

Publishing quantitative careers research: Challenges and recommendations

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Publishing Quantitative Careers Research: Challenges and Recommendations

Abstract

Design/methodology/approach: Based on their experience as an author, reviewer, and editorial team member, the authors identify the main criteria that a quantitative study must meet to be considered for publication in international peer-reviewed journals covering career-related topics. They emphasize the importance of contributing to the careers literature and of designing the study in accordance with the research question.

Purpose: To provide prospective authors guidelines that will hopefully enable them to submit more competitive manuscripts to journals publishing careers research.

Findings: Manuscripts are rejected because they are insufficiently innovative, and/or because sample, instruments, and design are not appropriate to answer the research question at hand. Cross-sectional designs cannot be used to answer questions of mediation but should not be discarded automatically since they can be used to address other types of questions, including questions about nesting, clustering of individuals into subgroups, and to some extent, even causality.

Originality: The manuscript provides an insight into the decision-making process of reviewers and editorial board members and includes recommendations on the use of cross-sectional data.

Publishing Quantitative Careers Research: Challenges and Recommendations

What is a novel and/or interesting contribution? If the very essence of research is to discover something new, why is it that some of the new discoveries are published and then start or contribute to broad new research streams, and others fail to make it past the journal editor's desk? Every researcher who submits a paper for review believes that their study makes a contribution. So, what is it that determines which paper is accepted for review and then hopefully publication? With this paper, we try to answer this question by discussing in detail two criteria that we believe are essential to get quantitative studies published in international peer-reviewed journals covering career-related topics, such as *Career Development International (CDI)*: contribute to the literature on careers and use effective study design and methods.

In the first section, we explore an understanding of what constitutes a contribution, highlighting exemplary papers that brought novel knowledge to light. We will consider two types of novel research, those which boldly consider new phenomena, and those that consider new subsets of research within a phenomenon. In addition, we consider how organizational researchers position the novelty of their work, which we call the hook. Here we position the hook as the craft of storytelling—both the identification of a research gap, and the positioning of the theoretical and practical contribution of addressing this gap.

The second section of this paper deals with methodological issues, including sample and instrument selection, the use and misuse of control variables, the practice of question trolling, and challenges related to testing mediation and moderation. We also discuss the limitations of cross-sectional data for testing cause-effect relationships and provide some suggestions that should allow researchers to make the best use of cross-sectional data. By way of summary, we conclude the paper with a list of recommendations for authors wishing to publish their

quantitative studies in *CDI*.

What Constitutes a Contribution?

We start by considering what it is that makes a topic interesting. At the most basic level, what is interesting to most readers is to answer questions that are of personal relevance to them. Consider for example the topic of work engagement. Bakker and Demerouti's (2008) paper provided a review of the engagement literature presented as an elegant conceptual model. The novel contribution of the paper was to suggest a model of engagement as initiated by resources, leading to positive performance outcomes. Such a paper is of interest to the reader because it answers a question that is of personal or societal relevance. Any reader would personally like to know what is involved in being or becoming more engaged in work.

Of similar note, when van Emmerik *et al.* (2012) studied the concept of employability, they touched on a phenomenon that is of both personal interest to the reader and one that is considered of significant importance to society. By integrating job resources, motivation and employability in a testable conceptual model, they addressed a gap in the research literature, and made a practical contribution by uncovering knowledge that is of interest to the reader and society at large.

Separate from capturing the interest of readers based on the topic of study, studies which use elegant and sophisticated research design and methodology are sure to be of interest to readers, who too are researchers. For example, Dobrow and Higgins (2005) capture the interest of readers by engaging in a true longitudinal investigation of the role of networks in the support of professional identity. The reader who learns that a cohort has been followed for 5 years, with data collected at three points over this period, has their curiosity peaked to want to understand the analytical approach used, and learn the findings of this study.

Now it is generally not enough to just capture the curiosity of the reader. For a study to be deemed novel, it must consider something new. Those studies which integrate divergent concepts have the potential to be of greatest interest because they integrate different research literatures and may be considered counterintuitive. Poon (2004) provides an excellent example for consideration. In this study Poon considers the relationship between commitment and career success. Because the reader to some degree experiences commitment and career success, understanding this relationship is of personal relevance. It is the latter that captures the reader's attention. What further adds both novelty and interest to this study is that Poon, considers how emotion fits within this relationship. Here the reader, at an intuitive level, believes that emotion will play a role. At the same time, it leads the reader to ask both "I wonder why" and "I wonder how" emotions play a role. In this study, Poon's moderator was emotion perception, the degree to which an employee can perceive and then potentially regulate emotional responses. At the time of this paper's submission, the consideration of emotion regulation at work as well as the concept of emotional intelligence was popular in the organizational consulting sphere. So, Poon's study was both novel and interesting because it investigated a gap that was of interest in that period and was able to intuitively resonate with the reader.

While some topics are a priori more interesting to readers because they are directly relevant to their lives, that alone is not sufficient to have a study be deemed interesting. The second element required for it to be of interest to the reader is that the idea is both understandable and novel. For the most part, it is of interest to the reader because it integrates and simplifies complex phenomena into a clear narrative. In short, it is the presentation of something novel which gently walks the reader from what we knew to what we now know, in a manner that does not lose the reader along the way. In the case of Bakker and Demerouti (2008)

by integrating the engagement literature into a conceptual model, they provided a simple and elegant integration of a complex phenomenon. Alternatively, research studies will use elegant and detailed theoretical development of hypotheses in order to build on existing research and theory to hypothesize the outcome they seek to test. Ballout (2009), for example does an excellent job of first introducing the concept of self-efficacy, and then explaining how self-efficacy should relate to career commitment and salary, providing a clear theoretical explanation of the hypotheses being tested.

One of the greatest frustrations for researchers, however, comes when they submit a paper that captures a relationship between variables that thus far has not been investigated, only to receive a rejection on the grounds that the paper has not contributed to theory, and as a result, is not deemed a contribution. To understand what is a contribution is to understand what constitutes theory. The first part of a contribution, as we have outlined, is to explore a phenomenon that is of interest to the reader as a result of its novelty. However, it is the use value of that novel idea which makes the novel idea worth publishing. The use value of a novel idea stems from its helping to explain why a phenomenon is the way it is, or why and how one phenomenon impacts another.

Theory is the answer to queries of *why*. Theory is about the connections among phenomena, a story about why acts, events, structure, and thoughts occur. Theory emphasizes the nature of causal relationships, identifying what comes first as well as the timing of such events. Strong theory, in our view, delves into underlying processes so as to understand the systematic reasons for a particular occurrence or nonoccurrence (Sutton and Staw 1995, p. 378).

Herein lies the greatest opportunity for researchers seeking to publish their work. Researchers who explain at a detailed level the why and how causal relationship between variables in under-researched phenomena will have no trouble publishing their work, because it carries the reader on a journey to explain something never before explained. At the simplest level, it is to explain the what, why, how, and when of the connection of variables and to explain not just how these variables should be connected in this study, but the interactions of the variables at all times (Whetten 1989). Conversely, the researcher who reports a statistical relationship between variables with little to no explanation on why and how that relationship exists, will likely not have this work perceived as a contribution, and so will have challenges in publishing these findings because the presentation of data and statistical results alone are not likely to make a contribution (Sutton and Staw, 1995).

Research which is interesting and makes a contribution is likely to make it into the review process. That is the science side of establishing the contribution of the paper. What makes excellent papers stand out from good papers comes down to the art of opening of the paper, which we call the hook. The hook is about quickly and elegantly walking the reader through a narrative of what we know, what we don't know, *why we need to know it*, and how we are going to study it. As highlighted, the most important step in this narrative is understanding why we need to know it as understood and appreciated by the reader. A successful hook leads a reviewer to a sense of wanting to help this paper be published to share these important findings with the world. A failed hook leads the reader to say, "so what," or even worse, to question the credibility of the researcher. In our view, authors often pay inadequate attention to the "so what" question. Given that career development is a practical field, it is important for authors to identify the

theoretical and practical implications of their work. When they struggle to do so, reviewers may conclude that the research question is too narrow or inconsequential to merit publication.

As we have already suggested, some topics are more or less intuitively interesting. Topics that are intuitively interesting, in essence, have a built-in hook. However, for topics that are less intuitively interesting, the hook plays an even more critical role. In these circumstances, it is the hook that creates the novelty and level of interest by carrying the reader on an intellectual journey from the ordinary to the extraordinary. For example, when Dikkers *et al.* (2010) sought out to study career ambition and the use of part-time work and family friendly practices, they were studying a novel dimension to a highly developed, and less novel research domain. However, this paper provides a wonderful example of the hook. While most papers use the formula of summarizing the literature to portray a clear and distinct gap, which the paper then fills, Dikkers *et al.* (2010) took a different approach. In the first page of the paper the authors provide a description of the myth and stereotype of working women in the Netherlands to paint a picture of a culture that portrays women as lacking ambition. The authors then-note a dearth of research examining gender differences in career ambition. Their research offers an opportunity to measure this phenomenon, as well as to look at the relationship with part-time work and career satisfaction. One cannot read the opening page and not be left wanting to read the paper.

Thus far, the model is quite clear. Papers which consider interesting and novel ideas, which contribute to theory, and are written in such a way to portray the contribution of the study as well as generate interest in the topic at hand are more likely to be on the road to success in terms of review and publication. However, that is only the start. While the consideration of a novel contribution to the literature creates the opportunity for research, it is effective methodology that provides an empirical solution to test the hypotheses developed. In the next

section, we review some methodological challenges. There is an abundance of research design and methods textbooks and courses, which detail with the way research projects should be developed. Our discussion will be limited to factors that, in our experience, often cause manuscripts submitted to career journals to be rejected, despite their innovative nature and potential for theoretical contribution. We discuss, respectively, sample selection, instrument selection, the use of control variables, the problem of question trolling, and research design.

Methodological Challenges

Sample Selection

The issue of sample selection has plagued all of the social sciences for as long as researchers have sought to study the commonality of behavior of people (Winship and Mare 1992). The essence of the challenge is that once researchers have identified phenomena to investigate, they need to find a collection of people representative of the potential for these phenomena and encourage their participation in the study. If the area of study is careers, logically then, it would be people who are working and those making career choices who would be the most relevant subjects. Furthermore, since people differ in terms of career stage (Bedeian *et al.* 1991), generation (Hess and Jepsen 2009), and gender (Malach-Pines and Kaspi-Baruch 2008), to survey just any random group of workers to consider a specific research question may be and often is problematic.

The challenge at present for researchers is that the easiest source for study samples arguably provide the least valid representation of careers phenomena. That source is the student sample. The student sample is still regularly employed as all a researcher needs to do is develop the research question and assemble an ethics review document establishing that completion of a survey will not harm participants and then offer a few participation marks in class. Within days,

a researcher may have surveys completed by hundreds of people. The researchers may even justify the sample as applicable to careers because participants hold part-time jobs or are preparing for careers. Alternately, they may argue that these are working professionals pursuing an MBA. Whether the justification makes sense obviously depends on the research question at hand. Although not an appropriate sample for many career-related research questions, student and other unemployed persons can be appropriate samples for investigating career-choice and other pre-employment issues.

Nonetheless, many otherwise strong manuscripts are rejected because their sample, either a student sample or from a data collection service or bank is deemed to not effectively represent the research phenomenon. For example, for a study intended to test job satisfaction as impacted by work-at-home initiatives, a researcher drawing from a student sample might ask respondents, if given the opportunity to work from home to what degree *would they be* more or less satisfied. While this sample would provide an empirically rigorous representation of student perceptions of how they think they will experience working from home and how that will influence their satisfaction, it is impossible to determine whether this is how actual workers will have their job satisfaction impacted by work from home initiatives. Dikkers *et al.* (2010), instead, provide an excellent example of the use of an appropriate sample. To do so they sent out surveys to 1000 workers working for Dutch companies, intended to be reflective of the workforce. Of the over 500 responses, they limited the data to 212 mothers and fathers as their study investigated working parents. While such an approach is far more difficult for researchers, because gaining access to organizations and having workers complete surveys is difficult, the result is a sample that better reflects the studied phenomenon and therefore, increases the external validity of the study.

While drawing from student samples limits relevant career research questions, so too may be the use of professional survey data collection companies. Some of the challenges with these firms, is that they may attract the repeated completion of different surveys from the same group of people, who do this as a way of supplementing their income. As a result of receiving compensation for completing the survey, respondents may complete surveys even if they are not fully qualified (Baker *et al.* 2010). For example, one who is otherwise unemployed may complete a survey directed to workers, using the rationalization that their employment is the completion of the survey. Alternately, if the purpose of using a survey firm to collect data is to get a sample which reflects the general population, this too is problematic, as research suggests that professional survey takers are a specialized group quite different than the general population in terms of both demographic and mindset (Hillygus *et al.* 2014). A review of studies using MTurk respondents (Aguinis *et al.* 2021) notes its use in management research has recently increased significantly and offers caveats and guidelines for its use.

In careers research, we too sometimes see the opportunity to use professional survey firms as a quick and easy way to gain access to a population to survey. The challenge, however, is that the external validity of these responses may be suspect. Additionally, without more specific detail regarding the career histories of survey participants, it is very difficult to assess the relevancy of survey participants and data they produce. In short, while there may be opportunities where the use of these services may support answering some specific research questions, for the most part the set of these services is likely to provide easy access to data which may not be accepted as a valid representation of the research phenomenon studied.

Once the sample has been selected, it is essential that authors describe as completely as possible the work and/or non-work situation of their subjects or respondents. In our experience,

too many authors do not provide adequate sample information resulting in rendering the external validity of their findings equivocal. For example, if a researcher collected data examining job crafting across multiple organizations and occupational groups, important differences in job crafting may be overlooked if organizational and occupational differences are not examined and reported. Another example for external validity is the importance of describing the economic conditions and state of the labor market where and when data were gathered for job search studies. Psychologists have examined the relative roles of individual characteristics including personality and cognitive ability versus situational factors for decades (Bleidorn *et al.* 2018; Mischel and Shoda 1995). Although personality is a fairly stable trait, recent research has shown that assuming a leadership role can create small changes in some Big Five personality traits (Li *et al.* 2021). That is, while individual attitudes, personalities and abilities are primary determinants of career behaviors, different working conditions enhance or limit career behaviors and, if possible, need to be accounted for, or at least clarified to the reader when describing the sample.

In addition to selecting the appropriate sample and describing it adequately, it is also important to have the right tools to correctly answer the research questions. In the next section, we discuss some of the challenges related to instrument selection.

Instrument Selection

Regardless of whether the research method is survey or experiment, choice of instruments for collecting data is a critical part of research design. For studies in which a researcher employs archival data, choice of scales and/or data utilized must be guided by the research questions and their underlying theory. Use of archival data requires detailed description of the purpose, sample and methods used to gather the data. This is important to establish the

external validity of findings from archival data to your study's research questions. Statements such as "these data are part of a larger study" without further explanation are not acceptable and require full description.

When selecting instruments and scales to measure independent and dependent variables, best practice is to choose among those that are well-established. For example, if perceived employability were part of a study, the Rothwell and Arnold (2007) scale is well-established and frequently used. It is not advisable and often leads to desk reject of a submission, to use some versus all items of an established scale without explanation of rationale for exclusion of some items. Why is this important? It is important for the external validity and generalizability of studies. Scales are developed to measure a construct and constructs often have multiple components. If, for example, a study is measuring perceived employability using the Rothwell and Arnold (2007) 11 item scale that captures internal (to respondents' organization) and external employability, but if an author uses only external items, their measure is deficient. Unless the rationale for the exclusion is stated, assuming the study is published, other researchers' citations regarding employability of findings from this study are not valid. The all-too-common practice of shortening and modifying existing scales is likely one cause of the problem of low replicability, 39 percent, of psychology experiments (Serra-Garcia and Gneezy 2021). Additionally, researchers are encouraged to gather relevant objective data such as tenure, and organization data such as attendance and performance reviews. For researchers desiring to make a contribution and receive many citations, it is critical to choose measures well, use them properly and describe them accurately and completely.

Another critical issue has to do with the lack of correspondence between the theoretical concepts and their operationalization. Oftentimes authors see their paper rejected because there is

a misalignment between the theoretical concepts that are introduced in the front-end of the manuscript and the way these concepts are measured in the empirical part of the study. For example, if researchers want to investigate the effect of perceived overqualification, it is necessary that this construct be measured using a valid instrument. Thus, it is not appropriate to use a proxy of perceived overqualification, such as educational attainment (which is an antecedent of perceived overqualification) or perceived fit (which is a consequence of perceived overqualification), because those measurements happened to be available. We understand that most readers are familiar with this advice. Nevertheless, we should note that it is a common problem, as is a misalignment between the theory section and the design of the study. Challenges related to research design are discussed later.

The Use of Control Variables

Despite the plethora of recommendations on the use of statistical controls (Becker 2005; Becker *et al.* 2016; Bernerth and Aguinis 2016; Breugh 2008; Carlson and Wu 2012; Spector and Brannick 2011), many researchers remain uncertain about when and how to use control variables in their studies. The most basic question in this regard is whether control variables are needed at all. Most methodologists agree that statistical controls should only be included if theory suggests that the potential control relates to one or more of the focal variables. Where a strong foundation in theory is not available, researchers should provide a logical explanation for why the variable is artificially related to one or more of the focal variables. If no such justification can be provided, control variables should be omitted from the analyses. The fact that previous researchers have included such control variables in their study or found empirical relationships with the focal variables are insufficient reasons to do similarly. We therefore urge researchers to add a theoretical justification or logical explanation for including each of the

control variables, either in the theoretical part of the paper or when introducing them in the method section.

Just because a variable acts as a statistical control does not mean that it should not meet the same psychometric requirements as the focal variables. As is the case for focal variables, control variables should be reliable and valid, and these measurement properties should be reported in the methods section. Control variables should also be treated the same as other predictors with respect to reporting descriptive statistics and correlations and should be included in the descriptive summary table. To examine the impact of the control variables on the relationship between the independent and the dependent variable, it is recommended to run the analyses with and without control variables, and to compare the results. If the results do not differ substantially (i.e., the standardized coefficient of the independent variable differs with less than 0.1, Becker *et al.* 2016), then only the analyses without controls need to be reported, along with an explanation that the results were nearly identical when control variables were included.

Question Trolling

Many researchers still believe that it is better to submit a study with than one without significant results. Consequently, when they don't find what they expected, based on theory, they resort to "kicking" or "massaging" the data "until they crack." By turning the data inside out, they still hope to construct a nice story, that is, finding notable results worth writing about. This practice, referred to as 'question trolling' (Murphy and Aguinis 2019), bypasses the most important step of the research process—the conceptual development of an interesting research question—and introduces bias into the cumulative scientific literature.

It is arguably more difficult to create a post hoc hypothesis based on unexpected findings than one based on theory and consistent with the study design. Question trolling may therefore

lead reviewers to state in their feedback that “the story is not well connected,” “variables do not fit together logically,” “hypotheses are not well argued,” and “theoretical concepts and measures are not well aligned.” Rather than searching through the data until something seemingly noteworthy pops up, it is preferable to follow a hypothetico-deductive approach, in which researchers use theory, empirical evidence, logical reasoning and even specific cases or examples to formulate hypotheses. If the hypotheses turn out to be insignificant it does not have to stop the researcher from reporting these results. Non-significant results may be as interesting as significant results, for example, if they can identify circumstances in which a theory does not apply.

For the sake of clarity, we do not advise against researchers ‘exploring’ their data. Further exploring the data can lead to a better understanding about why some of the hypothesized relationships were not significant and therefore can add value to the paper. It is important though to be transparent about the exploratory character of the findings. If researchers come across interesting findings while exploring data, they can report them, for example, in an additional paragraph labelled ‘auxiliary analyses and results.’ In our view, it is neither necessary nor desirable to adapt the theoretical part according to these additional results. Hence, we do not favor adding hypotheses to the study after the results have come in (i.e., ‘hypothesis proliferation,’ Murphy and Aguinis 2019).

Research Design

One of the most frequent reasons to reject submissions pertains to a misalignment between the theorizing and the research design. The nature of the research questions defines the appropriate research design. Research questions involving ‘change’ require at least three measurement moments (Ployhart and Vandenberg 2010). Questions involving ‘fit’ or ‘similarity’

may require the use of polynomial regression analysis (Edwards and Parry, 1993). Questions involving cause and effect such as “how much does a training program increase perceived employability or job crafting” may require (quasi) experimental designs. Questions of *mediation*, that is, questions that address the ‘why’ of a relationship, require at least two measurement occasions (see below). Yet, authors continue to erroneously use cross-sectional designs to answer ‘why’-questions. Admittedly, under some conditions, cross-sectional surveys may be appropriate, for example, for examining relationships among personalities, respondent demographics, attitudes, behaviors, and non-individual variables such as organizational practices or events. Later in the paper, we describe several ways in which cross-sectional data can provide valuable insights without violating assumptions regarding causality. But first we discuss in more detail why cross-sectional designs cannot adequately answer questions regarding causal relationships, followed by a discussion of how to investigate questions of *moderation*, that is, questions that relate to conditions that may affect the strength between relationships.

Testing Mediation

Most of the research questions in the domain of careers research ask *why* phenomena are related to each other. For example, Alessandri *et al.* (2018) wanted to find out why employees with higher levels of psychological capital generally perform better at work, while Van den Broeck *et al.* (2014) wanted to know why job-insecure employees are more likely to display counterproductive work behaviors. Although the primary goal of this type of research is (or should be) establishing causality (Antonakis *et al.* 2010; Zyphur *et al.* 2020), researchers tend to refrain from making causal claims because they understand that their research design does not allow them to do so. Especially problematic in this regard is the use of cross-sectional designs in the quest for intervening or process variables, the so-called mediators. Three such problems are

described by Gollob and Reichardt (1987). First, the causal relationships implied by the paths in the mediation model take time to unfold. However, the use of cross-sectional data implies that the effects are instantaneous. Clearly such an assumption is problematic on logical grounds. Second, it is well known that conclusions based on a causal model that omits a key predictor can be seriously in error, yet a model based on cross-sectional data leaves out several key predictors—namely the variables measured at previous times. When previous levels of the variables are not controlled for, the paths in the mediation model may be over- or underestimated relative to their true values. Maxwell *et al.* (2011) empirically demonstrated that the bias that typically exists in mediation analysis when using a cross-sectional design is so substantial that *p*-values and confidence intervals are “essentially meaningless” (p. 837). Third, effects unfold over time, and we would not expect the magnitude of a causal effect to remain the same for all possible intervals. The application of the mediation model to cross-sectional data assumes not only that the causes are instantaneous, but also that the magnitude of the effect is not dependent on the length of time that elapses between the measurements of the variables. In sum, cross-sectional designs are ill-suited to test mediation and the use of such designs therefore severely limits the potential to make a substantial theoretical contribution.

Given the limitations of cross-sectional designs to draw inferences about a causal process, researchers have turned to longitudinal designs. A specific design feature of longitudinal research is that at least one of the study concepts is measured at least twice (Taris *et al.* 2021). Others use a stricter definition and propose that longitudinal research contains at minimum three repeated observations on at least one of the substantive constructs of interest (Ployhart and Vandenberg 2010). Regardless of the number of repeated observations, we urge authors to pay sufficient attention to the length of time between data collection points in longitudinal studies.

These should be theoretically supported, based on the phenomenon in question, not just “long enough” to claim that the study is longitudinal.

Preacher (2015) distinguishes three major classes of longitudinal mediation models: (1) the cross-lagged panel model (CLPM), (2) the latent growth curve model (LGM), and (3) the latent change score (LCS) model. The CLPM is based on structural equation modeling (SEM) and can be used to test mediation if the three focal variables (i.e., causal, intervening, outcome variable) have been measured at three or more occasions, and if the interest is in their influences on each other time (Hamaker *et al.* 2015). A half-longitudinal design in which data are collected at only two occasions suffices to estimate an indirect effect, but findings are not as trustworthy as findings in a three-wave study (Cole and Maxwell 2003; Preacher 2015; Taris and Kompier 2006). Despite the benefits of the CLPM over cross-sectional designs, the former has been criticized because it does not account for stable, trait-like differences between units (e.g., individuals, dyads, work teams) (Hamaker *et al.* 2015). The random intercept cross-lagged panel model (RI-CLPM) is an extension of the traditional CLPM and is specifically designed to account for the nested structure of longitudinal data (i.e., measurement occasions nested within units) by decomposing the variance into a time-invariant part captured by the random intercept, and a time-varying part that is used to model the within-unit dynamics (Mulder and Hamaker 2021). The RI-CLPM is starting to gain popularity, also among career researchers (e.g., Alisic and Wiese 2020; Smet *et al.* 2016; Van Hootegem *et al.* 2021).

LGM is a popular method of analyzing longitudinal data and investigating mediational hypotheses. Like CLPM, LGM is used in the SEM framework. It allows for the assessment of linear and non-linear (e.g., exponential) changes in the variables that are repeatedly measured over time. Aspects of the longitudinal change in a variable (e.g., individuals' intercepts and

slopes) may then take the role of independent, mediating, or dependent variable in a mediation model (Preacher 2015; von Soest and Hagtvet 2011). Despite the measurement effort required – latent growth curve mediation models require a minimum of nine measurement occasions to explain the temporal order of events (Selig and Preacher 2009) – the use of LGM is well established in the career literature (e.g., Giunchi *et al.* 2020; Hirschi and Fischer 2013).

Like the previous models, LCS models are also based on the SEM framework. In LCS models, change is represented as the difference in scores in adjacent observation periods (Selig and Preacher 2009). Unlike other longitudinal mediation models, LCS models do not address the relationships among the variables themselves over time but instead focus on change in a variable (i.e., rate of change between occasions $t-1$ and t) and the relationships among those changes. Stated differently, LCS models are useful to examine how change in one variable relates to changes in another variable, rather than how levels of one variable relate to levels/change in another variable (Matusik *et al.* 2021). Also, unlike other models, change is not assumed to be constant across measurement occasions. As such, LCS models are particularly useful when change is expected to vary across measurement moments. In a full LCS mediation model, the predictor, mediator, and outcome variables are measured at four measurement occasions. LCS modelling is increasingly used by career scholars to investigate bivariate and reciprocal relationships (e.g., Gawke *et al.* 2017; Petrou *et al.* 2018; Zacher and Rudolph 2017; Zhang *et al.* 2018), but less so to investigate mediating relationships.

In sum, career scholars aiming to investigate *why* phenomena are related to each other are advised to employ longitudinal mediation models. These models, including the (RI-)CLPM, LGM and LCS model, allow researchers to examine how effects unfold over time, rather than modeling all effects simultaneously using traditional mediation models. Admittedly, some of the

above models require a massive data collection effort, which may not be possible given the limited time and resources available to the researcher. Below, we describe how cross-sectional data can still lead to a meaningful contribution in the event the above designs prove unfeasible. But first we turn to another question that is at the forefront of careers research: when and for whom is the relationship between two career variables more pronounced?

Testing Moderation

Many theories in careers research involve so-called moderating variables (or: moderators) that affect the strength or nature of the relationship between two other variables. In general terms, a moderator is any variable that affects the association between two or more other variables; moderation is the effect the moderator has on this association (Dawson 2013). In its most basic form, an X–Y relationship is hypothesized to be moderated by a single variable only (two-way interaction). In a survey study among permanent employees of a company in reorganization, Koen *et al.* (2020) confirmed one of their hypotheses that stated that job insecurity was only positively related to supervisor-rated overall performance among employees with low intrinsic motivation. Another study by Lavigne *et al.* (2019), among employees and their supervisors of two US-based organizations undergoing major changes, demonstrated that job insecurity was negatively related to adaptive performance for those employees experiencing low levels of change, but was not related to adaptive performance for those experiencing high levels of change. However, cases of multiple moderators of the relationship between two variables (three-way and higher-order interactions), are by no means an exception. For example, in their study among employees from a foreign-owned high technology company in China, Wang *et al.* (2020) found that a contextual resource (i.e., job social support) and a personal resource (i.e., occupational self-efficacy) jointly interacted with career dissatisfaction to result in job

crafting. Finally, things can get even more complicated by considering moderation of non-linear relationships between X and Y (e.g., moderation of a curvilinear relationship between training and job performance), or by predicting non-normal outcome variables (e.g., unemployed versus re-employed). For example, Zhou *et al.* (2020), in a sample of Chinese police officers, found that career calling had a U-shaped curvilinear relationship with work fatigue, and that COVID-19 event disruption moderated the curvilinear relationship, such that the U-shape only emerged when COVID-19 event disruption was high.

Probing a significant interaction effect should always be followed by interpreting it. This can, e.g., be done by first plotting it and then performing simple slope tests or slope difference tests. Dawson (2013) provides excellent statistical overviews of all the above cases. However, he also points out specific points of attention, amongst others, sample size (which is related to statistical power for detecting interaction effects), and when and how to perform ‘meaningful’ simple slope tests. Related to this, Murphy and Russell (2017) make a plea for a more skeptical approach in the pursuit of moderators. According to them, the lack of sufficient statistical power, and the type of designs and measures common in organizational research are cumbersome as these result in (usually) extremely small moderator effects found. Future attempts to identify and estimate moderator effects should be limited to situations where better measures, stronger research designs and a realistic cost-benefit assessment are available. In other words: career researchers should avoid moderator hypotheses in contexts where the measures and research designs employed do not allow them to be tested in a meaningful way and should be cautious about interpreting the very small effects they are likely to find.

In all cases, proper theorizing is key. Issues such as which variable should be considered the predictor and which the moderator, and whether a moderator increases or decreases the

association between two other variables should be theory-based and specified as part of a priori hypotheses. To guide researchers toward more precise ways of developing theory, advancing hypotheses, and interpreting results, the taxonomy of interaction effects by Gardner *et al.* (2017) may be very helpful. More specifically, it can be used to (a) predict what form the interaction will take, anticipate and identify meaningful values where the interaction will be operative (i.e., regions of significance) and if there will be any meaningful crossing points; (b) ensure that there is sufficient power to detect an interaction, including consideration of the reliability of the interaction term(s); (c) compare the results against the hypothesized form and features (e.g., crossing point, regions of significance); and (d) examine the results in greater detail to inform future research.

In sum, scholars aiming to investigate *when and for whom* the relationship between two career variables is more pronounced are advised to employ moderation designs that are well grounded in theory, using reliable measures of the variables involved, with a sample size that ensures sufficient statistical power, and taking regions of significance of (potential) interaction effects into account.

Alternative Approaches to Analyzing Cross-Sectional Data

In an earlier paragraph, we pointed out, as many have, the limitations of cross-sectional research. Does this mean that cross-sectional research is inevitably without value? Not necessarily. Despite their limitations, valuable insights can be gained from cross-sectional data by using data analysis techniques other than the traditional ordinary least squares regression. In what follows, we shortly discuss three such techniques: (1) multilevel analysis, (2) person-centered techniques, and (3) psychological network analysis. Needless to say, there are numerous other methods that can be considered. We picked these three based on their relevance to careers

research, the ease with which they can be applied, and our familiarity with the methods in question. However, it should be noted that most of these methods are unable to establish causality when used to analyze cross-sectional data.

Multilevel Analysis

Careers evolve over time, within and across organizations, geographic regions, social networks, with career actors holding different positions and jobs, and some even pursuing very different professions (Arnold 1997; Arthur *et al.* 1989; De Vos and Van der Heijden 2015; Greenhaus *et al.* 2010; Gunz and Mayrhofer 2018; Hall 2002). Because of the multilayered nature of careers, data about careers are oftentimes hierarchically structured, with some units of analysis nested *within* other, higher-level units (Schreurs *et al.* 2021). The most obvious example involves career actors nested within organizations: because career management practices differ across organizations, organizational membership is likely to explain part of the differences in career outcomes. Career actors are also nested within regions as career trajectories are heavily conditioned by geographic idiosyncrasies, such as national labor regulations, public policies, labor market and national cultures. Occupations are yet another meaningful level to consider. Occupations create objective (e.g., work performed) as well as subjective boundaries (e.g., professional identity), “which offer a variety of possible demarcations of context that span social or interpersonal elements, physical demands, values, norms, regulations, interests, and so on” (Schreurs *et al.* 2021, p. 227). Hence, data about careers are often hierarchical, with careers actors nested within, amongst others, organizations, geographical boundaries, and occupations. When data are nested, it is appropriate to analyze them using multilevel modeling.

Multilevel analysis allows testing to what extent the scores in the outcome variable are due to differences between or within organizations/regions/occupations. For example, multilevel

analysis may reveal that differences in job crafting not only reside at the individual level, but that organizational/regional/occupational membership also explains part of the variance in job crafting. Person-specific and higher-order predictors can then be added to the multilevel regression model to explain variance in job crafting at the lower and higher level. We may observe that proactive personality explains between-person variance in job crafting, and that organizational structure (e.g., degree of centralization) explains between-organization variance in job crafting. In a next step, one could test whether the effect of the person-level variable differs as a function of the higher-level group and whether these slope differences can be explained by higher-level variables. When applied to our example, it may well be that proactive personality is more strongly related to job crafting in some organizations than in others, and that the effect varies as a function of organizational structure.

Multilevel analysis is well established in the literature on careers (see Schreurs *et al.* 2021 for an overview). Given the nested nature of many career-related constructs, we see great potential in using a multilevel lens when researchers are left with cross-sectional data. At a minimum, this approach will allow them to make statements about the extent to which differences in outcome variables can be found at the level of individual career actors or the context in which they spend their careers.

Person-Centered Techniques

Most careers studies are variable centered: they examine relationships among variables across individuals (Hofmans *et al.* 2020). For example, career scholars have studied the extent to which job and personal resources covary with work engagement (e.g., Bakker and Demerouti 2008), proactive personality with career self-management (e.g., Chiaburu *et al.* 2006), and career commitment with career success (e.g., Ballout 2009). Implicit in such variable-centered studies is

the assumption that the population under study is homogeneous, and that therefore a set of “averaged” parameters can be used to describe it (Hofmans *et al.* 2020). However, the assumption of population homogeneity most likely oversimplifies reality and therefore calls have been launched for adopting a different approach, one in which attention is shifted away from a focus on variables to a focus on individuals, and in which population heterogeneity is explicitly accounted for (Woo *et al.* 2018). Whereas variable-centered methods study a limited set of variables and their interactions, person-centered methods focus on how specific *configurations* of variables act in concert to shape behavior (Bergman and Trost 2006). For example, rather than investigating the effect of a restricted number of job demands, job resources and their interaction terms on employee well-being—the approach taken by variable-centered methods—person-centered methods would cluster individuals into subgroups on the basis of the similarity in their scores on job demands and job resources, and then study the associations between these subgroups and employee well-being (Gameiro *et al.* 2020; Moeller *et al.* 2018).

Several person-centered methods have been developed, including *k*-means and hierarchical clustering, latent profile and latent class analysis, factor mixture analysis, mixture regression analysis, configural frequency analysis, Davison and Davenport’s (2002) criterion-based method, latent class growth modeling (and growth mixture modeling), and latent transition analysis. Some of the above methods are ‘internal techniques’, meaning that the subgroups are derived without taking into consideration their predictive value for outcome value(s) (e.g., latent profile and latent class analysis); others use subgroups to capture differential relationships between a set of predictors and an outcome variable (e.g., mixture regression analysis); or look for specific patterns of predictors that are uniquely associated to the outcome variable (e.g., configural frequency analysis). It goes beyond the scope of this article to discuss these methods

in detail.

Despite the growing popularity of person-centered methods, their use is not yet fully established among career researchers. Even though exploratory, person-centered methods may lead to interesting findings and inductive theorizing (Hofmans *et al.* 2018). Therefore, we believe that applying person-centered techniques can help researchers make better use of cross-sectional data in their goal to make a substantial contribution to the literature on careers.

Network Modeling

The use of psychological network modeling has become increasingly popular in recent years, especially in the fields of clinical psychology, personality research and health sciences (Epskamp *et al.* 2018; Epskamp and Fried 2018). In network analysis, each network consists of a set of *nodes* connected by a set of *edges*. Psychological variables, such as thoughts, feelings, or behaviors, comprise the nodes of a network, while partial correlation coefficients between these variables comprise the edges of the network. Psychological network analysis serves as an alternative to latent variable modeling and shifts the focus towards the direct relationships among the observed variables. That is, network modeling is particularly useful in cases where psychological variables are understood to directly affect each other rather than being caused by an unobserved latent entity (Epskamp and Fried 2018). Instead of taking observed variables to be indicators of (higher order) latent constructs, psychological network analysis considers them as autonomous causal entities in a network of dynamical systems (Schmittman *et al.* 2013). From a network perspective, individual differences in, for example, burnout, could arise from, and could be maintained by, vicious cycles of mutual relationships among symptoms. A symptom such as emotional exhaustion can cause other symptoms, such as concentration problems and worrying, which in turn can lead to feelings of personal inefficacy, which can

result in more worrying and so on (Costantini *et al.* 2019). From this perspective, burnout is not a multidimensional latent construct (the traditional view), but rather a complex system consisting of several dynamically interacting constituent elements, with some elements more central to the system and others more peripheral.

This network approach may also be of interest for careers research. Consider for instance the construct ‘workaholism’, the tendency to work excessively hard in a compulsive way (Schaufeli *et al.* 2008). Key attributes include having persistent thoughts about work, feeling guilty when not working, lack of work-life balance, and being highly work involved (Clark *et al.* 2020). In empirical research, scores on workaholism dimensions are usually combined to form a total score which then functions as a measure of workaholism. This practice ignores the likely presence of direct relations between dimensions. In a network framework, on the other hand, workaholism would be considered a constellation of dynamically interactive thoughts, feelings, and behaviors, all of which would function autonomously in the system rather than being passive indicators of a common construct. To illustrate, having a strong desire to work may lead to having work-related thoughts, which in turn may lead to feelings of guilt when unable to work, which then again spurs the desire to work. Such patterns of relationships can be identified by means of network modelling. Additionally, the method can be used to identify the elements that are most central to the syndrome of workaholism. We are not aware of any career research that has used network modeling. We believe psychological network analysis to be a promising technique, particularly if researchers want to draw conclusions about the causal relationship of the variables in their cross-sectional data.

Recommendations for Authors Who Want to Publish in *CDI*

Since the inception of *Career Development International* (CDI) a quarter century ago, the

number and quality of submissions has steadily risen as reflected in the journal's impact factor. The implications of this for prospective authors are twofold, i.e., (1) *CDI* has become a more desirable outlet for research, and (2) manuscript acceptance has become more challenging. This paper provides prospective authors a set of recommendations that will hopefully enable them to submit more competitive manuscripts to *CDI*. The recommendations are derived from the previous discussion and are summarized in Table 1.

Insert Table 1 about here

This paper contends that for a manuscript to make a contribution to the literature on careers, one must first begin with one or more interesting research questions and frame them in sound theory. Focusing on the interesting and novel aspects of a journal submission, the role of a good hook was highlighted. A good hook identifies a research gap and positions the theoretical and practical contributions of addressing a research gap. As such, it quickly and elegantly walks the reader through a narrative of what we know, what we don't know, *why we need to know it*, and how it will be examined. While a captivating hook is essential to draw the interest of reviewers and readers, a publishable contribution must be based in and contribute to theory. Strong theory delves into the underlying processes enabling understanding the systematic reasons for a particular occurrence or nonoccurrence. Strong theory provides the context for the study and justification for why we need to know answers to the research questions posed.

In the second section, the critical components of testing research questions were examined. When designing the study researchers need to decide on the sample size and composition, the type, number and timing of measurements, the use of control variables, and the degree of freedom in further exploring the data after the results are known. Unlike many areas of

organizational behavior, psychology and human resources, the essence of careers is longitudinal events and behaviors. The implications for this are that, for many research questions, working populations are the best sample sources. At the same time, student samples may be appropriate for topics such as career choice, perceived employability and other pre-employment issues. The contribution of empirical careers research depends on use of reliable, valid and relevant measures. We advocate use of established scales and measures in order to add to the nomological network of the careers domain examined. We discourage removal of items from established scales without justification and explanation. Use of archival, objective and organization-sourced data, consistent with research questions examined, is encouraged in addition to self-report surveys. Control variables should be included in the analyses only if there are strong theoretical or logical reasons to do so, and, like all other variables, should be operationalized using reliable and valid measures. We advise against ‘question trolling.’ Instead, prospective authors are recommended to report their nonsignificant findings and submit their work to *CDI* to the extent that it has a solid theoretical basis. Authors are encouraged to explore the data in search for explanations and articulate how their findings challenge, advance or change theory.

We discussed in some depth appropriate research designs for research questions asking why specific phenomena occur and those involving questions of direct and indirect causality. Specifically, three longitudinal mediation models were discussed: (1) the cross-lagged panel model (CLPM), (2) the latent growth curve model (LGM), and (3) the latent change score (LCS) model. These models allow researchers to examine how effects unfold over time, rather than modeling all effects simultaneously using traditional mediation models. Although we advise against the use of cross-sectional designs to test cause-and-effect relationships, this does not necessarily mean that cross-sectional studies cannot have a place within *CDI*. In our view, it

would be a wrong reflex to dismiss cross-sectional studies as inferior and incapable of contributing to the academic conversation about careers. Despite its limitations, cross-sectional data can be used creatively to still generate valuable insights. We referred to the possibility of performing multilevel analyses, using person centered methods or conducting psychological network analysis, but of course this is only a very selective sample of the various methods available to researchers to answer questions that circumvent the limitations of cross-sectional data.

To finish off, we hope this paper helps prospective authors to formulate their research questions and set up their quantitative research and look forward to receiving their contribution for publication consideration in *CDI*.

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