Handling Time in Occupational Stress and Well-Being Research: Considerations, Examples, and Recommendations

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Abstract

In this chapter, we consider the role of time for research in occupational stress and well-being. We first discuss temporal issues in studying occupational health longitudinally, focusing in particular on the role of time lags and their implications for observed results (e.g., effect detectability), analyses (e.g., handling unequal durations between measurement occasions), and interpretation (e.g., result generalizability, theoretical revision). Then, we discuss time-based assumptions when modeling lagged effects in occupational health research, providing a focused review of how research has handled (or ignored) these assumptions in the past, and the relative benefits and drawbacks of these approaches. Finally, we provide recommendations for readers, an accessible tutorial (including example data and code), and discussion of a new structural equation modeling technique, continuous time structural equation modeling, that can “handle” time in longitudinal studies of occupational health.

Keywords: time, occupational health, lagged effects, continuous time structural equation modeling

Handling Time in Occupational Stress and Well-Being Research: Considerations, Examples, and Recommendations

The issue of time is a perennial topic in the study of occupational stress and well-being, and a range of recommendations have emerged over the years for how to best “handle” time in longitudinal occupational health research (e.g., Dormann & Griffin, 2015; Kelloway & Francis, 2013; Taris & Kompier, 2014; Zapf, Dormann, & Frese, 1996). Forming an understanding of how phenomena, such as stressor–strain relationships, manifest and change over time is critical to the development of rigorous occupational health theories, studies, and interventions. However, studying phenomena *over time* (i.e., longitudinally) does not automatically translate into studying phenomena *with respect to time* (i.e., treating time as a substantive factor in research design, analysis, and interpretation). Although this is a subtle distinction to draw, it is an important one.

Without the latter focus, longitudinal data are, at best, underutilized, and, at worst, misinterpreted and misrepresented—particularly when collected data are unequally spaced, which is a common issue in longitudinal research (e.g., Mehta & West, 2000; Singer & Willett, 2003; Sterba, 2014). The adoption of structural equation modeling (SEM) approaches that treat time more focally and flexibly, such as continuous time SEM, present an opportunity for occupational health researchers to directly address such issues. Continuous time SEM allows for time intervals to vary both between and within participants, enabling flexible and more time-centered analyses of longitudinal data when compared to traditional and frequently adopted discrete-time analytic approaches. Thus, this approach addresses both the properties of one’s data, such as the unequal spacing of measurements, as well as the inferences one hopes to draw, such as those regarding relationships over different periods of time, or under the assumption of continuously operating processes.

We begin this chapter with an overview of temporal issues (namely, time lags) in longitudinal occupational health research, as well as their implications for observed results, analyses, and interpretation. Then, we provide a focused review of how time has been handled in past research and to what end (i.e., what time-based assumptions were made). Finally, we conclude with recommendations to readers for “tending to” time in occupational health research moving forward, providing an accessible continuous time SEM tutorial, including example data and code, and discussion of relevant time-based decisions for occupational health researchers.

THE ISSUE OF TIME IN OCCUPATIONAL HEALTH RESEARCH

In recent years, calls for more longitudinal occupational health research (i.e., repeated data collection of the same variable(s) with a given sample over three or more time points; Ployhart & Vandenberg, 2010) in intensive forms, such as daily diary, experience sampling, measurement burst methodologies, and more protracted forms, such as studying phenomena over longer periods of time like months or years, have been widespread (e.g., Brusso, Cigularov, & Callan, 2014; Kelloway & Francis, 2013; Zapf et al., 1996). Although an overreliance on cross-sectional research, particularly with respect to supporting causal claims, is certainly problematic (e.g., Maxwell & Cole, 2007), under-recognition of and attention to time in longitudinal occupational health research similarly challenges the practical utility and interpretability of the literature. Specifically, sufficient consideration of how time lags between data collections shape observed results, analyses, and conclusions is greatly needed. Then, our understanding of how occupational stress and well-being phenomena manifest, develop, and change over time can become more systematic and serve sound theory development as well as rigorous research and practical applications.

There are two primary ways to approach this shift: on the front end, during research design and methodological decision-making, and on the back end, during data analysis and reporting. The former approach has been frequently used in past work (Dormann & Griffin, 2015; Taris & Kompier, 2003, 2014), but remains daunting in many cases. For example, there is mixed guidance for and practice of choosing optimal time lags for studying occupational health phenomena (e.g., stressor–strain relationships; Dormann & van de Ven, 2014). This is made yet more challenging by the nature of conducting longitudinal research, including such issues as participant attrition, missing or incomplete data, and variability in recontact and responses. In contrast, the latter approach is not encumbered by the same issues and is one that we believe has received too little attention.

These approaches are by no means mutually exclusive: researchers should strive to design research that allows them to draw inferences of interest, and they should conduct analyses that pertain to such inferences. However, time-focused analyses should prove useful in a number of cases: the nature of timing decisions are without clear precedent in much of the social and organizational sciences (Dormann & Griffin, 2015; Mitchell & James, 2001), and time lag variability is often uncontrollable (e.g., as with archival data) yet consequential and practically significant. Moreover, dynamic processes, including those that unfold in nonlinear or oscillating ways, may be best studied in deliberately time lag-variable designs. Similarly, models of occupational stress that explicitly describe continuous, not discrete, effects (e.g., stress reaction models; Frese & Zapf, 1988) would benefit from a continuous and intentionally time-varying approach, as there is not one “true” lag (i.e., the “lag problem”; Cole & Maxwell, 2003; Gollob & Reichardt, 1987; Reichardt, 2011).

What are the potential implications of time lags for occupational health research? We focus on the absolute and relative influence of time in three main areas (results, analyses, and interpretation), taking time to “set the stage” for our discussion of continuous time models. In other words, we discuss both the implications of absolute lag lengths and conceptualization, as well as how lag lengths differ and compare within a sample. Many time lag implications span more than one area, but are reported where they originate or primarily “live” in research. That is, they are reported where they present challenges or raise questions for researchers in terms of whether, or in what form, results are observed, how data should be analyzed, and how data can be interpreted.

Time Lag Implications: Observed Results

First, time lags have direct consequences for the detectability of hypothesized and/or “true” effects in one’s sample. If the length of time that passes between data collections does not “match” the interval at which one would expect change to occur and/or phenomena to manifest, effects may remain undetected or may be misrepresented. Time lags can be “too” long, “too” short, or just generally misspaced across the data collections of a longitudinal study. All of these issues have consequences for the incidence, direction, and/or magnitude of observed effects (Cole & Maxwell, 2003; Collins & Graham, 2002; Reichardt, 2011), as well as model fit and relative construct “importance” (i.e., variance explained; Deboeck & Preacher, 2016).

Although the analyses we recommend later in this chapter do not remediate poorly chosen and/or executed lags, the nuance added through this time-focused analytic approach does provide ways of more directly thinking about both (a) the implications of time for observed findings and (b) the potential differences in effects that would be observed given different time lags. For example, they may give us a better idea of the range of effect detectability for

occupational health processes. They may also aid in making the choice of and adherence to equivalent lags less of an imperative. This, in turn, would free resources that can be dedicated to more substantive methodological concerns, such as sampling, measurement tools and modes that introduce more potential time variability, and avoidance of participant habituation. Resources could also be used to study occupational health phenomena in a wider variety of dynamic and innovative ways (e.g., oscillating processes, Voelkle & Oud, 2013; see also Ryan, Kuiper, & Hamaker, 2018; Selig, Preacher, & Little, 2012). Moreover, it would facilitate the use of data that otherwise might be discarded or manipulated ineffectively (e.g., mean imputation, listwise deletion) due to data missingness. By reframing “missing data” in continuous, temporal terms, data can still provide an opportunity to study processes (Oud & Voelkle, 2014).

To this point, time lags additionally have implications for the “meaning” of observed results depending on how time is conceptualized and measured in studies. Time can be defined and scaled in a variety of ways, mainly including time elapsed in a variety of units, and as a proxy for development or change (e.g., age/aging in a range of possible units; Li & Schmiedek, 2002). Both of these forms can be calculated between each data collection, such as between the first and second data collection, between the second and third data collection, and so on. Alternatively, time lags can be calculated in comparison to a reference point across the course of a study, such as the duration of time between the first and second data collections, the first and third data collections, and so on. Due to this malleability, and the fact that time lag variability can exist both within and across one’s sample, the way that researchers treat time in their studies can have wide-reaching implications. These include consequences for the nature of observed and reported results, including the level of nuance versus breadth captured, and the study’s focus on intra- versus inter-unit effects. In other words, aside from their impact on effect detectability,

time lags also impact whether the “right” effects are observed. Here, “right” refers to representativeness and both theoretical and practical significance.

Time-focused analytic methods do not, by any means, make lag decisions “for” researchers, nor should they. However, these methods push researchers to consider various ways of thinking about time lags within and across their sample, and to make both methodological and conceptual decisions that will be maximally informative and meaningful for theory and practice. Whether we can detect given effects, and do so representatively, depends largely on time lags, as does how we observe and report over-time effects.

Time Lag Implications: Analyses

Time lags have similarly profound implications for the analyses that researchers can and should perform with their data. If time lags are unequal within or across participants, many of the analyses that are commonly performed with longitudinal data in the social sciences are inappropriate to apply. Traditional cross-lagged and autoregressive panel models do not “know” whether time intervals are equal across data collections and participants. Instead, these analytic approaches model relationships under the presumption of equidistant measurement and, in case of unequal lags, return biased results (de Haan-Rietdijk, Voelkle, Keijsers, & Hamaker, 2017; Kuiper & Ryan, 2018; Mund & Nestler, 2019). Moreover, even under conditions of equal time lags, common panel analyses do not permit for cross-study comparability or parameter extrapolation to alternative time intervals. This makes it more challenging for researchers to explain why, for example, their findings contrast those of a previously published paper: one possible explanation, and one that could be tested in a continuous time framework, is that both studies are reporting “real” effects that manifest at different time intervals. This is untestable in traditional, discrete modeling, however. Incompatible and biased results are problematic from the

standpoint of individual study validity and literature-wide integration. Both could be remedied, at least in part, through analyses that place focus on the very implications that time lags have for data and observed effects.

The computational formulae to explain this principle are outside the scope of the present chapter, but we can essentially consider traditional, discrete time panel modeling approaches to be specific cases of a more general continuous time framework. Specifically, discrete time parameters are a function of continuous time matrices and are related to an assumed underlying model (e.g., a continuous process) over infinite time through stochastic differential equations (see Kuiper & Ryan, 2018; Voelkle, Gische, Driver, & Lindenberger, 2018; Voelkle, Oud, Davidov, & Schmidt, 2012, for more detailed discussion, formulae, and proofs). Thus, when lags are spaced equally, discrete time analyses provide only a “snapshot” of effects that are specific to a particular lag; when lags do not conform to the assumption of equal spacing, discrete time analyses result in biased parameters and test statistics. Continuous time analyses, in contrast, treat time lags in a more central and flexible fashion. This attunes the analytic process to both the general state of the literature at large and the nature of one’s data. Regarding the former point, this concerns how the time lags in a given study parallel or diverge from those already reported in the literature, and therefore if and how results can be compared. The latter point involves the length of time between data collections within and across sample units. Time lags have a clear role in determining the appropriateness of certain analyses, as well as the interpretability of these analyses alongside existing literature and theory, which will be discussed more next.

Time Lag Implications: Interpretation

The final area in which time lags have great impact is in the interpretation and interpretability of longitudinal study findings. This point has already been alluded to but bears

more elaboration. Specifically, time lags have implications for the generalizability of one's findings and their translatability to theoretical revision. Lags also have implications for the ways study findings can be interpreted in the context of theory and past studies. These points are interrelated: they are based around the idea that the lags used in a given study, whether uniform or variable, necessarily constrain the degree to which study findings can be expected to replicate across different conceptualizations and lengths of time. This idea is an offshoot of our earlier discussion of effect detectability. Still, it extends into how and whether studies should be interpreted as well as used to revise theory.

Based on the lag(s) used in a study and how they compare to other studies' lag(s) in the literature, it may or may not be appropriate to interpret a study as refuting or corroborating past findings. Similarly, it may or may not be appropriate to use a given study to support or prompt revision of theoretical perspectives. More integrative and meta-analytic work focused on time will help to this end (e.g., see Ford et al.'s, 2014, time-focused meta-analysis of stressor-strain effects; see also Dormann, Guthier, & Cortina, 2019; Guthier, Dormann, & Voelkle, 2020; Mäkikangas, Kinnunen, Feldt, & Schaufeli, 2016; Maricuțoiu, Sulea, & Iancu, 2017; for a discussion of time lags as a moderator in meta-analysis, see Card, 2019). In addition, a more thorough and explicit account of time at the individual study level is needed.

The concepts of effect detectability, stability, and replicability, and their dependency on time lags, are familiar to the psychological sciences (e.g., Dormann & Griffin, 2015); this is especially true when considering vastly different lags or effects in intervention studies. For example, no one is likely to assume a relationship studied and observed at the day-level will remain the same over the course of years. With regard to interventions studies, it is well acknowledged that intervention effects fade, strengthen, or otherwise change over time (e.g., see

Kelloway & Barling, 2010). However, at a high level, lag dependency seems to be recognized as a limitation in study conclusions, with authors claiming they could have observed or replicated certain effects if they had chosen a different lag. Lag dependency can also serve as a starting point for more nuanced and continuous thinking about time and occupational health phenomena, however. Just as time lags constrain how results can and should be interpreted, they also provide an opportunity, when considered more flexibly, to expand our understanding of stress and well-being in the work context. For example, this may be the case when time lags are acknowledged to be variable and analyzed as such, or when they are intentionally varied within a study.

The continuous time analyses discussed later permit a more integrative way of “handling” time within a single study, as well as for discussing study conclusions in light of past and present temporal characteristics. As Voelkle and colleagues (2018) write, “without considering how the dynamics of the system play out over the entire time range, it is easy to arrive at incorrect conclusions” (p. 789). Particularly for the study of occupational health, which is defined by dynamics, multivariate systems, and a focus on intervention effectiveness (see Voelkle et al., 2018), the role of time in shaping study interpretations and conclusions is apparent. Having temporally oriented analytic tools will help the occupational health field to fully utilize and accurately represent longitudinal data in the literature. Eventually, it can also enable researchers to prioritize integration and innovation over often unnecessary, and perhaps counterproductive, time lag uniformity in their studies.

PAST APPROACHES TO HANDLING TIME IN OCCUPATIONAL HEALTH RESEARCH

There are a number of ways that longitudinal studies in the occupational health psychology literature have “handled time” to this point. Each of these approaches bears various assumptions, benefits, and drawbacks that we will outline next. Importantly, and due to its

primacy in contemporary occupational health research, we focus only on longitudinal panel data analyses and ways of “handling time” therein. We do not discuss cross-sectional or time series data, wherein multiple participants at one time point, or one participant/unit over multiple time points, are studied, respectively. Still, many of the analyses described in this and later sections can be applied to time series data, as many panel SEM analyses are extensions of time series SEM analyses (McArdle, 2009; e.g., continuous time dynamic SEM; McNeish & Hamaker, 2019).

Broadly, these approaches can be classified into those that (a) ignore the issue of time lag variability entirely, (b) attempt to account for, but not directly consider or focally study, time through data restructuring or variable creation (e.g., phantom or definition variables, multigroup analyses), or (c) utilize non-SEM analyses that are unencumbered by the “lag problem” in the traditional sense but still have a number of drawbacks (e.g., linear mixed-effects modeling). In each case, these approaches still “fall short” of studying phenomena *with respect to time*, and many prove impractical or even inappropriate in particular longitudinal data contexts. Thus, even modifications of such approaches that purport to deal with time more directly, such as growth curve slope modifications (Bliese & Lang, 2016) or flexible scaling of time in linear mixed-effects modeling (Singer & Willett, 2003), still treat time discretely rather than continuously. Moreover, these approaches bear various limitations, including the degree to which (a) causality can be inferred, (b) within-person variability in timing can be addressed, and (c) inherently dynamic and continuous processes can be studied in appropriately dynamic and continuous ways. Continuous time modeling addresses these concerns, serving as both a more practical and more representative analytic approach for longitudinal data analyses (see Table 1 for an overview of the various approaches and their attributes and limitations).

INSERT TABLE 1 ABOUT HERE

Each of these analytic methods treats time and phenomena discretely and/or statically rather than continuously and/or dynamically (Voelkle et al., 2018). Such limitations create roadblocks to cross-study comparisons, the accuracy/representativeness of a given study's results, and furthering our understanding of development and change in occupational health phenomena (e.g., inter- vs. intra-individual dynamics). If we want to explore and chart the trajectory of stressor–strain relationships in the work context, including studies of exposure time, accumulation, and sleeper effect models (Frese & Zapf, 1988; see also Ford et al., 2014), adopting a dynamic and continuous approach to handling time in occupational health research will be greatly beneficial. This will allow us to take full advantage and account of the properties of our longitudinal data, and to better synthesize our findings across the literature. Thus, prioritizing analytic tools that focus on time as an integral part of our studies and processes, as well as tools that allow for the study of within- and between-unit stability and variability, is paramount.

The first category of approaches, those that ignore time lag variability entirely and assume lags are equidistant, includes such analyses as traditional cross-lagged panel models, latent growth curve models, and latent change score models (also known as latent difference score models). Each of these modeling techniques has been widely recommended and adopted in the occupational health literature for longitudinal data analysis (e.g., Kelloway & Francis, 2013; Liu, Mo, Song, & Wang, 2016), yet their limitations for studying phenomena “with respect to time” are often overlooked or inappropriately diminished.

Briefly, cross-lagged panel models allow researchers to consider lagged relationships and change. This is accomplished through the consideration of two or more constructs measured at

two or more time points, and modeling both cross-lagged (i.e., between a construct at one time point and another construct at the following time point) and autoregressive effects (i.e., the effect of a construct on itself over time), including alternative pathways that can help with causality claims (Liu et al., 2016). It is important to emphasize, however, that longitudinal research requires three or more data collections. With only two time points, cross-lagged panel models can solely assess between-person change (i.e., differences in mean levels, which are a form of change), while within-person change can only be identified with three or more data collections. Also, cross-lagged panel models are limited in the levels and forms of change they can identify: they consider rank-order change and do not parse within- from between-person effects (Hamaker, Kuiper, & Grasman, 2015). Halbesleben (2010), Liang et al. (2017), and Meier and Spector (2013) provide helpful examples of cross-lagged panel modeling using three waves or more of longitudinal data in the occupational health literature.

Latent growth curve and latent change score models address this gap in slightly different ways (Mund & Nestler, 2019). Latent growth curve models allow researchers to consider different aspects of change in their phenomena of interest, such as considering average (e.g., initial) construct levels and rates of change (i.e., an overall mean trajectory and how individuals differ from it), which are otherwise obscured by studying rank-order change alone (Liu et al., 2016; McNeish & Matta, 2018). Unlike cross-lagged panel models, these models can parameterize time flexibly (Singer & Willett, 2003). However, latent growth curve models' flexibility for studying different forms of change comes at the expense of causal ambiguity (Ferrer & McArdle, 2010). Latent change score models include latent variables to represent change in a given construct between adjacent measurement occasions, in addition to change trajectories as in latent growth curve models. This allows researchers to assess multiple forms of

change, dynamics, and trends more specifically and with a more causal orientation than cross-lagged panels or latent growth curve models (Liu et al., 2016; Mund & Nestler, 2019; Voelkle & Oud, 2015). We direct readers to Eschleman et al. (2014) and Keller et al. (2020) for examples of latent growth curve modeling, and to Taylor et al. (2017) and Zacher et al. (2018) for examples of latent change score analyses in the occupational health and organizational psychology literatures.

Cross-lagged panel, latent growth curve, and latent change score models represent both static and dynamic approaches to studying longitudinal panel data. The static approach focuses on a variable system's state as a function of time rather than causal relationships or within-person changes. In contrast, the dynamic approach focuses on a variable system's changes within-person over time, considering past levels as influential to this end (Voelkle et al., 2018). These approaches allow for longitudinal analyses either in their basic form or in more advanced variations, for instance to better separate between- from within-person sources of variance (e.g., cross-lagged panel models with random intercepts, Hamaker et al., 2015; adding an autoregressive component and standardized residuals to latent growth curve models, Curran, Howard, Bainter, Lane, & McGinley, 2014; dual change score modeling as a variation of latent change score models, McArdle & Hamagami, 2004).

Despite these modeling extensions, which help in adding nuance to our dynamic understanding of occupational health phenomena, the limitations of discrete time approaches prevail. Specifically, the basic and oft-adopted forms of cross-lagged panel and latent growth curve models “assume” that time lags are equivalent within and across units. They treat data collections categorically and do not consider lag length, returning parameters based on that often-false assumption. Latent change score models “assume” that latent variables are measured

at equally spaced time intervals even if their observed variables were not (McArdle, 2009). This is an intriguing, albeit potentially impractical and limited, assumption, depending on the temporal nature of one's focal construct and its theory of difference/change (see also Voelkle & Oud's, 2015, discussion of latent change score models and unequal intervals). It is worth noting that cross-lagged panel and latent growth curve models can be modified and suggested to "account for" unequal time intervals. This can be accomplished by freeing cross-lagged relationships to vary between data collections rather than holding them equal, or by taking a definition variable approach, discussed more next, by rescaling slope factor loadings to align with the unequal intervals (Liu et al., 2016). However, these models still do not account for potential within-subject variability in time intervals, and, by extension, for the continuous influence of variables on one another between measurement occasions (e.g., Kuiper & Ryan, 2018).

There are a number of additional ways in which researchers have modified these models to account for, yet not directly study, time (i.e., the second category of approaches mentioned above). Each of these approaches has their own limitations or challenges, depending on the phenomena and study characteristics in question. These include, but are not limited to, the use of phantom variables, definition variables, forms of multigroup analysis, and time recoding. Unfortunately, most of these approaches are implemented without explicit discussion in published manuscripts, and thus do not have many applied examples to consult in the occupational health or psychology literature (see the multi-group latent growth curve analysis in Gomez et al., 2013).

Phantom variables (Rindskopf, 1984) entail inserting latent variables with no observed variables into one's model to artificially create equal time intervals between data collections.

This approach thus treats unequal time intervals like missing data. However, this approach is only applicable to unequal intervals across measurement occasions and not to unequal intervals within participants. It can also become unwieldy to apply when patterns of “missingness” are complex (McNeish & Matta, 2018; Voelkle & Oud, 2015).

The use of definition variables overcomes some of these limitations by constraining model parameter values (e.g., slope factor loadings) to be equal to another observed variable in the model, such as individuals’ data collection time points. Definition variables thus allow for a degree of variability within as well as between individuals in data collection timing (Mehta & Neale, 2005; Mehta & West, 2000; Serang, Grimm, & McArdle, 2016; Sterba, 2014). However, this approach has still been observed to bias parameter estimates in some cases (e.g., in latent change score models; see Voelkle & Oud, 2015) as well as result in convergence issues (McNeish & Matta, 2018). It remains a static approach to modeling phenomena in other cases (e.g., latent growth curve models; Voelkle et al., 2018), with a high reliance on time coding decisions for model interpretation (e.g., Biesanz, Deeb-Sossa, Papadakis, Bollen, & Curran, 2004; Blozis & Cho, 2008; Mehta & West, 2000). The addition of an autoregressive component and the separation of within- and between-person sources of variance in latent growth curve models with definition variables would “solve” this static issue, in that it would allow for more causal investigation and interpretation. Continuous time structural equation modeling (CTSEM) appears to be the more logical solution, however, as it can address all of these components in continuous time. Yet more, even if we are to believe that variable adjustments help account or “correct” for the issue of time lag variability between and/or within participants, taking a discrete time approach to longitudinal data analysis still stunts our ability to compare findings across

studies. Discrete time approaches also implicitly assume processes do not continue to operate between data collections.

There are two other SEM approaches to the time lag issue taken in the literature. First, Preacher and colleagues (2008) discuss the use of a multigroup comparison approach, wherein a latent growth curve model is fitted to groups of individuals with the same measurement schedule (Preacher, Wichman, MacCallum, & Briggs, 2008). However, as Preacher and colleagues note, this approach is only feasible in cases where there are a limited number of patterns of measurement in a sample. This approach is also limited with respect to the nuance of time captured: it requires the identification of particular schedules, which implies the loss of temporal detail. Indeed, this represents another example of treating time discretely. Second, it is possible to rescale the timing variable in one's data so that time intervals appear to be equivalent. For example, one may move all participant timing variables into absolute year units and therefore "do away with" some variability. However, this comes at the expense of temporal detail (McNeish & Matta, 2018) and should only be attempted when deemed appropriate, for instance, when the time unit differences are otherwise without practical meaning.

Finally, non-SEM approaches to studying occupational health over time are adopted as well (i.e., the third category of existing approaches in the literature). These, too, bear limitations for our temporal understanding of phenomena. Linear mixed-effects modeling is chief among these approaches, and it is generally known to be equivalent to latent growth curve models (e.g., Curran, 2003; Curran & Bauer, 2011). As noted by McNeish and Matta (2018), linear mixed-effects models are not burdened with the same time lag issues and assumptions as are latent growth curve models: data are organized in long format for linear mixed-effects modeling and, thus, variables are treated univariately (i.e., repeated measures are represented within a single

column) with time easily incorporated as a model predictor. Indeed, in linear mixed-effects models, time can be coded explicitly, as in a latent growth curve model, and/or represented by modeling a time-varying predictor, such as age, as a within-person factor. Moreover, no special reformulations are required to study phenomena over time in a linear mixed-effects modeling framework. This analytic approach is growing increasingly common in the occupational health literature, and we direct readers to Urbach and Weigelt (2019) or Weigelt et al. (2019) for recent applied examples.

However, there are a number of time-relevant decisions that researchers must make when conducting linear mixed-effects modeling (e.g., centering, as with latent growth curve models; detrending, e.g., Wang & Maxwell, 2015), and researchers cannot specify latent variables with multiple indicators or capitalize on SEM's handling of measurement error in linear mixed-effects modeling. Moreover, time is not considered causally in linear mixed-effects models (i.e., as with latent growth curve models; see Voelkle et al., 2018; Voelkle & Oud, 2015). Relatedly, lagged associations can be approximated but may be inappropriate (e.g., Allison, Williams, & Moral-Benito, 2017) and difficult to specify (e.g., Hamaker & Grasman, 2015; McNeish & Hamaker, 2019; Schuurman, Ferrer, de Boer-Sonnenschein, & Hamaker, 2016). Thus, although time-based assumptions are not required when conducting linear mixed-effects modeling, issues related to time, and to studying processes dynamically, persist.

CONTINUOUS TIME SEM IN OCCUPATIONAL HEALTH RESEARCH

Unlike these methods, continuous time SEM (CTSEM; or, as it is more precisely called, continuous time dynamic SEM, Voelkle et al., 2018) does not assume time lags are equal across measurement points, nor does it use discrete time intervals to calculate rates of change over time (e.g., as in discrete-time latent difference score modeling). Instead, its parameter estimates, and

the matrices from which these estimates are derived, are based on the treatment of time as a continuum, and the underlying calculations require differential calculus. This entails allowing time to be continuous, with time values approaching zero and taking on infinitesimally small values (see Kuiper & Ryan, 2018; Voelkle & Oud, 2015; Voelkle et al., 2012). Moreover, these time intervals can vary both within and across participants, which is not easy to accommodate in the approaches discussed earlier (Voelkle & Oud, 2013). CTSEM can be applied to a variety of different (traditionally discrete time) SEM techniques, including both static and dynamic approaches (e.g., latent growth curve models, cross-lagged panel models; Voelkle et al., 2018). This is possible as CTSEM is analogous to existing approaches, returning the same or very similar values for discrete time intervals when certain conditions are met (e.g., Deboeck & Preacher, 2016; Kuiper & Ryan, 2018; Voelkle & Oud, 2015).

For purposes of the present work, and for the sake of parsimony, we present a relatively straightforward application of CTSEM to a cross-lagged panel model with two variables. We highlight a simple example to help readers familiarize themselves with and understand CTSEM fundamentals, which can be applied to specify a variety of other models (e.g., with more observed and/or latent variables, other path specifications). To complement this basic model, we also demonstrate how models can be expanded to include trait-like random intercepts that separate within- and between-person variance (i.e., as in cross-lagged panel modeling with random intercepts; Hamaker et al., 2015) and, therefore, best account for both time and dynamics. This is to say, we give an example of how CTSEM can account for inter- and intra-individual sources of variability, as well as change as a function of earlier variable levels, along with treating time continuously. Importantly, we refer to our two variables using highly familiar monikers from the occupational health literature to facilitate comprehension and to aid in

interpretation: “stressor” (e.g., workload, time pressure, incivility) and “strain” (e.g., burnout, depression, somatic complaints).

Simulated data and example code using the ‘ctsem’ package in R (Driver & Voelkle, 2018) are available in our online appendix (<https://osf.io/vd5h3/>) as a CTSEM tutorial, along with more detailed interpretation of simulated data results and plots. We spend the remainder of this section discussing CTSEM in more detail and its critical decision-points and considerations, particularly for occupational health research (see Figure 1 for a visual flowchart of conducting CTSEM analyses).

INSERT FIGURE 1 ABOUT HERE

CTSEM Tutorial

Continuous time modeling has existed for decades, originating in and most widely adopted by physics and other physical or natural science disciplines (see Oud & Delsing, 2010, for a review). However, continuous time approaches have more recently been adopted by the social sciences (e.g., economics and econometrics; Bergstrom, 1988), slowly filtering into the study of psychological processes and mechanisms with the rise in available software programs and computational advancements (Deboeck & Boulton, 2016; Oud & Jansen, 2000). Another driver of the increased adoption has been the recognition of fundamental flaws and limitations of discrete time modeling approaches. Still, the use of these methods, and the interpretation of resulting output, can prove daunting to researchers, particularly those unfamiliar with differential calculus and stochastic differential processes and equations therein. Our tutorial is meant to provide an accessible guide for occupational health researchers of all backgrounds who want to adopt CTSEM in their work, but we direct readers to a number of other works for details on the equations and proofs “behind” such analyses (e.g., Kuiper & Ryan, 2018; Oud & Jansen, 2000;

Voelkle et al., 2012) and further R package guidelines and customization options when using ‘ctsem’ (Driver, Oud, & Voelkle, 2017). The present chapter is geared as an adjunct to the existing technical CTSEM literature, striving to explain key terminology and concepts from CTSEM in terms familiar to psychology researchers, and providing a “hands-on” guide for occupational health psychologists looking to apply a continuous time approach in their own work.

Finally, although we do not delve deeply into this topic, we want to emphasize that many of the diagnostic and descriptive data assessments necessary with other forms of longitudinal data analysis are similarly important for CTSEM. For example, establishing measurement invariance, or the equivalence of measurement tool functioning over data collections, is an important first step in conducting CTSEM analyses (Oud, Voelkle, & Driver, 2018). Moreover, CTSEM uses a full information maximum likelihood (FIML) estimator (Driver et al., 2017), which operates under the assumptions of missing at random (MAR) and multivariate normal observed variables. Researchers need to visually and statistically assess their data to ensure normality and invariance assumptions are met, and, if not, will need to address violations accordingly. For example, if observed variables are non-normal, alternative estimation methods can be used (e.g., maximum likelihood estimation with robust standard errors; asymptotic distribution-free estimation), although these can only be specified and used in ‘OpenMx’ (Neale et al., 2016) rather than the ‘ctsem’ package presented herein (Driver et al., 2017).

Preparing the Data

As an important first step, researchers must structure their data (i.e., with respect to variable ordering and row/column organization) and name their variables according to ‘ctsem’ conventions. Specifically, data must be organized in wide format, with observed variables

grouped together by the time wave at which they were assessed (i.e., variable 1 at Time 1, variable 2 at Time 1, etc.; variable 1 at Time 2, variable 2 at Time 2, etc.) and followed by the time interval variables in chronological order (i.e., time interval 1, time interval 2, time interval 3, etc.). The observed variables must be named with the variable name followed by “_T” and the time interval at which the variable was measured, beginning at 0 (i.e., V1_T0, V2_T0, V1_T1, V2_T1, etc.), while the time intervals are denoted by “dT” and the time interval they represent (i.e., dT1, dT2, dT3, etc.). If other predictors are included in analyses, they are ordered in particular ways within the dataset as well (i.e., time-dependent, or -varying, predictors between the observed variable block and the time interval block; time-independent predictors following the time interval block) and named similarly (i.e., time-dependent predictors with “TD” followed by a number, “_T”, and the time interval at which the predictor was measured, e.g., TD1_T0, TD1_T1; time-independent predictors with “TI” followed by a number, e.g., TI1, TI2; Driver et al., 2017).

If data are not already in wide format, they can be converted from long (i.e., multiple rows of data for each participant, with each row corresponding to each time point) to wide (i.e., one row of data for each participant, with each column corresponding to each variable at a given time point) format in ‘ctsem’ using the `ctLongtoWide` function. Time intervals (i.e., passage between data collections) can also be calculated from absolute data collection times (e.g., time/date of specific collection) using the `ctIntervalise` function. Alternatively, these steps can be accomplished manually. Depending on the complexity of the data, including the number of variables considered and patterns of missingness, it may be unwieldy to convert the data manually. However, ensuring that appropriate time intervals are calculated, and taking the opportunity to do so in the time unit of most theoretical and practical significance, is best

accomplished by reformatting the data manually. This also provides an opportunity to better understand the structure of the data in CTSEM, so we recommend this approach whenever possible. Moreover, existing archival datasets for occupational health research often are structured in wide format once multiple waves are merged (e.g., Midlife in the United States data; Radler, 2014). With such datasets, the conversion to CTSEM formatting should be straightforward to accomplish manually: researchers would simply need to rename and reorder variables, as well compute time intervals depending on the nature of the time variables already included in the dataset.

When calculating time intervals, whether doing so manually or with the use of the `ctIntervalise` function, researchers will need to decide how to scale time: relative to individual participants, or relative to the full sample. Both approaches still account for continuous time, but they have different implications for the “spread” of one’s data. Individual-relative scaling sets each participant’s first measurement occasion to “T0”, whereas sample-relative scaling sets measurement occasions in relation to the first data collection in the sample; thus, the latter approach potentially results in a wider variety of time intervals represented, and potentially only one set of observations at each measurement occasion. We recommend that occupational health researchers base their decision about time scaling in their expectations for and knowledge of given phenomena within the scope of their research design (e.g., an intervention study would have different implications for this decision than would a more descriptive study), while also thinking flexibly and creatively about how time units and scalings can be used to study relationships and outcomes of interest (Singer & Willett, 2003). Driver and colleagues (2017), for example, discuss the use of individual-relative time scaling with age as a timing variable when studying aging and/or developmental processes. Alternatively, if the focus

is more directly on chronological age itself (i.e., rather than aging and developmental trajectories within individuals), sample-relative time scaling may be useful to leverage with age as a timing variable. This is particularly true if intensive longitudinal data are collected over a shorter period of time, allowing one to mimic an accelerated cohort design (Bell, 1953; Miyazaki & Raudenbush, 2000).

Scaling considerations are moot if processes at the initial time point are assumed to be stationary rather than predetermined, which is another important consideration for occupational health researchers. The stationarity assumption entails that the latent processes being studied are independent of their initial states and are estimated to be at asymptotic equilibrium values, or the model-predicted means and variances. In contrast, predetermination makes no assumptions about latent processes before one's initial data collection and thus estimates latent variable parameters freely at the first time point. Importantly, this is a separate (albeit related) discussion from the stationarity of variables over time, which is an often adopted and appropriate assumption to make: without reasons to believe variable properties change over time (Dormann & Griffin, 2015, p. 5), opting for the 'ctsem' variable stationarity default is acceptable (i.e., holding between-subject variances, factor loadings, manifest variable error terms, and drift and diffusion parameters stationary; see also Oud, 2002). Regarding time point stationarity, however, researchers should again consider their research design, processes of interest, and the timing of their study relative to the "start" of these processes when defining their initial time point. Driver and colleagues (2017) provide more discussion of this point as well as other functions that can be used (e.g., specifying T0 as preceding the start of data collection, in the case of the predetermination assumption), which we direct interested readers to consult.

For our tutorial, we simulated participant-nested data (i.e., a longitudinal panel data collection) using the `sim.multi` function in the ‘psych’ package (Revelle, 2019) with a sample size of $N = 100$ observed with respect to two variables over five time points (i.e., total $n_{obs} = 500$). We encourage readers to modify the sample size, number of time points, number of variables, and other data simulation specifications (e.g., between and within-person standard deviations, with `sigma` and `sigma.i` arguments, respectively), as well as data missingness, to explore how these changes translate into different continuous time models and results.

After simulating this data, we recoded the automatically generated time variable into absolute data collection terms: that is, we recoded each time value (which were all standard across participants) to represent data collections 1, 2, 3, 4, and 5, as this is more straightforward to interpret. We then created a separate variable called “lag” that we added to our simulated dataset, composed of random, normally distributed values ($M = 50$, $S.D. = 15$) to serve as individual-relative time lags between each data collection. For purposes of simplicity, we treated these as time intervals themselves, rather than as absolute time values from which we then calculated time intervals; however, readers are encouraged to take this approach instead to mimic datasets with absolute rather than relative times reported. Moreover, readers can adjust the values used to generate the random time lags to better align with their time scale of interest (e.g., years vs. days). They can also convert these intervals into sample-relative lags, assuming the first time point is treated as pre-determined and not as stationary as in our tutorial.

As our data was constructed in long format, we next restructured relevant variables from our dataset into wide format using the base R `reshape` function and participant ID as our grouping variable. Once this was accomplished, and each variable had its own column, we removed the fifth “lag” column, as only four time intervals would exist in a five-wave dataset

(i.e., between Time 1 and Time 2, Time 2 and Time 3, etc.). Finally, we renamed our variables to correspond to CTSEM requirements (e.g., V1.1 became V1_T0) and reordered variables such that the variable columns were organized by time point (i.e., V1_T0, V2_T0; V1_T1, V2_T1) and followed by columns for time intervals (i.e., dT1, dT2, etc.).

Model Specification and Fitting

Once data are prepared, researchers can proceed to specifying their model. Importantly, the ‘ctsem’ package interfaces with ‘OpenMx’ (Neale et al., 2016) and uses the same specification conventions thereof, so researchers more familiar with ‘lavaan’ (Rosseel, 2012) model specification may need to familiarize themselves with how to define factors in ‘OpenMx’.

In our tutorial, we specify a straightforward cross-lagged panel model (see Figure 2), wherein V1 and V2 are observed variables (`n.manifest = 2`) that load individually onto two latent process variables (`n.latent = 2`; i.e., with each latent process measured by one observed variable) over five time points (`Tpoints = 5`). Each of these latent variables have continuous cross- (i.e., on one another) and auto-effects (i.e., on themselves, later in time) considered in the model. The terms “auto-” and “cross-” are used in lieu of “autoregressive” and “cross-lagged” when describing specific model paths and parameters in the continuous time framework. These are the preferred terms in CTSEM, in contrast with those used elsewhere in SEM (e.g., with cross-lagged panel models; Hecht & Voelkle, 2019).

INSERT FIGURE 2 ABOUT HERE

Due to the simplicity of this model, we can rely on a basic 2 x 2 diagonal matrix (`LAMBDA = diag(2)`) to specify which observed variable loads onto which latent variable. In other cases, such as when multiple observed indicators load onto different latent variables, researchers will need to manually input their observed variable loadings in matrix format.

Researchers will also need to specify their observed variable names (i.e., V1, V2) using the `manifestNames` argument if default naming is not used (i.e., Y1, Y2), and desired latent variable names (e.g., stressor, strain) using the `latentNames` argument. Many other specification options are available (see Driver et al., 2017), which may or may not be relevant depending on the nature of the phenomena being modeled and researchers' expectations. These include constraining means, variances, or other parameters to particular values, or including time-independent and/or -dependent predictors in one's model. Printing the specified model with the `print` function can help to highlight which components of the model are being specified by default and which have been specified by the researcher.

Once the model is prepared, the model is fit to the data using the `ctFit` function. Researchers will need to consider whether they want to leverage the `carefulFit` argument, which by default is specified to be 'TRUE'. This feature can help with model fitting in some cases by holding some values asymptotically close to zero and using these values for estimation. However, it can be inappropriate in others, such as when models are highly complex and dynamic (Driver et al., 2017). One of the challenges of CTSEM is the complexity and computational load required to specify models, and we recommend readers use the recommendations and diagnostics provided by Driver and colleagues (2017) in fitting their model. For example, readers may want to build and test their model iteratively, such that model complexity is increased in a stepwise fashion.

Model Output and Fit

Model output for CTSEM analyses can be extensive, and we recommend that researchers call for specific parts of the output, as we demonstrate in the tutorial. We expect that the components of most interest to occupational health researchers are the drift and diffusion

matrices, as well as model fit indices. The drift matrix presents the model's continuous auto- (on the diagonal) and cross-effects (on the off-diagonal), which are used in tandem with the time interval to calculate unstandardized discrete time auto- and cross-effects for particular intervals (e.g., see the `discreteDRIFT` call in our tutorial, which presents a drift matrix using a time interval of 3). The diffusion matrix presents the model's continuous variances (on the diagonal) and covariances (on the off-diagonal), which are used in tandem with the time interval and drift matrix, to calculate latent variable variances (i.e., stochastic "innovations") and can similarly output specific unstandardized values based on an imputed time interval (i.e., the `discreteDIFFUSION` call with `timeInterval = 3`; standardized matrices are also available, as described by Driver et al., 2017). By considering both matrices, occupational health researchers should locate much of their results of interest. Specifically, they could consider continuous and discrete stressor-strain relationships, autoregressive parameters, or latent process residuals. In the tutorial results, the auto-effects observed at a time interval of three units (e.g., three months) suggest that both stressor and strain (e.g., workload and burnout) positively predict themselves. Specifically, higher previous levels of workload and burnout predict higher later levels of workload and burnout, respectively. The results also suggest that at a time interval of three months, both workload and burnout display countertheoretical cross-effects, such that higher previous levels of burnout are predictive of lower workload levels at the next time point and vice versa. Comparing these findings with other time intervals or model specifications, discussed in the next section, can help researchers pinpoint the source of surprising findings, identify when certain findings may be observed (or even exist), and more.

Researchers will likely want to assess and report the fit of their model to the data, as well as compare their model to other viable or more/less constrained alternative models. If researchers

use raw data in their analyses, ‘ctsem’ will provide -2 log likelihood values, whereas with covariance matrix input, the package will return chi-squared values. While these can be used to hand calculate fit indices in many cases, researchers may find it easier to specify a reference model in ‘OpenMx’ that will then allow them to generate fit indices (e.g., AIC, BIC, CFI, TLI, RMSEA values) for their focal model. Notably, they will not be able to automate the calculation of SRMR via this approach, as ‘OpenMx’ does not recommend utilizing this fit index (Boker et al., 2020). We present a basic way of calling each relevant value and placing it into a matrix in our tutorial, which suggests our model fits our simulated data well.

Additional Options and Considerations

There are many additional options and “add-ons” that one can utilize in the ‘ctsem’ package, but we focus on the two of most relevance to adopting a dynamic, continuous time approach in occupational health research: adding “trait-like” intercepts to continuous time models, and plotting model parameters at specific time intervals. The former option, which helps separate and account for within- and between-person sources of variance (i.e., as discussed earlier with respect to dynamic vs. static SEM approaches), is accomplished by adding either the “`TRAITVAR = "auto"`” (i.e., intercepts at the latent variable level) or “`MANIFESTTRAITVAR = "auto"`” (i.e., intercepts at the manifest variable level) arguments to model specification (see Voelkle et al., 2018, for further discussion of how to effectively specify “traits” in models). Although both forms can be included in the same model, this can pose challenges and should only be done in cases where overarching, stable, between-person differences would be expected to exist at both the observed and latent levels. Intraclass correlations can also be calculated to assess variance attributable to within- and between-person sources (see Hecht & Voelkle, 2019, for how to use long-range parameters to this end). For our

tutorial, we specify a model with intercepts at the latent variable level and provide code for comparing the fit of this model to the original model (i.e., using the `mxCompare` function to compare the ‘OpenMx’ model objects for both models).

The latter option (plotting) is accomplished with the `ctPlot` function and can be used to return a variety of plotted parameters, of which we provide examples for auto- and cross-effects in the model including latent variable level intercepts (i.e., `plotType = 'AR'` and `= 'CR'`, respectively; see Figures 3 and 4). As with other plotting tools in R, researchers can customize these plots in many ways, of which choosing an appropriate time scale for the y-axis is chiefly important.

The results of our tutorial analyses suggest of the cross-effects (see Figure 4) that almost no predictive relationship would be observed when regressing strain onto stressor (e.g., burnout onto workload) at certain time intervals (e.g., between two and three time units, around five time units). Conversely, the parameter estimate would be positive between six and eight time units or even negative around four time units. Thus, depending on the intervals at which data were collected in a study, researchers might observe theoretically consistent, inconsistent, or null findings. Similar parameter variability is observed for regressing stressor onto strain (see Figure 4), as well as for auto-effects: specifically, past levels of burnout and workload may or may not predict future levels of themselves depending on the time interval used (see Figure 3). These findings differ from those reported in the original model (i.e., the model without a trait-like latent variable level intercept), which suggests that distinct workload and burnout patterns emerge when accounting for stable, between-person differences in the latent constructs.

Particularly if the plots are used to extrapolate values “out” over time, care is needed to balance the potential of these inferences with the limits of the study design and data. It might not

be reasonable to predict out the relationship in the distant future, absent multiple waves of data, relevant time intervals represented, or under other conditions. Moreover, it is important to bear in mind that these are plots of the relationship between latent variables depending on the time interval between (actual or projected) data collections. This is a subtle distinction from a plot of these relationships over time, but one that is important to remember when interpreting and reporting such plots, especially depending on the time scaling in one's study.

INSERT FIGURES 3 AND 4 ABOUT HERE

Caveats to CTSEM

Although CTSEM presents many opportunities to develop and innovate in the study of occupational health over time, it also comes with limitations. First, and perhaps foremost, estimating continuous time models is computationally intensive, and complex models are often cumbersome to specify and fit (McNeish & Hamaker, 2019; Voelkle et al., 2018). Moreover, CTSEM is subject to many of the same shortcomings and assumptions as SEM, which must be borne in mind when weighing the benefits of its use. For example, they are unwieldy with a large number of data collection time points, and there is inflexibility with respect to individual differences in model coefficients (McNeish & Hamaker, 2019). Alternative approaches such as dynamic SEM (e.g., Asparouhov, Hamaker, & Muthén, 2018; McNeish & Hamaker, 2019) can be taken to address these and other issues by combining the benefits of both SEM and multilevel modeling, although different ways of approaching time continuously therein are required (Asparouhov et al., 2018; Hamaker & Wichers, 2017). Second, we wish to note that there are other analytical approaches to “handling time” continuously that, although seldom used by the occupational health literature, bear further exploration (e.g., latent pattern mixture modeling; Lin, McCulloch, & Rosenheck, 2004). Similarly, more work using time lag length as a moderator in

analyses (e.g., within a given study to consider between-person differences: Selig et al., 2012; between-studies in meta-analysis: Card, 2019) to assess the time-dependence of observed effects would be fruitful. This addresses a somewhat different temporal issue—it studies the time lag without “accounting for” it, *per se*—but should complement work treating time continuously.

Finally, we believe that a shift toward conceptualizing time continuously will move us away from an overreliance on time interval constraints and the search for time lag “optimality.” Still, there are certainly cases in which equally and/or precisely spaced measurement points are appropriate and necessary (e.g., where periodic or punctuating effects are expected; Collins, 2006; Voelkle & Oud, 2013), and we do not suggest otherwise. Rather, we urge occupational health researchers to think critically and continuously about what significance(s) time and time intervals hold in the context of their research (i.e., their focal phenomena, research design), and to approach data analysis with both its limitations and opportunities in mind. Many of the analytical methods discussed earlier with respect to limitations may well be appropriate for certain research projects. Researchers need not limit themselves to traditional longitudinal panel data, either: there are alternative collection modes, many of which may better “tap into” our phenomena of interest, that bear consideration in future research (e.g., accelerated cohort designs, intensive longitudinal design; see CTSEM discussion of such data in Estrada & Ferrer, 2019; Ryan et al., 2018). Moreover, the advent of continuous time meta-analysis (Dormann et al., 2019; Guthier et al., 2020) is an exciting recent development in this literature, and it stands to contribute to time-cognizant occupational health research designs, analyses, and practical applications moving forward.

CONCLUSION

In order to address the “lag problem” in occupational health research, and to more broadly create an interpretable, integrative, and innovative body of knowledge about occupational health phenomena, taking time-focused approaches in longitudinal data analysis is necessary. The present work aimed to introduce the prospect of CTSEM to occupational health researchers, while highlighting the challenges and opportunities that time (including time lag variability) presents and the ways it has been overlooked or inadequately addressed in the past. In short, CTSEM allows researchers to more substantively address issues of time within and across studies, including its conceptualization, its statistical treatment, and/or its role in processes, measurement, and the (in)comparability of effect sizes across studies.

It is our hope that our guide will better enable the field of occupational health to move beyond viewing time interval variability as a nuisance, or as something requiring optimization and/or remediation. We similarly hope that this guide will help the field refocus on time’s ability to teach us about change and stability in theoretical processes—particularly with new, flexible analytic tools at our disposal. This way, we can better, and more temporally, align theory, methods, and analysis (Collins, 2006) in the service of causal understanding and, ultimately, better practical applications to promote occupational health. Studying occupational stress and health over time (i.e., over multiple data collection points) can document what occurs, as well as where and for whom, during the period of study. But, this alone does little to inform specifically when, how, and why these certain relationships emerge: at what temporal junctures, under what conditions, and for what reasons. Longitudinal data affords us the ability to ask both sets of questions, but we can only address the latter by treating time as a substantive, continuous variable. Continuous thinking about time not only refocuses our research on temporality, but it also allows us to think about and study other variables more dynamically, interpretably, and

generalizably. This produces research that can, in turn, be used to craft maximally effective interventions and representative theory.

All studies have their limitations—all measurement tools, their unreliability; all data, their noise. We do the best we can to minimize the latter threats and maximize the validity, reliability, and utility of our research. To take this endeavor further, we must turn to time as a source of information rather than of error. At its core, studying phenomena *with respect to time* improves our ability to understand mechanisms and processes “as they are,” while studying phenomena simply *over time* relegates nuance to noise. In order to fully leverage the power and information offered by longitudinal data, continuous thinking about time is necessary. All psychological research requires some degree of abstraction and approximation, but time need not—and should not—be a place for continued coarsening.

In the words of McArdle (2009), “any repeated measures analysis should not start by asking, ‘What is your data collection design?’ or ‘What computer program can you use?’ ...all repeated measures analyses should start with the question, ‘What is your model for change?’” (p. 601; see also Voelkle et al., 2018). By treating time continuously, we can refocus on this latter question, even with (and perhaps even because of) temporally challenging data structures, to better utilize and represent causal processes, emergence, stability, and change in the data we collect *over time*. This, in turn, will provide us with a more nuanced and informative knowledge base for occupational health phenomena *with respect to time*, unfettered by discrete time lags and positioned to improve worker health and well-being in the years to come.

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Table 1

Comparison of Approaches to “Handling Time” in Occupational Health Research

Analytic Approach	Attributes/Capabilities	Limitations	Variations
<i>Traditional Discrete Time Structural Equation Modeling (DTSEM)</i>	<ul style="list-style-type: none"> Traditional DTSEM methods “ignore” time lag variability (i.e., assume lag equivalence) 	<ul style="list-style-type: none"> Cannot account for within and/or between-person variability in time lags Assumes processes do not continue to occur/unfold outside of measurement occasions Impossible to compare to other studies and to generalize findings 	<ul style="list-style-type: none"> Can be modified to better account for dynamic nature of phenomena, and some methods allow for flexible (but not continuous) time scaling
<i>Cross-lagged panel model</i>	<ul style="list-style-type: none"> Assesses rank-order change Considers both autoregressive and cross-lagged effects, which helps with causal claims 	<ul style="list-style-type: none"> Cannot assess additional forms of change (e.g., change trajectories) Traditionally assumes time lags are equivalent 	<ul style="list-style-type: none"> Inclusion of random intercepts (RI-CLPM) can parse within- from between-person effects Can free cross-lagged and autoregressive parameters to vary across lags at between-person level Can add autoregressive component and standardized residuals to make analysis more dynamic and separate within- from between-person sources of variance
<i>Latent growth curve model</i>	<ul style="list-style-type: none"> Can assess multiple forms of change (construct levels, rates of change) More flexibility with time parameterization 	<ul style="list-style-type: none"> More causally ambiguous than other DTSEM methods Traditionally assumes time lags are equivalent 	

Analytic Approach	Attributes/ Capabilities	Limitations	Variations
<i>Latent change score model</i>	<ul style="list-style-type: none"> • Can assess multiple forms of change (constructs at adjacent measurement occasions, change rates) • Better able to address causality 	<ul style="list-style-type: none"> • Assumes latent variables are assessed at equal intervals (even if observed variables are not), which may or may not be appropriate 	<ul style="list-style-type: none"> • Dual change score models provide more dynamic assessment, but still do not fully parse between- from within-person variance
<i>Modified DTSEM</i>	<ul style="list-style-type: none"> • Statistical techniques used to account for, but not directly study, time lag variability in structural equation model (SEM) analyses 	<ul style="list-style-type: none"> • Impractical or inappropriate in many cases • Often results in loss of important temporal information • Still does not study phenomena with respect to time (e.g., does not allow for cross-study comparisons, assumes processes do not operate between data collections) 	<ul style="list-style-type: none"> • Variations include data restructuring and variable creation methods
<i>Phantom variables</i>	<ul style="list-style-type: none"> • Insertion of latent variables with no observed variables to create (artificially) equal time intervals between data collections 	<ul style="list-style-type: none"> • Only addresses unequal time intervals at the between- rather than the within-person level • Hard to apply when time interval variability is complex/diffuse 	

Analytic Approach	Attributes/ Capabilities	Limitations	Variations
<i>Definition variables</i>	<ul style="list-style-type: none"> Constraining model parameters, such as slope factor loadings, to be equal to other observed variables, such as individual's data collection time points 	<ul style="list-style-type: none"> Various issues reported (e.g., convergence, parameter bias) Still limited with respect to causality when applied to particular models (e.g., latent growth curve models), and/or the degree to which both between- and within-person time lag variability is addressed 	
<i>Multigroup analysis</i>	<ul style="list-style-type: none"> Fitting latent growth curve model to groups of individuals with the same measurement schedule 	<ul style="list-style-type: none"> Feasible only when limited number of measurement schedule patterns exist in sample Loses temporal detail depending on the time scale used to identify schedules Potentially major and consequential loss of temporal detail 	
<i>Time recoding</i>	<ul style="list-style-type: none"> Rescaling time variables such that intervals appear to be equal 	<ul style="list-style-type: none"> Only appropriate when time unit differences lack theoretical and/or practical meaning 	

Analytic Approach	Attributes/ Capabilities	Limitations	Variations
<i>Non-SEM (Linear mixed-effects models)</i>	<ul style="list-style-type: none"> • Equivalent to latent growth curve models but easier to include time as model predictor • Data are considered univariately rather than multivariately, which requires less data reformatting and provides flexibility with how time is a predictor in the model 	<ul style="list-style-type: none"> • Lacks advantages of SEM (latent variables with multiple indicators, measurement error) • Difficult or inappropriate to model lagged relationships, and does not consider time (or other phenomena) causally • Centering and detrending can complicate the degree to which/how time is studied 	<ul style="list-style-type: none"> • Time can be entered into models explicitly (as in latent growth curve models) or as a time-varying within-person predictor (e.g., age), with a variety of centering options available
<i>Continuous Time Structural Equation Modeling (CTSEM)</i>	<ul style="list-style-type: none"> • Can be applied to various DTSEM techniques while addressing time lag variability at both the within- and between-person levels • Produces results that are more comparable across the literature, nuanced, and temporally informed 	<ul style="list-style-type: none"> • Daunting/inaccessible for many researchers who are unfamiliar with differential calculus • Computationally intensive • Subject to similar issues as other SEM techniques (e.g., challenges with a large number of data collection points) 	<ul style="list-style-type: none"> • Various model customization options (e.g., random intercepts to parse within- from between-person variance) • New extensions to meta-analysis, dynamic SEM

Figure 1
Continuous Time Structural Equation Modeling (CTSEM) Flowchart

Figure 2
Tutorial Model Path Diagram

Note. Model simplified to facilitate interpretability (i.e., some specification components are not included; e.g., latent residual variances or “innovations”, innovation covariances, mean structure constants). “STRS” = stressor, “STN” = strain. Circles denote latent variables, while boxes denote observed variables. Diagonal arrows denote cross-effects, with the righthand latent variable regressed onto the lefthand latent variable at the preceding time point, while horizontal arrows denote auto-effects, with the righthand latent variable regressed onto itself (i.e., the lefthand latent variable) at the preceding time point.

Figure 3
Example Auto-Effect Plot

Note. Solid gray line = “stressor” auto-effects, black dashed line = “strain” auto-effects. Plot indicates parameter values (y -axis) across various time intervals (x -axis).

Figure 4
Example Cross-Effect Plot

Note. Solid gray line = “strain” regressed onto “stressor”, black dashed line = “stressor” regressed onto “strain”. Plot indicates parameter values (y-axis) across various time intervals (x-axis).