrast to other younger researchers in that a long and fruitful career were already in place – and the student very quickly caught on and showed interest in what his supervisor was saying, in methodological terms, and regarding the possibility of joining intuition and science together in a novel way, to fill a gap identified regarding qualitative research. Essentially, very experienced practitioners may have acquired certain truths and knowledge, accessible intuitively, which is correct and deems no further primary data collection to confirm it. The research methodology was subsequently tested with individuals also seeking to become researchers. We perceive, following our research, that intuition is a major topic of interest to many people and is still under-researched. Bringing one's intuition into the research domain brings with it new possibilities, especially for the experienced individual, as intuition is based on experience. Our research question is as follows: How can the experience and expertise of certain researchers who have had successful careers in business and management as practitioners over several decades be utilised? This is the central research question of this study to expand and improve future research. It is not a substitute for structured literature research, but rather, as Kahneman, Sibony and Sunstein (2021) aptly describe in their book *Noise* - what distorts our decisions and how we can improve them, the research results are characterised by the experience and wide range of experts involved (Barlev, Mermelstein & German, 2018). This question aims to explore the potential of utilising the in-depth knowledge and experience of experienced practitioners to enrich the field of research, particularly in the area of business and management. It encourages an exploration of the ways in which this experience can be systematically utilised to gain new insights and/or solve existing problems in the field.

The article continues with a section on the research basis followed by a section on the development of a hypothesis. We have sought to enrich the text with figures and diagrams to better illustrate the concepts and six-step process of IFRes. Finally, the article concludes on what we have done with our article and what we seek to achieve in the future.

2. Background and Discussion

We detected a gap in the literature regarding research by experienced practitioners. The research question that led to this study is hence: how may one capitalise on the experience and expertise of certain researchers who have developed successful careers over several decades in business and management, as practitioners? On the one hand, it is fairly obvious that this is a different case to that of a young researcher without work experience and who wishes to research businesses and their management processes. For example, when talking to an experienced executive (PhD student) on management and leadership he was quick to distinguish between the two - management does not involve people but rather only machines; when at least one human being is involved then we are in the presence of leadership. This seemed very true, in the age of technology. Teams may indeed be mixed - involving machines or artificial intelligence - as well as people. When dealing with such a team then you are leading - as the human component is present. Where did this knowledge and insight come from? It was automatic and the result of working in industry for decades, in this case in high tech firms linked to silicon chips. On several continents. The knowledge was thus the result of intuition and previous experience.

The methodology and the promotion of a broader application of Intuitive Field Research (IFRes) by researchers in qualitative research, particularly in the fields of business and management, will be structured as follows: *Research Paradigm*: IFRes typically aligns with a constructivist research paradigm, emphasizing the subjective interpretation (interpretivism approach) (Elharidy, Nicholson & Scapens, 2008) of experiences to generate knowledge. This paradigm acknowledges the complexity of reality and supports the idea that understanding comes from engaging with the environment. In business and management, this approach can reveal nuanced insights into organizational culture, leadership dynamics, and consumer behavior, which are often overlooked by positivist paradigms relying strictly on quantifiable data (Hakak & Bioria, 2011).

Ethical Principles: Researchers adopting IFRes must adhere to ethical principles such as confidentiality, informed consent, and reflexivity. Given the method's reliance on personal experience and intuition, scholars must be vigilant against biases and ensure transparency about their perspectives and potential influence on findings. Ethical considerations also include the respectful representation of all participants and the mindful interpretation of experiences (Vossoughi et al., 2021).

Trustworthiness of Findings: To argue for the trustworthiness of IFRes findings, researchers should employ strategies like triangulation – using “multiple approaches or tools or data in order to obtain a greater understanding of the phenomenon being studied... a method of cross-checking the credibility or validity of what is being discovered” (Remenyi, 2017, p.228), member checking, thick description, and audit trails. These

strategies enhance the credibility, transferability, dependability, and confirmability of the research. In business and management, linking intuitive insights with existing theories and empirical data (both primary and secondary data) can further validate the findings (Liebowitz et al., 2019).

Suggestions for Data Analysis and Overcoming Bias: Data analysis in IFRes can incorporate thematic analysis, narrative analysis, or grounded theory, depending on the research question and data nature. To overcome potential bias, researchers should engage in reflexivity, critically examining how their background, assumptions, and emotions influence the research process. Peer debriefing and maintaining an audit trail of analytical decisions can also help mitigate bias (Knight et al., 2018; Luo et al., 2018).

Complementing Existing Methodologies: IFRes can complement existing qualitative methodologies like autoethnography (table 1), ethnography, and phenomenology by adding depth to understanding phenomena through the lens of intuition and experience. IFRes may support case study research, for example (even in a multimethod approach). In business and management research, combining IFRes with the above can enrich the analyses of complex issues like organizational change, strategic decision-making, and consumer engagement.

Table 1: Key Differences Between IFRes and Autoethnography

Feature	Intuitive Field Research (IFRes)	Autoethnography
Focus	Broad, encompassing any aspect of human and machine interactions	Mainly on culture and the researcher's personal experience within it
Basis	Empirical research from field experience and intuition	Personal narrative to explore cultural, emotional, and social implications
Application	Any field, particularly useful in business and management	Cultural studies, anthropology, sociology
Process	Six-step process emphasizing iterative reflection and analysis	Focus on narrative exploration of the researcher's experiences
Objective	To leverage practitioner's expertise and intuition in generating insights	To understand and represent one's cultural experiences

A new avenue for qualitative research has been created and though similar to autoethnography (autobiography plus ethnography – please see Ellis, Adams & Bochner, 2011) (table 1) it is different in so far as it may be applied to any area (leadership, process management, ergonomics, etc.) hence moving beyond cultural analyses and appreciations (Gouzouasis & Ryu, 2015).

Relying on one's experience and expertise in a given area Intuitive Field Research - or IFRes, for short - is a six-step process. These steps are as follows (adapted from a previous publication of the authors - Au-Yong-Oliveira, Kuehnel and Andrade-Campos, 2023):

The six steps of IFRes (a qualitative research method that uses a researcher's personal experience in a field to construct an informed version of reality) are seen to be (please also refer to Au-Yong-Oliveira, Kuehnel and Andrade-Campos, 2023):

1. Acquire expertise in a subject matter (e.g., over ten, twenty, thirty or even forty years) – Note that, according to Gladwell (2008), ten years or 10,000 hours of practice are required to become an expert in a given area. Up and above the hours put in, the influence of family, culture and friendship (the supportive relationships) also have a big influence on creativity and results (see also Wong, 2015).
2. Find an unanswered research question (Remenyi, 2013, 2017), following a literature review.
3. Sit [alone] in a quiet room or atmosphere (e.g., office setting) where one may focus / concentrate on the topic – slow down (please see Kahneman (2012), for notions on thinking fast and slow – automatic versus more deliberate type thinking (or modes 1 and 2, as regards thinking processes)).
4. Summon thoughts and feelings cemented over the years about e.g., a production process environment, management or leadership – regarding the research question. Write them down. Note that the late renowned 20th century author George Orwell engaged in what we see as autoethnography in so far as, in Orwell (2021), for example, he engaged in telling a story about his own experiences (while fighting for the Republicans, in the Spanish Civil War) while sharing insights and observations about other cultures (principally about the Spanish, but not only about them). The difference between IFRes and autoethnography is that the former may be about almost any previous

- experience, including business and management, on which one may be considered to be an expert. Orwell had a “unique ability to capture in prose the mood of a country” (Orwell, 2021, p.8). Orwell also discussed intuition, which he described as “the mysterious art of knowing” (Orwell, 2021, p.80).
5. Compare to fact-based knowledge from a database (e.g., Web of Science, Scopus or Science Direct) to encourage the documentation process. “Glimpses” of the literature [review] should inspire the writing and documentation process.
 6. Let the feelings flow (note that ideally one will be in a state of “flow” - “A person is in a state of flow when they are totally immersed in a task. When a person is “in flow,” they may not notice time passing, think about why they are doing the task, or judge their efforts. Instead, they remain completely focused.” (Villines, 2022)) and continue to write them down in an iterative process. Challenge your intuitive conclusions several times before making them definitive (Kahneman, 2012) warns to be cautious about intuition and mode 1 thinking – fast thinking mode – which is how we think most of the time; a problem is that when we are intuitively right or wrong they both feel the same; hence the need to “sleep on it” and slow down and be iterative (figure 1). Iterative means “doing something again and again, usually to improve it” (Cambridge Dictionary, 2023). You first develop, then go into the operations area, and find ways to improve (a standard software improvement process; in a loop or cycle).

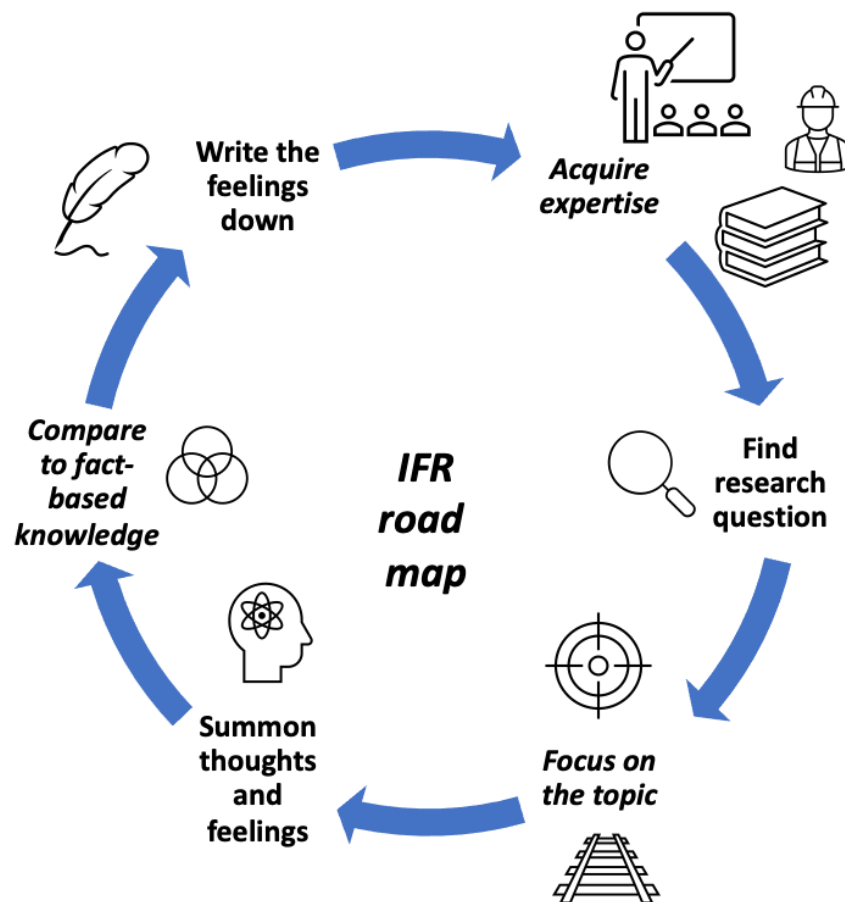


Figure 1: The IFRes road map – the methodology is an iterative cycle and process

Intuition and feelings are closely related concepts. Initially, the methodology was called Intuitive Feeling Research and indeed with this denomination the authors won an award in a business research methodology competition (The Innovation in Teaching of Research Methodology Excellence Awards), in September 2023, hosted at ECRM 2023, in Lisbon, and organised by ACI (Academic Conferences International, based in Reading, in the UK). So as to not repeat concepts in the title the authors changed the name of the methodology to Intuitive Field Research to also place an emphasis on what is involved - namely empirical research, resulting from field experience, and intuition. We also consulted with several experts on methodology who advised us to make this change to the name of the methodology.

In the age of Artificial Intelligence, or AI, human beings have an edge over AI as we have feelings and intuition which exist due to previous experience. Such feelings and intuition are unique to each individual and each individual may be an expert in any given activity.

This research method was born, and later tested for its acceptance, at the University of Aveiro, after analysis and approval by a senior researcher (the third author of the article). The idea is to have three immersive doctoral weeks for students per year (e.g., in November, March and June, three separate moments of the academic year, from the beginning to the end) in the DBI (Doctorate in Business Innovation) program. Why immersive weeks? Because the students of this program are to develop practical research projects closely linked to their companies (where they work) and previous experience and with direct application in industry. Due to work time constraints DBI students are urged to find time to write and research in particular during these three immersive weeks, when, ideally, they will also meet with their academic supervisors, on site, at the University of Aveiro.

It was during one of these immersive research weeks that IFRes was communicated and tested and feedback received from a workshop with around ninety participants - all PhD candidates doing various different PhD programs (the immersive week was opened up to all PhD degrees at the University of Aveiro) – channelled to the workshop by the third author of the article, a firm supporter of the methodology. The feedback was really encouraging. Ranging from “I was going to give up and drop out of my PhD because I felt I was not moving forward with my research. It all seemed so complicated. I did not realise that I could write about my previous experience (which is substantial) and hence I feel so much better and more positive about my future in research now.” (Informant 1). Another student stated: “I have actually written in the manner described here, at the workshop, about my previous experiences, I still have that [unpublished material] and now realise that that is a form of research and is publishable. I am so excited.” The research training session went so well and was so encouraging that another workshop, this time 3-4 hours long, instead of 1.5 hours long, was arranged for. So as to be able to go more in-depth and to give exercises to students to do - related to their own research studies and projects and interests. The authors are firm believers in doing rich, interesting, relevant research - relevant to the social world in which we live in (Mason, 2002). Such IFRes research is to be based on words but not excluding the possibility of statistics – though the statistics are not the central issue (Mason, 2002).

Upon further, deeper discussion with the workshop participants – after the training session / workshop – the conclusion was reached, just as had been suspected, that this research methodology could be applied to the social sciences in general and to tourism, for example, in particular. Another participant said: “We all have two sides to our brain – the creative or more intuitive side, as well as the more analytical side. When our brain functions, we use both sides of our brain. Some people do not realise that we cannot be purely analytical or purely creative – we will always have a mix of both in our thought processes.” This was actually as an answer to some scepticism voiced by some workshop participants as to the acceptance of IFRes. Their concerns were that certain firms do not regard or accept certain individuals’ experience as being definitive and still require standard research to be done in order to reach a conclusion. While this is the case, certainly, for most firms, some do practice what the late Steve Jobs defended – namely, that customer research is useless and not worthwhile because customers do not know what they want until Apple shows them (Isaacson, 2011). Hence, certain primary data collection may not be worthwhile in view of existing expertise in the research team. Another reservation was linked to the acceptance of IFRes by the academic community. “Your methodology will not be accepted by your peers in academia as being proper research.” they stated. The answer to this was that autoethnography studies are now widespread on Scopus. IFRes is similar but also different. It is a simple process whereby intuition backed by experience and a thorough literature review (e.g., reading, a lot of reading) can lead to novel knowledge being created and transferred and to research questions being answered.

Note that when one speaks of an expert that expert may exist amongst other experts and does not have to be the sole owner of the “truth”. More voices may exist on a theme. This realisation was met with general acceptance but also with excitement. There were many years of accumulated experience in the workshop training room, at the University of Aveiro. Could they really consider themselves to be experts – even in the absence of a PhD? Would that expertise be useful to them in publishing and in the ultimate attainment of their doctoral degree? Our answer was yes. An unequivocal yes. And we could see in the room how refreshing and motivating that idea was. IFRes was born earlier that year and a vision for it was developed further that day – the 8th of November 2023. A memorable day, despite the wind and the rain in Aveiro, central Portugal. How had this birth and development occurred? Through working in teams. And in realising one’s differences and challenges and what one “brings to the table” in a unique way. And by recognising that in diversity one may see change and creativity. IFRes was essentially developed (the eureka moment) by a seasoned management researcher and lecturer (and previous practitioner – the first author of this article), who had a passion for and

was very knowledgeable about qualitative research methodologies, and who was aware of what already existed (and of qualitative methodological gaps to be filled). In essence, the first author of this article recognised in his PhD student (the second author of this article - with decades of experience in industry) certain deep knowledge, accessed intuitively, and without excessive thought – which could be deemed scientific, as a part of a broader process described herein. An exciting “debrief” of the student followed. The realisation was that knowledge, all sorts of knowledge, is valuable – and that the path to that knowledge may be different in each case. As long as the path to knowledge is systematic and repeatable, we all may benefit as a community. Which will make us stronger. As advocates for reaching the “truth”.

To elaborate on the importance of Intuitive Field Research (IFRes) in the context of AI, emphasizing human intuition and experience:

Even in what is now becoming known as the age of Artificial Intelligence (AI), a consequence of the advent of the Internet age, we are confirming that the distinct and unique human capabilities such as intuition and emotional intelligence offer a competitive edge that AI cannot replicate in its current or perhaps even future and more advanced state (Miyazaki et al., 2023). Unlike AI, humans possess the ability to draw on feelings, intuitions, and experiences that are deeply personal and contextually rich, providing insights into complex social and organizational phenomena that are often nuanced and multifaceted. This unique human aspect is critical in fields such as business and management, where understanding human behavior, cultural nuances, and ethical considerations play a pivotal role in decision-making and strategy formulation (Gross & Lorenz, 1990).

Recent literature supports the argument that while AI can process and analyze data at unprecedented speeds, it lacks the capacity for empathy, moral reasoning, and the intuitive leaps that come from lived experience (Polanyi, 1966; Dreyfus, 1972; Nonaka & Takeuchi, 1995). Polanyi's concept of 'tacit knowledge' emphasizes knowledge that is personal, context-specific, and often unarticulable, underscoring the limitations of AI in capturing the depth of human understanding. Dreyfus critiques the over-reliance on formal logic and algorithms in AI, arguing for the irreplaceable value of intuition and expertise that develops through experience. Nonaka and Takeuchi's theory of knowledge creation further highlights the role of tacit knowledge in innovation, suggesting that human intuition is essential for creating new knowledge and understanding complex situations.

Given these perspectives, IFRes' emphasis on leveraging the intuition and experience of researchers is particularly relevant (Díaz-Chang & Arredondo, 2022). It offers a methodology that not only complements AI's analytical capabilities but also enriches research outcomes with the depth and breadth of human understanding. In business and management scholarship, where the interpretation of social interactions and organizational cultures is crucial, IFRes provides a framework for integrating intuitive insights with empirical research, thus ensuring that the richness of human experience informs and guides the research process.

Furthermore, as AI continues to evolve, there is a growing need for research methodologies that can bridge the gap between quantitative data analysis and qualitative, intuitive understanding. IFRes positions itself as a critical tool in this regard, enabling researchers to navigate the complexities of modern organizational environments with a balanced approach that values both data-driven insights and the irreplaceable nuances of human intuition (Pope, Penney & Smith, 2018).

This expanded narrative situates IFRes as a valuable methodology in the era of AI, supported by literature that underscores the irreplaceable role of human intuition and experience in understanding complex phenomena.

3. Research Basis

Even the first approach to researching SCOPUS, with 961 articles, shows that this topic has become very important worldwide in recent years (figure 2).

Above all, the wide range of applications across the breadth of the subject areas (figure 3) shows that a proprietary method is being developed here that significantly improves quality in addition to classic structured literature reviews - SLR. Intuition, i.e., relating experience to a broad knowledge base, accelerates the process and increases the quality of decisions.

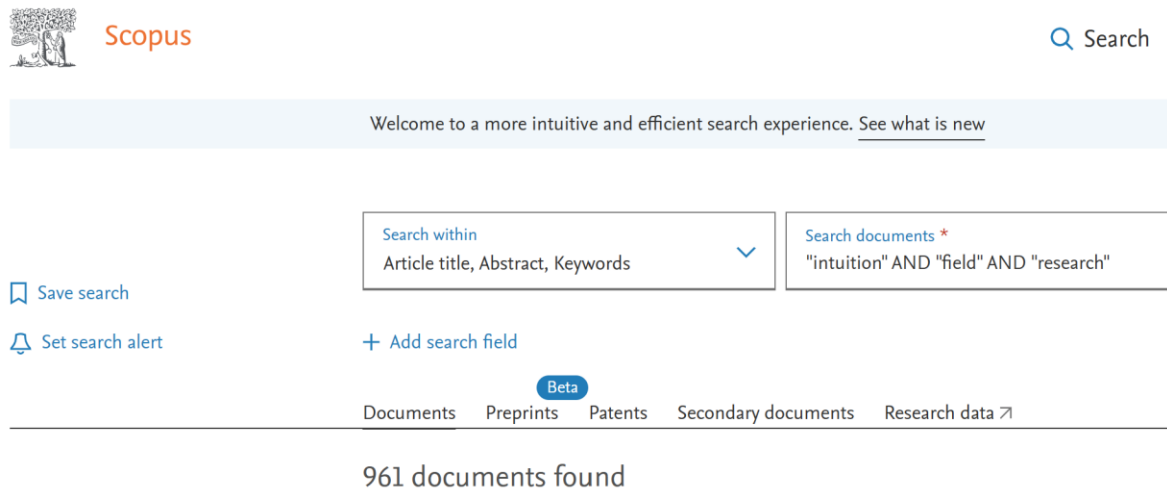


Figure 2: SCOPUS search - "intuition "AND" field "AND" research"

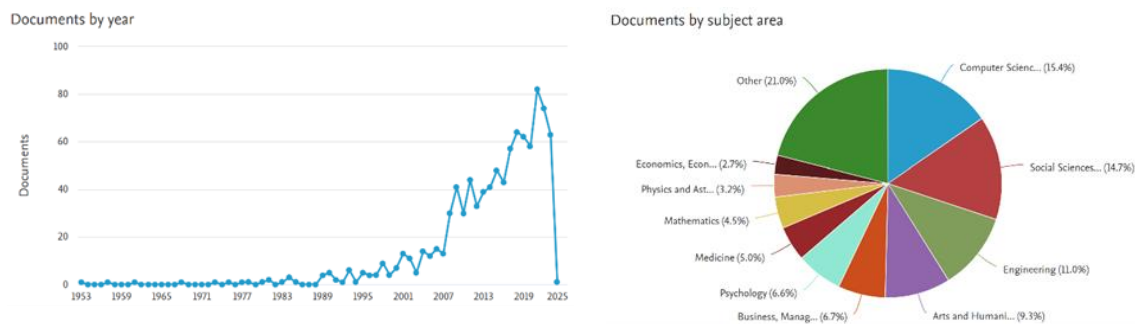


Figure 3: SCOPUS Analysis - Amount of documents and diversification of areas of application

The analysis of the central basic terms of this article via SCOPUS shows that the citations of the 961 articles on the term "Intuition" essentially form two focal points (Figure 4). Referring to the graphical representation, the reference to experience, judgement, rationality (Thaler, 2016), strategic decisions based on a good feeling is pronounced on the one hand, while the area of additional breadth, mindfulness and expertise leads to a very pronounced task performance.

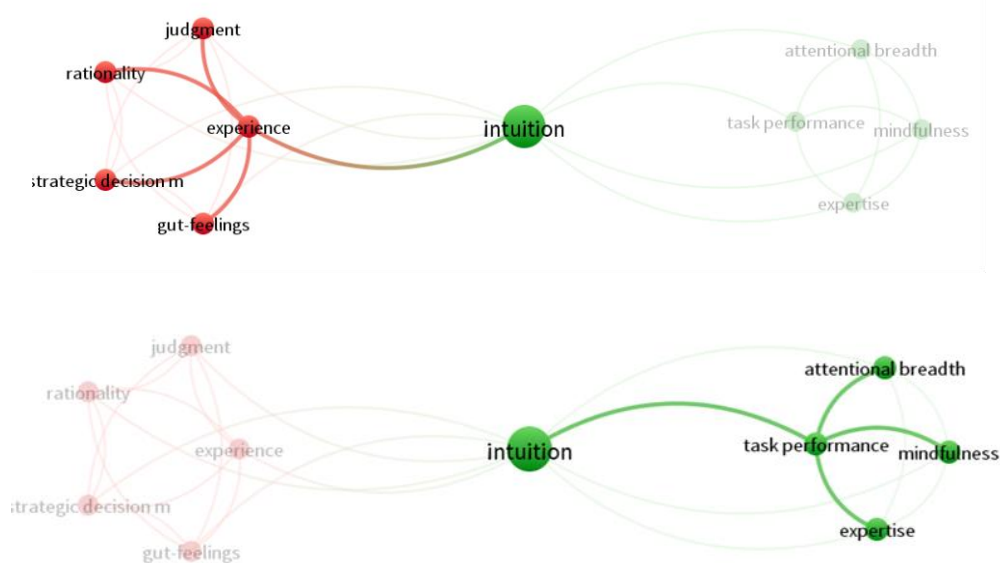


Figure 4: VOSviewer-outcome - First approach to interpreting the research data

4. Development of a Hypothesis

Based on many years of scientific work (including with complex systems in manufacturing companies through the systematic application of statistical analysis and synthesis methods), the idea of an innovative approach was born. Inspired also by Daniel Kahneman's book *NOISE* (Kahneman, Sibony & Sunstein, 2021), the decision was made to create a formal method that would make it possible to integrate the great potential of the experience of experts in an extended environment (figure 5).

In their book *NOISE*, Kahneman, Sibony & Sunstein (2021) describe very clearly the process that led to this complementary methodology based on the treatment of a cancer patient whose method was suggested by doctors. Using the traditional structured literature analysis SLR [green hits in figure 6], the doctors are very close to the best treatment, but the accuracy of the decision still has a large variance. In addition to this, the intuitive field approach from the daily working environment can complement the SLR with still great variance but on average this is closer to the best treatment (figure 6). Finally, the combination of SLR + IFRes [yellow hits in figure 6] significantly increased the precision by adding the experience of a large community of experts and thus found the maximum treatment quality currently available.

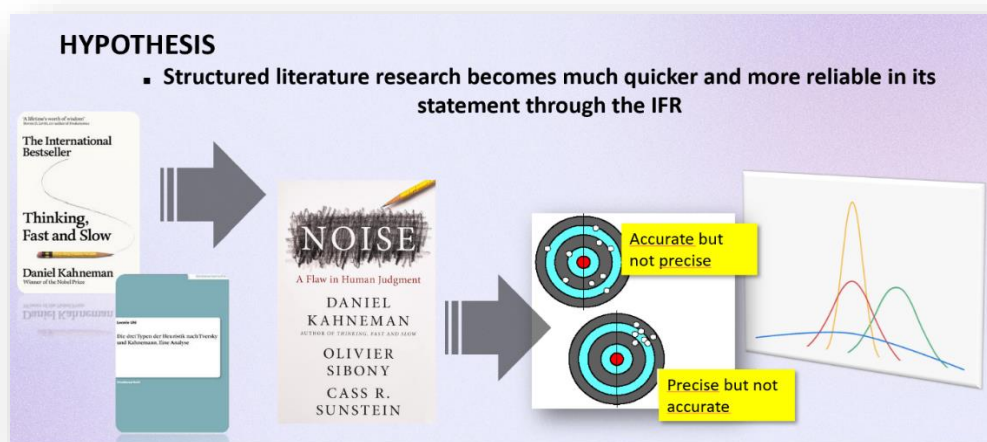


Figure 5: The concretisation of the IFRes idea through Daniel Kahneman's book *NOISE* (Kahneman, Sibony & Sunstein, 2021)

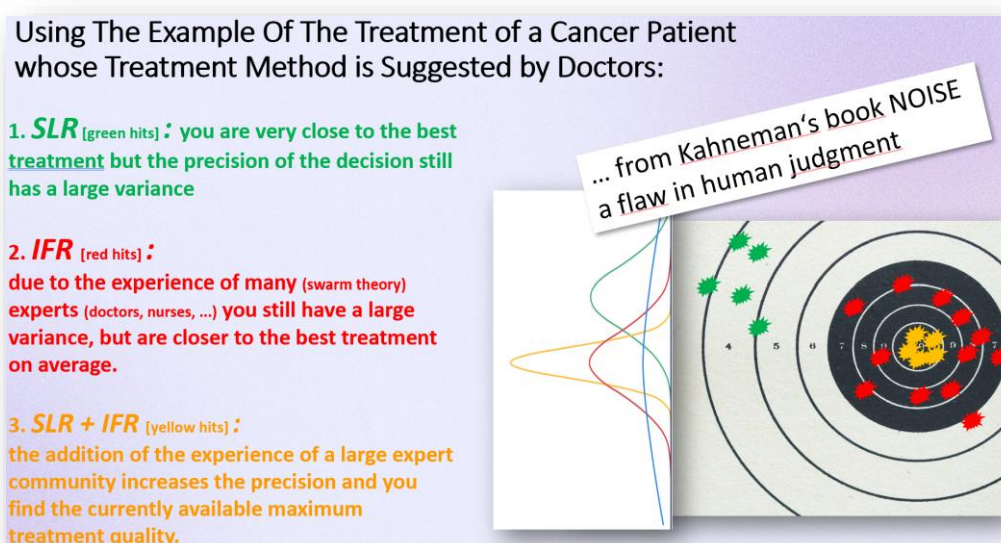


Figure 6: Development of the IFRes method from the process stabilisation toolbox

The potential limitations of the Intuitive Field Research (IFRes) method, while offering unique insights into qualitative research, may include:

- *Subjectivity and Bias*: The reliance on intuition and personal experience can introduce subjectivity, potentially leading to biased interpretations of the data. This is particularly challenging when the goal is to achieve objectivity and reproducibility in research findings (Silveira et al., 2003). However, as other lines of research have emphasized, human emotions are present everywhere, even in the workplace, so why not in research (Kahneman, Sibony & Sunstein, 2021)? Triangulation and other such techniques, as mentioned above, will help to minimize bias.
- *Difficulty in Verification*: Given its qualitative nature and the emphasis on intuition, verifying the findings through traditional quantitative measures or replication studies may be challenging, but it is possible. This may affect the perceived reliability and validity of the research outcomes, if overlooked as a research verification possibility (Silveira et al., 2003).
- *Training and Expertise Requirements*: Implementing IFRes effectively requires researchers to have a high level of expertise and experience in their field, as well as training in recognizing and interpreting their intuitive insights. This may limit the method's accessibility to early-career researchers or those in fields where such depth of experience is rare (Stengel et al., 2023).
- *Generalizability*: The insights gained through IFRes are deeply rooted in the individual experiences and contexts of the researchers, which may limit the generalizability of the findings to broader populations or different contexts (Schmidt & Stockly, 2023). Albeit certain truths are universal and may be generalized.
- *Ethical Considerations*: The deep immersion in the field and reliance on personal intuition may raise ethical considerations, especially concerning participant privacy, informed consent, and the interpretation of participants' experiences through the researcher's subjective lens (Vossoughi et al., 2021).
- *Time and Resource Intensity*: The process of IFRes, involving extensive fieldwork and the iterative analysis of intuitive insights, can be time-consuming and resource-intensive compared to other qualitative methods, which are already often seen to be cumbersome compared to the positivist paradigm (e.g., statistics based). This may impact its feasibility for certain projects with limited timelines or budgets (Ramalho et al., 2019). On the other hand, IFRes aims, through the application of intuition, to be a more natural way to access certain types of experience-based information and data and may even be quicker and less time consuming than other methods reliant on third parties (e.g., interviews, focus groups, surveys – qualitative and/or quantitative).
- *Integration with Existing Methodologies*: While IFRes can complement other qualitative methodologies, finding effective ways to integrate these insights into traditional research frameworks can be somewhat complex. Researchers must navigate combining intuitive knowledge with empirical data in a manner that maintains the integrity and coherence of the research design (Galman, 2019).

Addressing these limitations requires careful methodological planning, ethical considerations, and transparency in the research process. Researchers should be explicit about the limitations of their approach, the steps taken to mitigate bias, and the specific contexts in which their findings are applicable. Additionally, triangulation with other data sources and methods can enhance the credibility and depth of the insights generated through IFRes.

5. Conclusion and Future Steps

This article has presented, quite succinctly, the novel IFRes method. An aim for the future is to expand on the article and publish a book on IFRes. With examples and different contributions from various practitioners who are also researchers. The essential aspect is those who turn to academia after a full and rich career in industry. Those are the people who are best suited for IFRes. However, all individuals may be experts on something and at a young age – so we do not want to limit the possibilities of the application of IFRes. Our first 1.5-hour workshop on the topic was very gratifying in so far as the feedback was very positive. One participant was close to tears with the new possibilities which IFRes presented to them. A whole new future was envisioned – one which would seek to capitalize on previous experiences – worth sharing with the academic and practitioner communities.

The potential limitations of the Intuitive Field Research (IFRes) method – it is important to consider several aspects that could challenge its application and interpretation within business and management research:

- *Subjectivity and Bias:* A primary limitation of IFRes stems from its reliance on the intuition and personal experience of researchers, which can introduce subjectivity and bias into the research process. While these aspects are valuable for gaining deep insights, they may also skew the interpretation of data if not carefully managed (Silveira et al., 2003).
- *Replicability Issues:* Due to the personalized nature of intuitive insights and experiences, studies utilizing IFRes may face challenges in replicability. The unique contexts and perspectives that contribute to a researcher's intuition might not be easily duplicated, potentially limiting the generalizability of findings (Grof, 2003).
- *Methodological Rigor:* Critics may question the methodological rigor of IFRes, particularly in comparison to more traditional, quantitative research methods, even though a lack of time and availability may affect the results attained via surveys, among other data collection methods, hence skewing the results. Ensuring that IFRes maintains a systematic and transparent approach is crucial for its acceptance and credibility within the academic community (Aly et al., 2021).
- *Training and Expertise Requirements:* Effectively applying IFRes requires researchers to possess a deep level of expertise and experience in their field, as well as the ability to introspectively access and analyze their intuitive insights. This prerequisite may limit the method's applicability to seasoned researchers, potentially excluding those early in their careers (Massey, 2021).
- *Ethical Considerations:* IFRes' emphasis on leveraging personal experience and intuition necessitates a heightened awareness of ethical considerations, particularly concerning confidentiality and the potential for personal bias to affect interactions with research subjects or data interpretation (Gallagher, Little & Hooker, 2018).

Benefits for Future Research in Business and Management:

Adopting IFRes in future business and management research offers several benefits, including:

- *Deeper Insights into Complex Phenomena:* IFRes' focus on intuition and experience enables researchers to uncover deeper, more nuanced insights into complex business and organizational phenomena that might elude traditional methodologies (Pope, Penney & Smith, 2018).
- *Enhanced Innovation and Creativity:* By valuing intuitive knowledge, IFRes encourages innovative thinking and creative solutions to business challenges, fostering a culture of innovation within research and practical applications (Stein, 2019).
- *Flexible Methodological Approach:* IFRes' adaptability to various contexts and research questions makes it a versatile tool for exploring a wide range of issues in business and management, from consumer behavior to organizational culture (Cetina, 2007).
- *Bridging Theory and Practice:* IFRes offers a unique avenue for integrating theoretical knowledge with practical insights, thereby enriching both academic research and business practices.
- *Promoting Reflective Practice:* Encouraging researchers to engage with their intuitive insights fosters a reflective practice that can enhance personal growth, professional development, and the generation of impactful research findings (Pope, Penney & Smith, 2018).

In summary, while IFRes presents certain limitations, its potential to enrich business and management research by providing deep, nuanced insights and fostering innovative solutions to complex problems makes it a valuable addition to the researcher's methodological toolkit. Future research will benefit from its unique approach to integrating intuition with academic inquiry, offering new perspectives and contributing to the advancement of the field.

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