Addressing Common Method Variance and Endogeneity in Vocational Behavior Research: A Review of the Literature and Suggestions for Future Research

Abstract

For various reasons, research on vocational behavior often has to rely on self-report measures. Although it is well known that the exclusive use of self-report measures in a given study can pose major threats to the validity of that study, for example via common method variance (CMV) or endogeneity, we still have to witness a systematic literature review of study designs particularly prone to CMV and endogeneity, and of procedural and statistical remedies used in the field of vocational behavior. To determine the vulnerability for CMV and endogeneity, and the extent to which researchers have already taken action and eased concerns over CMV and endogeneity in vocational behavior research through their research design/data collection (procedural remedies) and data analysis (statistical remedies), we review articles published from 2015 to 2018 in the *Journal of Vocational Behavior*. We found that 81% of all quantitative studies in this period relied exclusively on self-report measures gathered from the same respondent. Of these studies, the majority used procedural remedies to ease concerns of CMV (68%), mainly through the temporal separation of the focal variables (53%). However, statistical tests to detect and/or control for CMV (13%) are still rarely used, and we found no examples of techniques such as instrumental variable estimation to address potential endogeneity. To encourage and guide vocational behavior researchers to further minimize concerns over CMV and endogeneity arising from the exclusive use of self-report measures in future research, we summarize existing recommendations from the methodological literature and provide an updated discussion, specific to vocational behavior, on how to design and conduct impactful vocational behavior research.

Keywords: Self-report; Common method variance; endogeneity; research design; research methods.

1. Introduction

Researchers studying vocational behavior topics are currently presented with a dilemma. Our field, probably more than parallel fields such as organizational behavior, relies on self-report measures to accurately capture the attitudes, beliefs, values, and behaviors of participants. We use the term self-report to refer to data obtained when a participant reports on their own beliefs, attitudes, values, traits, and behaviors, most commonly through questionnaires, rating scales, or interviews (Podsakoff & Organ, 1986; Tharenou, Donohue, & Cooper, 2007). Self-report measures are most appropriate for subjective constructs (introspective or private), where the respondent is in the best position to report their subjective experience (Conway & Lance, 2010). For example, self-report measures are widely used to capture constructs such as career satisfaction, support, and adaptability.

While self-report measures have a number of advantages, they can also contribute to various biases threatening the validity of studies (Podsakoff & Organ, 1986; Schwarz, 1999). Specifically, when studies include more than one self-report measure from the same respondent and then examine links between these self-report measures, biases such as common method variance (CMV) and endogeneity can arise. Both CMV and endogeneity have received growing attention in the recent methodological literature (e.g., Antonakis, Bendahan, Jacquart, & Lalive, 2010, 2014; Podsakoff, MacKenzie, Lee, & Podsakoff, 2003; Podsakoff, MacKenzie, & Podsakoff, 2012; Spector, 2006, 2019; Spector, Rosen, Richardson, Williams, & Johnson, 2019). Editorials from leading field journals in business sub-disciplines, such as *The Leadership Quarterly* (Antonakis et al., 2019) and *Journal of International Business Studies* (Chang, Van Witteloostuijn, & Eden, 2010), warn of the perils of using self-report data from the same respondent to measure all the substantive constructs, and have expressed their expectations on authors to avoid it where possible.

For various reasons, avoiding self-report data from the same respondents is not always an option in vocational behavior research. For example, the very subject of vocational behavior research, the individual (embedded in a career/work context), can often be considered as the ‘best expert’ and source for data in such research endeavors typically concerned with individual vocational development, decision-making, attitudes, and behavior. After all, a person’s vocational development and behavior is a very personal, subjective, and even intimate matter – so self-report studies have their own right of existence in vocational behavior research (cf. Chan, 2008). Unlike other fields (e.g., applied psychology and organizational behavior), vocational behavior research questions are often not answerable using objective (‘hard’) data and require perceptual measures. Hence, many of our research questions may require self-report measures to understand the attitudes, values, and cognitions of study participants. As interdisciplinary research continues to rise (Eby & Allen, 2008), we need to be mindful of the methodological shifts in parallel fields, and ensure that our research designs address concerns raised concerning the use of self-report data.

To a certain extent, the vocational behavior field is already self-correcting. We find that in our review of the 236 quantitative articles published in the *Journal of Vocational Behavior* between 2015 and 2018 that used solely self-report data from the same respondent to measure their substantive constructs (and may thus be vulnerable to validity threats), nearly 40% have explicitly highlighted how they are addressing concerns with CMV and, to some extent, endogeneity. A further 40% protect against CMV and endogeneity through their procedural (research design and data collection) and statistical analysis choices, but do not explicitly discuss CMV and endogeneity within their paper. However, 20% of studies failed to address concerns (explicitly or implicitly) with the use of self-report measures. While overall this is promising, as a field we cannot rest on our laurels.

The purpose of this paper is to provide a systematic literature review of prior quantitative work in the field of vocational behavior in terms of its proneness to CMV and endogeneity, summarize the procedural and statistical remedies that may be used to address CMV and endogeneity, and present recent methodological advancements that are particularly promising for vocational behavior research. We thereby provide vocational behavior researchers with a new resource to talk with field-specific authority on how they justify and deal with self-report data in their studies. Given our focus on CMV and endogeneity, we have to stress that there are excellent and often-cited resources for organizational behavior and applied psychology scholars, such as Podsakoff et al. (2003; 2012), but there lacks a piece that discusses concerns and remedies from the specific perspective of vocational behavior research. We draw on the broader methodological literature and recent methodological advancements to highlight how a range of procedural (design) and up-to-date statistical remedies such as marker variables (Williams & O'Boyle, 2015) and instrumental variables (Antonakis et al., 2014) can be utilized in vocational behavior research to ease concerns with the use of self-report measures, particularly addressing concerns over CMV and endogeneity.

To do so, we comprehensively reviewed every article published in the *Journal of Vocational Behavior* between 2015 and 2018 (i.e., Volume 86 to Volume 109)[1], coding for potential procedural and statistical remedies that had been undertaken to address bias associated with self-report measures (see Appendix 1 for an overview of the procedure). In total, the *Journal of Vocational Behavior* published 353 articles in this time; however, our focus is on the 293 quantitative studies, of which 236 (81%) used self-report measures in a single-source design, that is, *where the same respondent was used to measure all the*

[1] 2015 was chosen as the starting point for our review as it is three years after Podsakoff et al. (2012) influential work on CMV, which provided an updated roadmap for CMV in psychological science. The three-year gap (starting in 2015 rather than 2012), was a conscious decision as we believed that this would have been the first time research that was designed with Podsakoff et al.'s (2012) recommendations in mind appeared in the literature, rather than retrofitting their article during the submission stage.

substantive constructs. For brevity, we hereafter refer to these single-source, self-report studies as "exclusive self-report." We then draw on the methodological literature to illustrate how biases associated with the exclusive use of self-report measures have been addressed in the vocational behavior literature that was reviewed.

Second, we present six overarching suggestions for how vocational behavior researchers can address bias associated with the exclusive use of self-report measures based on our review of the methodological literature and articles published in the *Journal of Vocational Behavior*. In particular, we highlight how vocational behavior research designs and data collection procedures might be improved to minimize the potential for both CMV and endogeneity; how statistical remedies can be utilized to reduce concerns over CMV in exclusive self-report data; and how instrumental variables estimation, a technique from the epidemiology and economics field, can be used to reduce concerns related to CMV and endogeneity. By taking stock now, we can ensure that the important findings from the vocational behavior field are not dismissed in the future as a product of CMV or endogeneity biases.

1.1. What are the concerns with using self-report measures in vocational behavior studies?

Concerns over the reliability and validity of self-report measures are well known in the literature (e.g., Bing, LeBreton, Davison, Migetz, & James, 2007; Heneman, Heneman, & Judge 1997; Stone & Stone, 1990) and not reiterated here. There are now many sophisticated psychometric techniques, including reliability analysis and factor analysis to validate multi-item, self-report measures to provide evidence of construct validity (Hinkin, 1995). However, there are two significant methodological concerns vocational behavior researchers should be aware of if they are exclusively using self-report measures in their research, namely, shared method variance (i.e., CMV) and endogeneity.

1.1.1. Common Method Variance. CMV refers to systematic variance shared between study observed variables that are attributable by the measurement method (e.g., a self-report measure) adopted rather than the constructs the variables represent (Podsakoff et al., 2003; Podsakoff et al., 2012; Spector, 2006; Spector et al., 2019). CMV arises when researchers collect the focal independent (predictor) and dependent (criterion) variables from the same rating or measurement source (Antonakis et al., 2010). For example, when a participant self-rates their career meaning (predictor) and career satisfaction (criterion).

Although some authors (e.g., Spector, 2006) have argued that concerns over CMV biasing findings are often over-stated, it has been highlighted by many scholars as a significant problem in the social and psychological sciences, as CMV typically leads to artificial inflation of parameter estimates, resulting in a greater risk of type I errors (false positives; i.e., a significant relationship detected when there is not one; Podsakoff et al., 2012). However, in some cases, CMV can also have deflationary effects on parameter estimates. For example, in the case of interaction effects and non-linear relationships, findings can only be deflated in the presence of CMV, resulting in less statistical power and a risk of type II errors (false negatives; i.e., a non-significant relationship is detected when there is a significant relationship; Siemsen, Roth, & Oliveira, 2010). Although CMV can occur in any design reliant on the same measurement or rating source, the use of self-report measures to assess relationships between variables may lead to greater risk of CMV (Podsakoff et al., 2012). This risk may be especially high when the substantive variables are perceptual (subjective) measures gathered from the same respondent and at the same time (Chang et al., 2010). Indeed, Cote and Buckley (1987) found that CMV was more common in research examining subjective constructs such as job attitudes (41%) compared to more concrete and behavioral measures such as job performance (23%). Well-known sources of potential method biases in self-report measures include social desirability, and response styles such as acquiescence and extreme responding (Podsakoff et al., 2003). As noted by Spector (2019) the risk of shared method bias is heightened when researchers use self-report measures from the same respondent in the commonly used cross-sectional (single point in time) design due to potentially biasing transient occasion factors. For example, a participant might be in a momentary positive mood after a productive meeting with their manager. If participants complete a self-report questionnaire straight after the meeting, their responses to measures of career support and job satisfaction will probably be higher than if they had a non-productive meeting with their manager. Of course, not all measures of constructs are equally susceptible to the same potential method biases (Chan, 2008). For example, social desirability is likely to be an issue for studies using self-report measures of socially sensitive topics, for example, an individual's experience of bullying, whereas demographic variables or otherwise objective measures are not likely to pose significant problems for method bias (Spector, 2006).

1.1.2. Endogeneity. Endogeneity refers to where the effect of an independent variable on a dependent variable cannot be casually interpreted because it includes omitted causes leading to biased (i.e., inconsistent) estimates (Antonakis et al., 2010). In Antonakis et al.'s (2010) seminal work, they argue that CMV is a source of endogeneity. In the case of CMV, the omitted cause is a method factor (cf. Fuller, Simmering, Atinc, Atinc, & Babin, 2016). Aside from CMV, Antonakis et al. (2010) showed that other sources of endogeneity include omitted variables, simultaneity (reverse causation), and measurement error, all of which can lead to biased estimates. For instance, in a cross-sectional study, any bi-directional (reciprocal) effects will both be reflected in the data and are difficult to disentangle (Sande & Ghosh, 2018). Put more technically, endogeneity describes a situation where a predictor variable and the error term of the outcome variable are correlated (see Antonakis et al., 2010, 2014). In other words, an endogenous predictor is related to the measured criterion in multiple ways, perhaps in the way theorized (e.g., as a meaningful antecedent), but also in some unanticipated way(s) (e.g., reciprocal effects, relationship with a common cause or a common method factor). Endogeneity poses a significant issue for the social sciences above and beyond CMV (Antonakis et al., 2014). While scholars have highlighted research designs and statistical remedies that can reduce concerns over CMV, many of these solutions do not quell concerns related to endogeneity. For instance, using different sources of data to measure the independent and dependent variables can reduce CMV (Podsakoff et al., 2003). However, doing so is not enough to ensure the exogeneity of the modeled independent variable (Antonakis et al., 2010).

2. How has past research published in the *Journal of Vocational Behavior* addressed CMV and endogeneity concerns arising from self-report measures?

The purpose of this section is to understand how vocational behavior researchers have designed and analyzed their studies to counter potential issues of CMV and endogeneity arising from self-rated data gathered from the same respondent. We discuss how the common procedural and statistical remedies used in the *Journal of Vocational Behavior* address concerns with potential bias associated with the exclusive use of self-report measures, and highlight exemplar studies that can be used as a guide in designing future vocational behavior research. We summarize our findings in Tables 1 and 2 and Figure 1. Table 1 is a breakdown of the quantitative research designs used in the literature (N = 293). Table 2 focuses on our primary interest in studies that exclusively use self-report measures and summarizes the procedural and statistical remedies used to address concerns related to CMV and endogeneity (N = 236). Figure 1 is a graphical overview of the procedural and statistical remedies used in these studies between 2015 and 2018.

Insert Tables 1 and 2 and Figure 1 about here

2.1. Procedural remedies to address CMV and endogeneity concerns with self-report measures in recent vocational behavior research

We find that 68% of the 236 exclusively self-report studies have used procedural (research design/data collection) remedies to limit concerns related to CMV. These procedural remedies include temporal separation and general procedural remedies in questionnaire/instrument design. As we show below, far fewer studies have addressed other sources of endogeneity in their research designs (e.g., to examine the possibility of reverse causation).

2.1.1. Temporal separation. As noted earlier, when self-report measures of the independent and dependent measures are coupled with a cross-sectional research design, there is a risk of transient occasion factors (e.g., mood) causing CMV. One way to reduce transient occasion factors is to introduce a temporal delay (lag) between the independent and dependent measures. Studies have shown that temporal separation (typically measured over a period up to 4 weeks) can reduce the magnitude of same-source zero-order correlations by approximately 30-40% (Johnson, Rosen, & Djurdjevic, 2011; Ostroff, Kinicki, & Clark, 2002).

Our analysis shows that temporal separation of the measurement of the independent and dependent variables has become commonplace in vocational behavior research. For example, of all the exclusive self-report studies, there was almost an equal number that had used some form of temporal separation, as there were those that had used a cross-sectional design. This trend has remained relatively stable over time (see Table 2).

Researchers in the *Journal of Vocational Behavior* who used temporal separation typically collected data across two (or sometimes more) timepoints to temporally separate the measurement of the independent variable from the dependent (and in some cases, mediating) variables (e.g., Koen, van Vianen, van Hooft, & Klehe, 2016; Tellhed, Bäckström, & Björklund, 2018). Positively, the temporal separation used by *Journal of Vocational Behavior* researchers has been driven predominantly by the research question at hand (i.e., to demonstrate change in their dependent variable), thus there was no common temporal separation used. This temporal separation in measurement offers protection against CMV. However, temporal separation has two key disadvantages (Kammeyer-Mueller, Steel, & Rubenstein, 2010; Podsakoff et al., 2012). First, adding one or more additional waves of data collection adds to the cost and feasibility of conducting a study, often leading to significant attrition. For example, employees may have left their employers, or students may have left their university by the time the second or third wave of data is collected. Second, it is often difficult to determine the appropriate time lag. If the time delay is too long, intervening factors may impact the relationship between the independent and dependent variables. If the time lag is too short, the participant's memory may not be cleared to avoid method bias (Podsakoff et al., 2012).

Despite these challenges, a growing number of studies have also collected the same variables across multiple timepoints in a longitudinal design to understand the extent to which variables change (and why) over time. For example, Sun, McHale, and Updegraff (2017) utilized 11 timepoints, and Zhou, Zou, Williams, and Tabvuma (2017) utilized 18 timepoints. While some studies had temporal separation of a few weeks, other studies have implemented greater distance between timepoints. For example, Eberly, Bluhm, Guarana, Avolio, and Hannah (2017) collected data on their dependent variable (turnover intentions of soldiers returning from war) 12 months after their independent variables were collected (transformational leadership and extreme context exposure) to ensure there was enough lead time.

Moreover, several studies used longitudinal designs to check for potential reverse causation. For example, Bickerton, Miner, Dowson, and Griffin (2015) tested reverse causality in their model testing the links between resources to engagement to turnover intention using a longitudinal design. Similarly, Griep and Vantilborgh (2018) specifically designed their study to examine the potential reverse relationship between psychological contract breach and both organizational citizenship behaviors and counterproductive work behaviors. Both of these studies provide good exemplars of how a longitudinal design can be adopted to protect against both CMV and endogeneity in the form of reverse causation.

2.1.2. Multiple sources. Data collected from multiple sources can help minimize the possibility of CMV (Podsakoff et al., 2012). A growing percentage of articles have adopted research designs where the independent and dependent variables are measured from different sources (see, for example, Demerouti, Bakker, & Gevers, 2015; Strauss, Parker, & O'Shea, 2017). This has included different people (e.g., employees, peers, or supervisors) or combining archival (secondary) data (e.g., company records on employee performance) with perceptual data (e.g., self-reports of employee attitudes).

In our review, 14% of all the 293 studies reviewed used different participants to measure the independent and dependent variables, and 8% of studies reviewed drew on other non-self-report sources of data (such as archival records). While we admit these numbers are low, the nature of many research questions in the vocational behavior field often requires researchers to use self-report data to measure all the substantive variables (e.g., career satisfaction, support, and adaptability), which might contribute to this low number. Nevertheless, we encourage researchers to think more strategically about how they can obtain non-self-report data. For example, using supervisor ratings of employee performance or using objective absenteeism data as a proxy to measure burnout.

The effectiveness of using multiple sources to deal with concerns of bias is mixed. For example, Podsakoff et al. (2003) reported the mean correlation between measures of predictor and criterion variables decreased from .36 when they were obtained from the same source to .18 when they were obtained from different sources. While this is an impressive reduction in the magnitude of correlations attributable to CMV, Spector (2006) has noted that ‘other-reports’ (e.g., supervisor ratings of job performance) and archival measures (such as company records on turnover) can be inaccurate. Thus, it is not the case that non-self-report measures are superior to self-reports (Chan, 2008; Conway & Lance, 2010). Indeed, it can be argued that while using a different rater to measure the dependent variable may reduce CMV, it may introduce unshared- or uncommon-method variance (UMV) that can also bias correlations (Spector et al., 2019). An example of UMV is that supervisor ratings of job performance may be influenced by measurement error (e.g., a halo effect) that is not shared with the subjective reports of subordinates (cf. Borman, 1975). Hence, designs using separate data sources to correct for CMV may be at risk of UMV; that is, *unshared s*ources of method variance that attenuate rather than inflate parameter estimates.

2.1.3. Experimental designs. Nineteen of the total 293 articles used experimental designs in their research, generally to test the effectiveness of careers-based interventions (e.g., Hodzic, Ripoll, Lira, & Zenasni, 2015; Ogbuanya & Chukwuedo, 2017; Spurk, Kauffeld, Barthauer, & Heinemann, 2015). By definition, the independent variable is manipulated rather than measured (e.g., self-reported) in an experiment. Hence, the use of rigorously designed experiments (e.g., randomized controlled experiments) can effectively eliminate endogeneity and CMV that may confound the internal validity of findings (cf. Cook & Campbell, 1979). This is because such experiments are more likely to establish that an independent variable has a causal impact on a dependent variable through the direct manipulation of the independent variable and the randomization of participants to treatment and control conditions (Lonati, Quiroga, Zehnder, & Antonakis, 2018). However, despite the ability of such experimental designs to make strong causal inferences, they are rarely utilized within research in the field of vocational behavior. One of the probable reasons for the lack of experimental designs in this area is because of concerns regarding their ecological validity (the real-world relevance), with some arguing that experimental designs do not realistically simulate organizational settings (cf. Levitt & List, 2007), and they frequently rely on samples that are not characteristic of employees in organizations (Highhouse, 2009). There are also concerns over the extent to which experiments have external validity, that is, can be reproduced and replicated (Podsakoff & Podsakoff, 2019). Furthermore, many independent variables in the field of vocational behavior cannot be easily manipulated (e.g., subjective states or attitudes), and this may explain why non-experimental designs remain the method of choice for many vocational behavior researchers. That said, we encourage vocational behavior researchers to consider an experimental design, perhaps in addition to conducting a field-based survey study.

2.1.4. Additional procedural remedies. Only very few articles reported using other procedural design remedies to reduce concerns with CMV. These procedural design remedies included simpler to administer procedures such as *reducing ambiguity in the questions* (7%), *having different response formats* (4%, such as Likert and semantic differential scales), and *psychological separation of questions* (2%). While these remedies may not be as powerful in protecting against CMV as the other procedural remedies discussed, given the ease of implementation, we would like to see greater use of such remedies. Although some scholars may have adopted such remedies as part of good methodological practice without reporting their use, we believe it is important for future work to be transparent by explicitly highlighting the steps taken in designing the research.

2.2. Statistical remedies to address CMV concerns with self-report measures in recent vocational behavior research

Statistical remedies, on the whole, were used significantly less than procedural remedies to limit concerns of CMV. We find that 13% of the 236 exclusively self-report studies used statistical remedies to detect and/or control for CMV. These statistical remedies included Harman's single factor test, the method factor technique, and the marker variable technique.

2.2.1. Harman's single factor test. The most commonly used statistical procedure was *Harman's single factor test*, used by 12% of the exclusively self-report studies (e.g., Ren & Chadee, 2017b). In this technique, the researcher loads all the items of all the study variables into an exploratory factor analysis (cf. Andersson & Bateman, 1997; Schriesheim, 1979), and then examines the unrotated factor solution to determine if a single dominant factor emerges. A single factor emerging that accounts for the majority of variance (> 50%) suggests that CMV is present. A variant of this technique which involves testing the fit of a one-factor model has also been developed for confirmatory factor analysis (CFA; Kline, 2013). While we are encouraged that the use of Harman's single factor test has increased over time, our enthusiasm is tempered. Although simple to implement, a major disadvantage of this technique is that it does not statistically control for (or partial out) CMV from the observed relationships of interest. Hence, this test should be the bare minimum researchers perform, rather than the gold standard.

2.2.2. Modeling a method factor. The second most common statistical test (2%) was where the researcher modeled a method factor to detect and/or control for CMV. Increasingly, structural equation (latent variable) modeling using confirmatory factor analysis (CFA) is used to detect and/or statistically control for CMV. For example, Guo, Baruch, and Russo (2017) compared standardized regression weights between the models with and without a common method factor. Other examples are Jiang, Hu, and Wang (2018), Doden, Grote, and Rigotti (2018) and Lee and Shin (2017), whom all applied an *unmeasured common latent method factor* technique developed by Podsakoff et al. (2003). Finally, Thoroughgood, Sawyer, and Webster (2017) performed a multiple method factor technique (i.e., Multi-Trait Multi-Method (MTMM; Williams, Cote, & Buckley, 1989)) to address CMV.

2.2.3. Marker variable technique. One statistical remedy that does not require the researcher to directly measure the source or sources of method variance is the marker variable technique (Lindell & Whitney, 2001). At the heart of the marker variable technique is the idea that a variable that is theoretically unrelated to the substantive variables in the model can be used as a marker or surrogate for CMV. For example, organizational bureaucracy could be used as a marker variable when assessing the relationship between career adaptability and career decidedness, as no theoretical link is expected between organizational bureaucracy and these two substantive variables. Any shared variance between the marker variable and another theoretically unrelated substantive variable can be used as an indicator of CMV (Richardson, Simmering, & Sturman, 2009). In essence, if a correlation between two substantive variables becomes non-significant after controlling for the marker variable, this suggests that CMV is biasing the results.

Building on an earlier correlational marker variable technique developed by Lindell and Whitney (2001), Williams, Hartman, and Cavazotte (2010) and Williams and O'Boyle (2015) developed a comprehensive Confirmatory Factor Analysis (CFA) marker variable technique. In the CFA marker variable technique, a series of latent variable measurement models are compared (with and without a marker variable) to detect the presence of CMV and examine if CMV biases the observed relationships.

The marker variable technique was only used in three of the exclusively self-report studies (Presbitero & Quita, 2017; Ren & Chadee, 2017a; Rofcanin, de Jong, Las Heras, & Kim, 2018). In each of the studies, the authors outlined that they performed the marker variable technique in line with the procedure outlined by Lindell and Whitney (2001) and then suggested that CMV was not an issue and proceeded to analyze the data. We prefer future studies to provide additional information such as the variables used and the values obtained to assist readers in understanding their chosen procedure and analyses. The recommended comprehensive CFA marker technique (Williams & O'Boyle, 2015) has not been used to our knowledge in the studies reviewed here.

3. Updated suggestions to address concerns with CMV and endogeneity in self-report measures in vocational behavior research

Taking stock of the quantitative research published in the *Journal of Vocational Behavior* from 2015-2018, many researchers are addressing concerns arising from CMV and, to some extent, endogeneity with the exclusive use of self-report data. Nevertheless, 20% of studies do not report any procedural or statistical remedy to address concerns with CMV and endogeneity in the exclusive use of self-report measures. A further 40% do not explicitly state in their manuscripts why they have undertaken the remedies they have. Further, as many vocational behavior research questions lend themselves to cross-sectional designs, this leaves many studies in our field prone to endogeneity, especially due to the possibility of reverse causation (Antonakis et al., 2010, 2014). Therefore, we present six suggestions as a helpful guide to assist the vocational behavior field in addressing concerns that may arise from the exclusive use of self-report measures, in relation to CMV and endogeneity. Specifically, this section takes the literature on self-report measures and presents it in a language understandable to vocational behavior researchers, speaking directly to the studies we perform. Please note that not all suggestions will fit all research questions. Some of our suggestions speak just to CMV, and others to the broader issue of endogeneity (e.g., reverse causation and omitted variable bias). Thus, researchers need to use their discretion when deciding on which suggestions to implement.

3.1. Suggestion 1: Collect self-report measures across multiple timepoints

We recommend that researchers consider, where possible, temporal separation of the measures of the independent and dependent variables to minimize the risk of CMV when exclusively using self-report measures. In addition, many vocational behavior researchers seek to understand how an independent variable influences the *change* in an outcome variable over time. In these cases, we strongly encourage researchers to conduct longitudinal research (e.g., using a cross lagged panel design) and collect data on the same variables at preferably three or more timepoints. Such a design with repeated collection of data on the same variables allows the researcher to test for reverse causation. In designing longitudinal studies, researchers must ensure that *the length* of the time lag between timepoints is appropriate (Singer, Willett, & Willett, 2003). Hence, there should be a sensible metric for clocking time (Singer et al., 2003). For example, in the case of vocational behavior research, to test the effects of abusive supervision on job search behaviors, two weeks between surveys may not be enough time for workers to have decided they are going to search for a new job. A 1-month or 3-month time lag might be more appropriate in this situation.[2]

There will be some cases where it is impractical to conduct longitudinal research, and a cross-sectional design may indeed be preferred to answer the research question (see Spector, 2019 for discussion). However, in our analysis of the literature, we could not find one manuscript which explicitly justified why the authors were using a cross-sectional

[2] For complex statistical formulas to analyze optimal time lags, we suggest reading Dormann and Griffin (2015). We have not included a detailed description of their work in this paper, as the formulas are specific for the variables measured.

design. If researchers are going to use a cross-sectional design (e.g., to examine correlations/associations between variables in a large representative sample), we encourage them to provide a considered rationale for their research design.

While temporal separation of the measures of the independent and dependent variables is an effective strategy in reducing CMV, it can only do so for method biases that are more transient (e.g., momentary mood; Spector, 2019). More generally, longitudinal research, while useful in establishing temporal precedence for stronger causal inferences, may fail to address all concerns over the exogeneity of the independent variable (e.g., the possibility of omitted variable bias). Hence other remedies (including instrumental variables estimation), as discussed below, may be needed to ensure robust inference.

3.2. Suggestion 2: Collect data from multiple sources

The majority of vocational behavior research questions do require subjective data to understand the factors which shape vocational attitudes and behaviors in students, job seekers, or employees. Thus, only a small percentage of articles (14%) in our review drew upon non-self-report sources of data that can address concerns over CMV. As our field continues to develop, we urge researchers to draw on data from multiple sources particularly where at least one of the substantive variables is a readily observable behavior that can be accurately captured by other-reports (e.g., supervisor ratings of job performance).

Authors may also look to obtain objective (including unobtrusive) measures of career behaviors such as job search behaviors instead of relying solely on self-report measures. For example, the length of time the participant spends on job websites or LinkedIn might be used to measure job search behaviors. Second, data may be obtained from significant others with a close relationship to the focal individuals. For example, teachers or parents in the case of students, employment counselors or career advisors in the case of job seekers, and coworkers, supervisors, or spouses in the case of employees. Specifically, employment counselors might be in a good position to rate variables such as the job seeker's employability, and spouses might be in a good position to measure variables such as their spouse's work-life conflict or interference.

3.3. Suggestion 3: Adopt a fuller range of procedural remedies

Our review demonstrated that researchers tended to choose one procedural remedy, rather than using several, or even the entire suite of remedies to address concerns over CMV. While we applaud vocational behavior researchers who have introduced such safeguards into their research designs and data collection procedures, we implore researchers to take the next step and help to establish this as a regular research procedure where possible and appropriate. The following procedures should become the norm in cases where researchers are exclusively using self-report measures and especially where temporal separation is not possible.

First, researchers might ensure participants' *responses are anonymous* to minimize social desirability, especially on sensitive topics (e.g., bullying) or where participants feel they have to respond in a particular way to appease their supervisors, teachers, or coworkers. Second, they might *randomize the order that questions* are asked in a survey, so the questions are presented to participants in different orders. Survey data collection software such as Qualtrics and SurveyMonkey provide this feature for researchers. Third, researchers might try using *different response formats* to Likert-scales, such as rank order, images, sliders, hot spots, and drill-downs. Again, software such as Qualtrics or Survey Monkey offer many readily available alternatives for researchers. Fourth, researchers might use a cover story or ask participants to do a short writing task between measures of the independent and dependent variables to ensure the *psychological separation of measures*. Finally, researchers may spend time *improving the wording of scale items*, especially in scale construction or translating the scale to a new language. In doing this, researchers might pilot the survey items, ask participants what they believe the question is asking, and then change the wording as necessary (cf. Podsakoff et al., 2003).

3.4. Suggestion 4: Adopt statistical remedies

Some vocational behavior studies will be unable to address potential CMV associated with the exclusive use of self-report measures through procedural remedies due to the nature of the research question, or the requirements of the organization or institution they are working within. For example, researchers may only be able to survey participants at one timepoint, or may not have access to appropriate, non-self-report data, including objective measures (e.g., archival records). In these cases, we suggest that researchers consider statistical remedies to detect and/or control for potential method bias.

We encourage vocational behavior researchers to apply one or more of three statistical remedies to alleviate potential CMV with the exclusive use of self-report measures. First, researchers can perform *Harman's single factor test* or a one-factor CFA to detect CMV. These tests require no additional variables to be measured in the study. Second, researchers can model one or more *measured method factors* to directly control for potential method biases. For example, social desirability may be controlled in a multiple regression analysis, where the dependent variable is based on a self-report of a sensitive topic (e.g., psychological contract breach, sexual harassment, bullying). This strategy is in line with Spector's (2006) argument that method biases are a complex function of the interaction between methods of measurement, their underlying cognitive and affective response processes, and the nature of the substantive constructs. Third, we recommend the use of the comprehensive CFA *marker variable technique*. The marker variable technique requires the researcher to identify a variable that is theoretically unrelated to the substantive variables in the model and include it in the analysis. The effectiveness of the marker variable technique is largely a function of the extent to which a marker variable is theoretically unrelated to the substantive variables but shares the same causes of CMV as those variables (Simmering, Fuller, Richardson, Ocal, & Atinc, 2015). Some methodologists have also recommended using multiple marker variables, given the limitations of any single marker variable as a proxy for CMV (Williams et al., 2010). Building on this, it is recommended to choose a marker variable that is likely to share the same causes of CMV as the substantive variables. Unfortunately, this is rarely done in studies using marker variables. Consider a study examining the relationship between reported experience of racism and perceptions of fair treatment in promotion, both rated using a conventional Likert scale. An ideal marker variable is one that is likely to tap into the same sources of CMV shared with the substantive variables, for example, social desirability or the use of a common response format such as the use of a Likert scale. Hence, an ideal marker in this situation could be a Likert scale rating of marital relationship quality as although it would not be expected to be theoretically related to the substantive variables, it may tap into one or more sources of method bias shared with the measurement of the substantive variables (e.g., social desirability or the use of a common response format). In practice, researchers have often used a theoretically unrelated demographic variable in their dataset (e.g., job tenure or self-reported height) that has the least correlation with the substantive variables as a candidate marker variable. Unfortunately, these objectively reported variables are not likely to capture sources of CMV typically associated with perceptual measures. Finally, it is important to remember that a marker variable is only a *surrogate* for CMV; it does not *directly* capture the source or sources of potential method bias. Hence, the marker variable technique is of most value where the potential cause(s) of CMV cannot be directly measured in the study (Simmering et al., 2015). We refer the interested reader to Williams and O'Boyle (2015) for detailed guidance on the selection of marker variables.

The procedural and statistical remedies presented in our first four suggestions alleviate potential bias associated with CMV. However, they do not address broader issues of endogeneity, which we cover with our subsequent suggestions.

3.5. Suggestion 5: Undertake more experimental work

Research on vocational behavior has started to embrace experiments, with 19 experimental studies completed from 2015 to 2018 in the *Journal of Vocational Behavior.* As randomized experimental designs are an effective way of eliminating CMV and endogeneity (Antonakis et al., 2010), we call for their greater use in the vocational behavior literature where the research question dictates. This is not to say experiments are a panacea, particularly given concerns over their replication (see Lonati et al., (2018) for a review). Similarly, in many cases, independent variables of interest to vocational behavior researchers cannot be easily manipulated in an experimental context (e.g., measures of subjective states such as attitudes). Hence, non-experimental designs may remain the method of choice. In such designs, researchers should strongly consider the use of instrumental variables estimation to address endogeneity (see suggestion 6). We offer an example of how experiments can be applied to vocational behavior research questions below.

A key vocational behavior research question answerable with an experimental design is the effectiveness of career interventions in promoting positive vocational attitudes and behaviors, such as mentoring programs, competency training, and career counseling (cf. Egan & Song, 2008; Hodzic et al., 2015). For example, if a researcher wanted to examine the effect of career mentoring on variables such as career optimism or career self-efficacy (Eva, Newman, Jiang, & Brouwer, 2020; Zhao, Lim, & Teo, 2012), they could randomly allocate a sample of participants to one of three groups. The first, a treatment group who receive career mentoring. The second, an 'active' control group who get general mentoring (e.g., job-specific mentoring) but not career mentoring. The third, a control group who receive no mentoring (i.e., no treatment). By testing levels of career optimism and career self-efficacy before and after the intervention, the researchers can examine the extent to which career mentoring enhances career optimism and self-efficacy relative to other forms of mentoring. The control group allows researchers to filter out any natural development or maturation that may occur over time. The active control allows researchers to demonstrate that their intervention is having a unique effect, rather than having demand effects (Lonati et al., 2018). Demand effects are a method factor where the participants respond in a particular way because they believe that is the appropriate response to have (Zizzo, 2010). In our example, when organizations spend money on a mentoring program, respondents, who appreciate the opportunity, may over-report levels of career optimism and self-efficacy. Therefore, by having an active control condition, we can examine the demand effects of mentoring in general and demonstrate the causal effect that career mentoring has on career optimism and self-efficacy.

3.6. Suggestion 6: Use instrumental variables

While rigorous experimental designs can eliminate endogeneity, it is also possible to address endogeneity in non-experimental studies. Consider a study in which employees rate their perceptions of their job characteristics (independent variable), their levels of motivation (mediator), and their performance (dependent variable). This study may be afflicted by CMV, and to further complicate the issue, endogeneity biases in two other domains may also be influencing the observed correlations. If the study is cross-sectional, it is difficult to account for simultaneity effects (i.e., reverse causation), and it is entirely possible that higher-performing employees become more motivated and see their job more positively. In addition, employee ratings of job characteristics may be influenced by external factors, such as employee personality (cf. Judge, Bono, & Locke, 2000). External factors such as personality might also predict employee motivation and performance, leading to omitted variable bias.

Omitted variable bias refers to a situation where an important confounding variable is missing from the model that might influence the nature of the causal effects between the substantive constructs (e.g., job characteristics and motivation). Careful selection of control variables can reduce omitted variable bias, but it is not always possible in practice to identity and control for all potentially confounding variables (Sande & Ghosh, 2018).

As highlighted in our review, measured—and not manipulated—variables like job-related attitudes and emotions are common in vocational research because it is often difficult, perhaps impossible, to effectively and realistically manipulate them. However, estimating causal relationships among measured variables with conventional techniques such as ordinary least squares or maximum likelihood procedures will produce potentially misleading estimates (Angrist & Pischke, 2008). One way to reduce the issues of endogeneity in survey research is by using instrumental variable estimation, developed in econometrics (e.g., Angrist & Pischke, 2008). The underlying idea of this technique is to regress only the exogenous part of the variation in the independent variable in order to accurately estimate its effect on the dependent variable. To do so, it is first necessary to find a variable, termed an instrument, which influences the independent variable but appears unlikely to affect the dependent variable except through its effect on the independent variable (Antonakis et al., 2010). Once an instrument is identified, instrumental variable regression allows for examining causal effects even in the presence of omitted variables or other sources of endogeneity (Antonakis et al., 2010; Podsakoff et al., 2012).

We suggest that researchers consider adding instrumental variables to their model and estimate the effect of the independent variable on the dependent variable using two-stage least squares (2SLS) regression. 2SLS uses instrumental variables: exogenous predictors of the endogenous predictor (x), which will be associated with the outcome (y) but only through the endogenous predictor (z). The logic of this approach is that because the instrumental variables are exogenous, they can be used to account for the variance within *x* that is also exogenous. This essentially removes the endogenous association (e.g., that due to CMV or omitted variables) between *x* and *y*, meaning that the effect of *x* upon *y* can be estimated accurately, and is free from endogeneity (for technical details see Antonakis et al., 2010, 2014).

Although empirical work published in the *Journal of Vocational Behavior* between 2015 and 2018 has not considered such instrumental variable techniques, growing work in the wider field of applied psychology has begun to utilize instrumental variables (e.g., Bollmann, Rouzinov, Berchtold, & Rossier, 2019; Obschonka et al., 2018; see also Maydeu-Olivares, Shi, & Fairchild, 2019). For example, Bollmann et al. (2019) used personality traits as exogenous instrumental variables to study the effect of job satisfaction (variable x) on career adaptability (variable y).

Although undertaking the actual 2SLS analysis is relatively straightforward, arguably the most difficult aspect involves identifying suitable instrumental variables in the first place. For example, one could question the suitability of using personality traits as an exogenous instrument in the above-mentioned study by Bollmann et al. (2019). Angrist and Pischke (2008) suggest that effective instruments come from a combination of domain knowledge and ideas about the processes determining the variable of interest. Because researchers in vocational behavior address a wide array of topics and contexts, suitable instrumental variables may vary across topics. For instance, instrumental variables may be found among genetically based and relatively stable individual differences (e.g., personality traits, intelligence, genetic markers (cf. DiPrete, Burik, & Koellinger, 2018)), events/conditions outside the influence zone of participants (e.g., organizational characteristics; cf. Brown, Gray, McHardy, & Taylor, 2015; Stone et al., 2007), or natural experiments (cf. Bollen, 2012). It is also worth noting that instrumental variables are unlike marker variables (see above on the marker variable technique) in that a marker variable should be theoretically *unrelated* to any of the substantive variables in the model. Further, the use of instrumental variables requires specific analysis to be conducted (e.g., 2SLS analysis).

Whether one or more instruments are suitable for instrumental variables estimation can be determined using two tests (Sajons, 2020). First, an instrument can be considered as relevant or strong if its F-statistic exceeds the critical values calculated by Stock and Yogo (2005). This F-statistic is a typical post-estimation command included in statistical packages. If there is a strong enough statistical association between the instrumental variable and the exogenous predictor, and if it also fulfills the other conditions for a good instrument, it can be used in instrumental variable estimation. The second test focuses on whether the instrumental variable(s) only affects the outcome variable via the instrumented endogenous predictor once the endogenous regressor has been conditioned on the instrument. If there are more instruments than instrumented variables (i.e., the model is overidentified), this can be tested with a Hansen-Sargan test or a chi-square fit statistic if using structural equation modeling (Antonakis et al., 2010). Furthermore, a test of endogeneity should be conducted whereby the coefficients from the instrumental-variables estimation are compared to those obtained for the same model when instrumental variables estimation is not used. Doing this can help researchers ascertain whether it is necessary to use instrumental variable estimation. If the results are significantly different, the regressor in the non-instrumental variable estimation is likely endogenous and the resulting coefficient estimates biased (see Sajons, 2020 for further details).

Researchers outside the vocational behavior field have begun utilizing instrumental variables when investigating relationships between measured variables such as individuals' perceptions, attitudes, or well-being. Such studies are relevant for the study of vocational behavior. For example, positing that the relationship between job satisfaction and well-being may be influenced by the presence of omitted variables, Sironi (2019) utilized an instrumental variable approach in order to isolate the effect of job satisfaction on optimal well-being variation that was independent of unobserved individual characteristics. The author included membership in a trade union and the size of the enterprise as instruments, finding a significantly positive influence of job satisfaction on optimal well-being. In a study with a similar focus, Cannas, Sergi, Sironi, and Mentel (2019) firstly used variables such as the frequency of working at weekends and overtime with a short notice to predict job satisfaction of individuals and subsequently used these fitted values to establish whether job satisfaction has an impact on subjective well-being. The variables which were selected as instruments were highly correlated with job satisfaction, but not directly with overall subjective well-being (Cannas et al., 2019).

To assist vocational behavior researchers in the process of addressing CMV and endogeneity, we present Figure 2, a simple checklist outlining the procedural and statistical remedies that can be undertaken to protect against CMV and endogeneity. While this is not intended to be exhaustive, it does provide an overview of the remedies outlined in this article.

Insert Figure 2 about here

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4. Conclusion

The purpose of our article was two-fold. First, we reviewed articles published in the *Journal of Vocational Behavior* from 2015 to 2018 to ascertain how the current vocational behavior literature has addressed concerns over CMV and endogeneity in studies using self-report measures gathered from the same respondent, and integrated these findings with the broader methodological literature. Second, we provided six suggestions to assist vocational behavior researchers in limiting such potential biases in their studies, specifically to address concerns related to CMV and endogeneity.

Self-report studies are ubiquitous in the field of vocational behavior. Our study revealed that 81% of the 293 quantitative studies reviewed relied exclusively on self-report measures gathered from the same respondent. The present study has demonstrated that while there have been promising steps taken to address concerns over CMV and, to a lesser extent endogeneity, in the vocational behavior literature, as a field, we can do more to address CMV and endogeneity issues in our studies. For studies that require the exclusive use of self-report measures, and especially where temporal separation is not possible, researchers can still utilize a range of powerful statistical remedies to identify if CMV is present in their data and to control for it. For studies that can utilize non-self-report data, we encourage researchers to build these measures into their research where appropriate. We also believe that instrumental variable estimation is useful for robustness in non-experimental research (especially cross-sectional) to address potential endogeneity. Our review has also highlighted the importance of careful conceptual work required in selecting marker variables, instrumental variables, and when modeling the influence of specific method factors. For reviewers, we hope that this provides a helpful reminder on how studies can address concerns over CMV and endogeneity, especially with the exclusive use of self-report data. For journal editors, if there are concerns with the exclusive use of self-report measures, editorial policies, such as the one present at the *Journal of Business and Psychology*[3] or editorials, such as in the *Journal of International Business Studies* (Chang et al., 2010), may assist improving standards in the field, while being mindful of the general reliance on self-report data that is such an obvious part of the DNA of contemporary vocational behavior research, as shown in our review. Such

[3] The guidelines asked authors (and reviewers) to refer to Conway and Lance (2010) for advice regarding how to deal with CMV. Conway and Lance (2010) is a highly cited paper in the CMV literature that addresses both authors and reviewers targeting some misconceptions about CMV in self-reports.

orchestrated, multi-stakeholder efforts in the field can also strengthen the positive side and the various advantages of self-report data in vocational behavior research.

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Table 1: Summary of the quantitative articles (2015-2018) based on the research design characteristics

Research design	**2015 (*N* = 94[2])**		**2016 (*N* = 51)**		**2017 (*N* = 71)**		**2018 (*N* = 77)**		**Total (*N* =293)**	
	N	***%*[3]**	***N***	***%***	***N***	***%***	***N***	***%***	***N***	***%***
Temporal										
Articles with a longitudinal design	48	51.06%	29	56.86%	37	52.11%	35	45.45%	149	50.85%
Articles with a cross-sectional design	55	58.51%	24	47.06%	35	49.30%	45	58.44%	159	54.27%
Articles with both longitudinal and cross-sectional designs	9	9.57%	2	3.92%	2	2.82%	4	5.19%	17	5.80%
Respondents/data sources										
Self-report measures of DV & IV from same respondent	78	82.98%	47	92.16%	51	71.83%	60	77.92%	236	80.55%
Different respondents for IV & DV	10	10.64%	3	5.88%	13	18.31%	14	18.18%	40	13.65%
Objective measures	8	8.51%	4	7.84%	2	2.82%	9	11.69%	23	7.85%
Multiple raters[1]	6	6.38%	3	5.88%	4	5.63%	13	16.88%	26	8.87%
Experiments										
Articles with an experimental design	6	6.38%	1	1.96%	9	12.68%	3	3.90%	19	6.48%

Note: Quantitative articles consist of all survey-based studies, experiments, and quasi-experiments

[1] Multiple raters from the same source (e.g., an organizational climate survey)

[2] Number of all quantitative studies in the respective year

[3] Percentages are in regard to all the quantitative studies in each respective year and are multiple response, thus do not sum to 100%.

Table 2: Procedural and statistical remedies addressing concerns with CMV and endogeneity in self-report measures in vocational behavior research (2015-2018)

	2015 (*N* = 78)[4]		2016 (*N* = 47)		2017 (*N* = 51)		2018 (*N* = 60)		Total (*N* = 236)	
	N	***%***[5]	***N***	***%***	***N***	***%***	***N***	***%***	***N***	***%***
Procedural Remedies										
Temporal separation of IV and DV	43	55.13%	28	59.57%	26	50.98%	27	45.00%	124	52.54%
Questionnaire design (anonymity)	14	17.95%	13	27.66%	13	25.49%	10	16.67%	50	21.19%
Questionnaire design (reducing ambiguity)[1]	4	5.13%	1	2.13%	5	9.80%	6	10.00%	16	6.78%
Different response formats[2]	2	2.56%	0	0.00%	5	9.80%	2	3.33%	9	3.81%
Psychological separation[3]	0	0.00%	1	2.13%	1	1.96%	3	5.00%	5	2.12%
Statistical Remedies										
Harman's single factor test	6	7.69%	2	4.26%	7	13.73%	14	23.33%	29	12.29%
Method factor technique	0	0.00%	0	0.00%	3	5.88%	2	3.33%	5	2.12%
Marker variable technique	0	0.00%	0	0.00%	3	5.88%	0	0.00%	3	1.27%
Instrumental variable technique	0	0.00%	0	0.00%	0	0.00%	0	0.00%	0	0.00%

[1] Number of articles that had undertaken measures to reduce ambiguity in terms of questionnaire items
[2] Number of articles that had used different response formats such as semantic differential, Likert scales, faces scales, open-ended questions
[3] Number of articles that had used a cover story in a questionnaire
[4] Number of all quantitative studies in the respective year
[5] Percentages are multiple response and do not sum to 100%.

Figure 1: Procedural and statistical remedies to address CMV and endogeneity in self-report articles from 2015 to 2018 (*N* = 236)

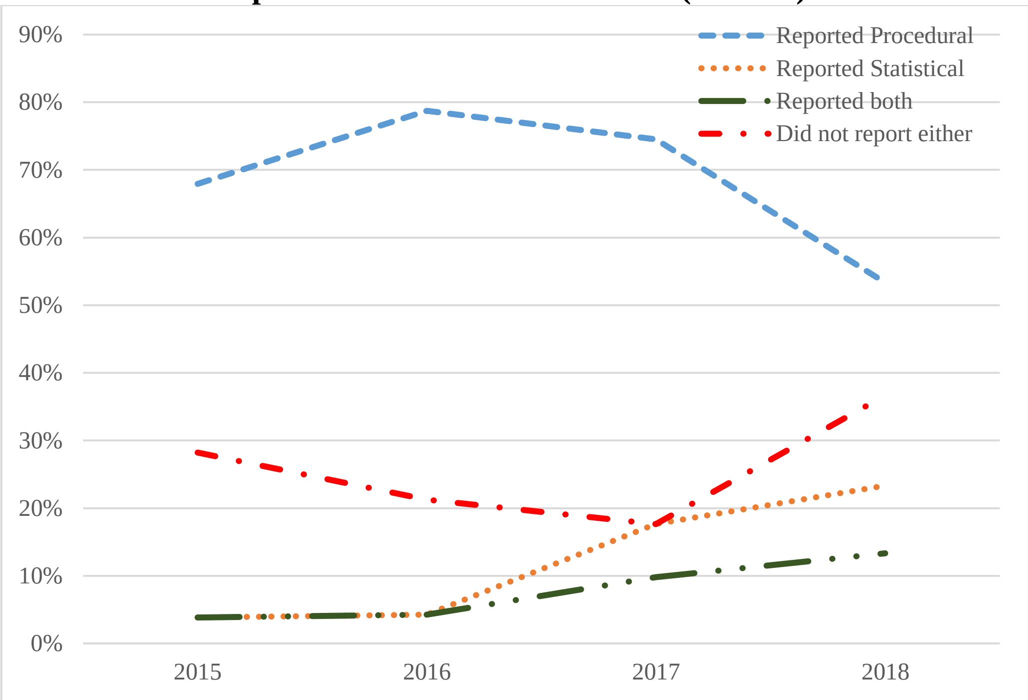

Figure 2: Checklist for designing vocational behavior studies

Study Design

For the design, consider:

- ❑ Temporal separation
- ❑ Different respondents for IV and DV (objective measures if possible)
- ❑ Experimental methods

If not, must

Use recommended statistical remedies (see below)

Instrument Design

With data collection, where appropriate:

- ❑ Ensure anonymity of participants
- ❑ Reduce ambiguity of questions
- ❑ Use different response formats
- ❑ Counterbalance the questions
- ❑ Psychological separation of questions

Statistical Tests

With analysis, consider

- ❑ Harman's one factor test (not recommended on own)
- ❑ Directly measured latent factor technique
- ❑ CFA Marker variable technique
- ❑ Instrumental variables (2SLS analysis)

Appendix 1: Coding Book for Journal of Vocational Behavior Studies

Procedure
We analyzed the research design, methodology, and limitations[4] sections of these studies to obtain the procedural and statistical remedies researchers used to address concerns with self-report data. This resulted in a list of 49 items to obtain from each article. The author team split the articles to review between them and coded them accordingly in an excel spreadsheet. Two members of the research team completed cross-checks of a random selection of articles to ensure the information was coded correctly across the sample.

Demographic details
Paper Number (for our reference)
Authors
Title
Year
Volume

Research Design
Number of studies
Type of study (e.g., experiment, survey)
Sample size
Country
Different respondents of independent and dependent variables (Y/N)
If experimental design, was there separation of mediator and dependent variables?
Respondents (e.g., employees, students, managers)
Respondents of the dependent variable (if different)
Survey design (e.g., online, in person, paper)
Type of sampling (e.g., convenience, stratified)
Was the study cross-sectional? (Y/N)
Number of timepoints
Distance between timepoints
Proximal /methodological separation for measuring independent and dependent variables (e.g., different locations (rooms, sites); different response formats (semantic differential, Likert scale, faces scales, open-ended questions); media (computer-based vs paper & pencil vs face-to-face interview)).
Psychological separation method (e.g., cover story)
Procedural remedies regarding questionnaire design (e.g., anonymity; item ambiguity reduction; counterbalancing questionnaire order; reducing evaluation comprehension)
Repeated measures design (Y/N)
Were there incentives used? (Y/N)

Methodology
Unit of analysis (e.g., individual, team)
Reliability measure (e.g., Cronbach's alpha)
Rating source (i.e., triangulation by using more than 1 rater for variables)
Measures (e.g., subjective, objective)
Control variables (Y/N; justification Y/N)
Non-response bias test (Y/N)

[4] The limitation section was coded as it often referenced how they dealt with self-report data.

Pilot study (Y/N)
Confirmatory Factor Analysis (CFA; Y/N)
CFA Competing Models (e.g., chi-square difference test)
Exploratory Factor Analysis (EFA for new measures; Y/N)
Harman's single factor test (Y/N)
Method factor technique (e.g., single, multi)
Partial correlation approach (e.g., partialling out social desirability; affectivity; marker variable; general method factor)
Marker variable (Y/N)
Endogeneity checks (Y/N)
Reverse causation checks (Y/N)
Additional Robustness Checks (Y/N)
Program (e.g., Mplus, SPSS)
Estimators (e.g., OLS, MLR)
Analysis (e.g., regression)
Additional comments

Mentions of CMV / Endogeneity
Does the manuscript mention CMV / Endogeneity (Y/N)?
Where was CMV / Endogeneity mentioned (section)
Has a procedural or statistical remedy been performed (Y/N)
Reason for CMV / Endogeneity checks
Additional comments