

Process Cookbook

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Abstract

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8 Begin here. . .

9 *Keywords:*

10 Word count: 95

Process Cookbook

Hook thoughts

Hook from last meeting

A “it is confusing and we would like to organize” argument.

- New researchers are increasingly asked to collect longitudinal data. We care about longitudinal data.
- The longitudinal literature appears more confusing than it is because people propose different hypotheses, use different models, and make different inferences.
- We organize and discuss the similarities.

Bliese paper hook

A “this other technique can augment what you are doing” argument.

- We increasingly have access to longitudinal data that contain discontinuities.
- Examples.
- These studies use a variety of techniques to understand discontinuous patterns, but we believe that discontinuous growth models can augment existing techniques. . .
- Practical advice is spread across numerous sources and is basic – we review.

Aguinis paper hook

A “this literature is technical and mathy, not accessible to org researchers” argument.

- We care about A or B.

- There is a large technical literature on A or B.
- Much of this work is not easily accessible to researchers with the usual methodological and statistical background obtained from doctoral level training in management.
- We provide recommendations.

Thoughts from last meeting

A no argument but describing paper.

- We care about longitudinal data
- Our literature now contains a lot of cool examples and inferences
- We are going to describe them
- This paper is for newcomers who want some examples and for longitudinal modelers who want other options to augment what they are doing

Organizational researchers are increasingly interested in longitudinal data structures. These data align with the processes we study, which “are not static but instead develop, change, and evolve over time” (Pitariu & Ployhart, p. 405) or are “sequences of events that play out within each person’s stream of experience” (Beal, 2015, p. 5). If researchers can collect longitudinal data, they are then in a better position to understand patterns over time. Bell and Kozlowski (2003), for example, state that “longitudinal designs... will be far more revealing of the team phenomenon under investigation” (p. 59). Similarly – in their review of emotional labor – Grandey and Gabriel (2015) suggest that future researchers may be much better equipped to demonstrate emotion regulation patterns “with longitudinal methods” (p. 329). Not only do longitudinal data collections help researchers observe relationships over time, many argue that doing so helps improve our theories. For instance, Pitariu and Ployhart (2010) suggest that collecting longitudinal data, observing change, and testing dynamic models “stimulates greater refinement in our existing theories” (p. 411), and

Grandey and Gabriel (2015) urge for greater theoretical development of emotions by studying their “reciprocal and unfolding... processes... through momentary assessments or lagged effects” (p. 322). These quotes reveal our field’s emphasis on collecting longitudinal data to sufficiently observe a process and build better theory.

A greater emphasis on longitudinal data is also apparent in our empirical literature, where collecting repeated measures is now common. For instance, Jones et al. (2016) observed the work attitudes of pregnant women in their second trimester every week until they gave birth. (???) assessed job satisfaction across three time points that were each separated by six weeks. Matthews, Wayne, and Ford (2014) studied work-family conflict across several months. Meier and Spector (2013) examined counterproductive work behavior over five waves. Hardy, Day, and Steele (2018) investigated self-regulation over 20 lab trials. Gabriel, Diefendorff, Chandler, Moran, and Greguras (2014) measured fit and affect five times per day for 10 consecutive work days. Finally, Johnson, Lanaj, and Barnes (2014) observed justice behavior and resource depletion across 10 consecutive workdays.

Armed with repeated observations, these studies then explore a variety of interesting inferences. Hardy et al. (2018) propose and find support for growth trends in self-regulation, metacognition, and performance. Jones et al. (2016) conclude that concealing behaviors among pregnant women lead to greater subsequent physical health. Johnson et al. (2014) establish that “justice is dynamic: The frequency of actors’ justice behaviors varies day to day” (p. 10), and these daily fluctuations predict daily changes in depletion. Finally, Meier and Spector (2013) suggest that the effects of work stressors on counterproductive work behaviors are not substantially different across different time lags.

Moreover, we find different types of sophisticated modeling strategies throughout. Meier and Spector (2013) present a sequence of path models that test increasingly longer time lags. Hardy et al. (2018) and Jones et al. (2016) employ bivariate cross-lagged latent growth curves, an approach similar to the latent change model used by (???). We also find

complex hierarchical linear models in various event-sampling studies (e.g., ???; Rosen, Koopman, Gabriel, & Johnson, 2016).

In summary, our increasing theoretical emphasis on longitudinal data and its growing prevalence in our empirical literature has led to many interesting inferences and model applications. Researchers are beginning to propose hypotheses with lags and examine the reciprocal nature between two or more variables. Studies now commonly make inferences about change, growth, and dynamics. And sophisticated models, such as multi-level and latent growth curves, make their appearance in almost every longitudinal study.

We want to bring attention to this new and exciting literature. Specifically, in this paper we describe some of the common inferences and models researchers employ with longitudinal data. Sometimes these studies appear unrelated due to the different language used among various content or statistical modeling areas – but we believe our discussion will reveal some of their covert similarities. We discuss the inferences, identify literature examples and hypotheses that are consistent with each, point to various models being used to support them, provide the code necessary to both estimate and understand what the models are doing, and unpack some of the strengths and weaknesses of each approach. Our paper is meant for two audiences. First, we believe this summary will help any newcomers who want to make inferences with their longitudinal data but are unaware of what types of inferences and models are available. Second, this paper is meant to show seasoned researchers other possibilities – other inferences and models that may augment how they currently approach longitudinal data.

Below, we discuss four common inferences researchers make with longitudinal data: relationships over time, growth, change, and dynamics. These do not represent every possible domain we can explore with longitudinal data, but they do cover a large portion of the techniques currently employed in our literature. We begin by explaining what we mean by longitudinal research. We then unpack a framework proposed by Xu and DeShon that

relates the four different research streams. In the core of the paper, we then discuss each stream in depth.

Intro

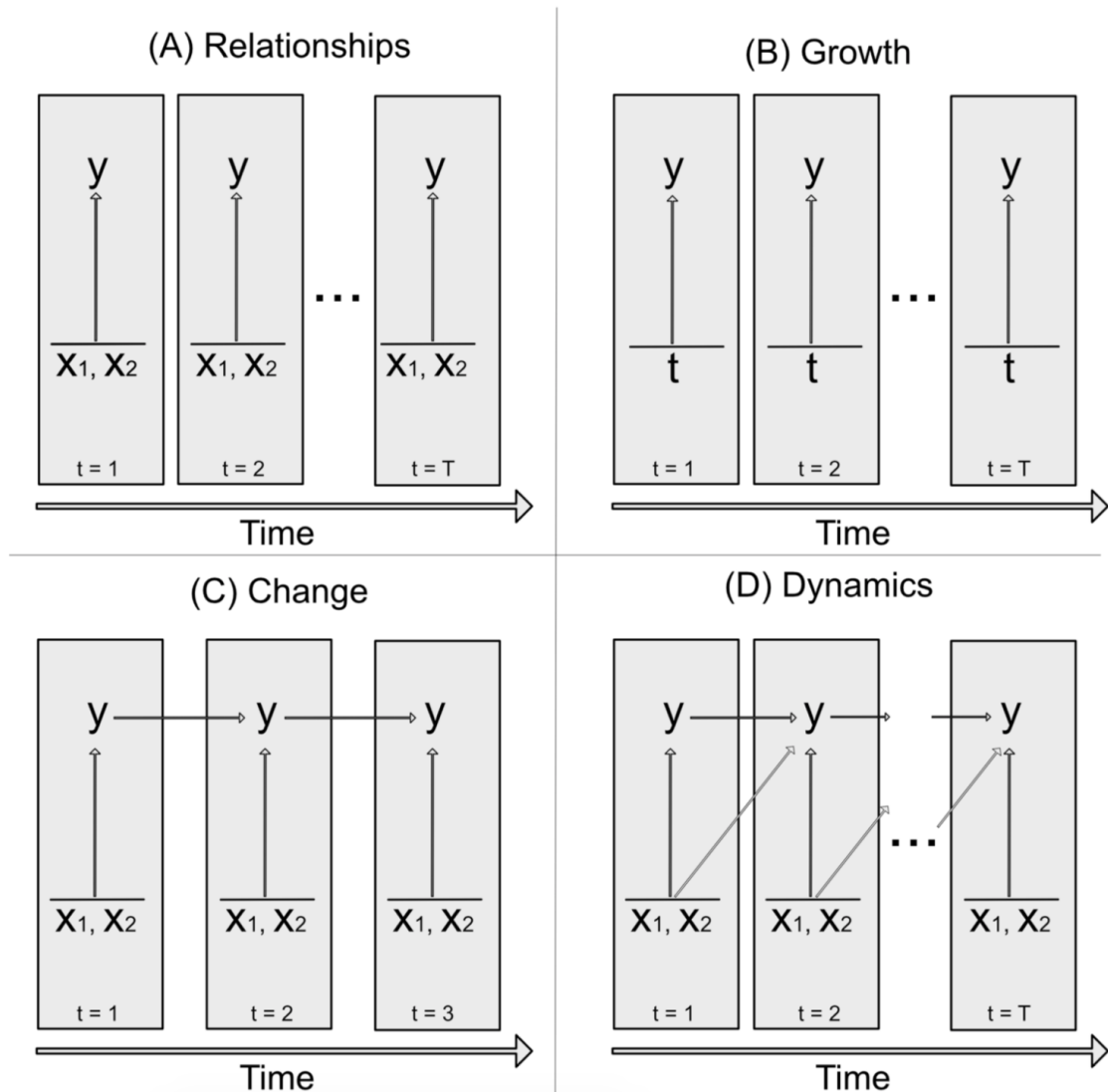
Define longitudinal

This paper is exclusively devoted to the inferences we make with repeated observations, so we begin by identifying a few labels and definitions. Authors typically identify a “longitudinal” study by making a contrast with respect to either a) research designs or b) data structures. Longitudinal *research* is different from cross-sectional research because longitudinal designs entail three or more repeated observations (Ployhart & Bliese, Singer & Willett). We therefore emphasize differences on the number of observations when we distinguish longitudinal from other types of research. Longitudinal *data* are repeated observations on several units (i.e., N or $i > 1$), whereas panel data are observations of one unit over time – a distinction that focuses on the amount of people in our study (given repeated measures). Most organizational studies collect data on more than one unit, therefore our discussion below focuses on longitudinal research with longitudinal data, or designs with $N > 1$, $t \geq 3$, and the same construct(s) measured on (potentially) each i at (potentially) each t .

Introduce framework

Presenting the entire inference and modeling literature that uses longitudinal data would be impossible. Instead, we focus on four related streams that we feel can be organized using a framework proposed by Xu and DeShon. Figure one shows each inference we will discuss in this paper: relationships, growth, change, and dynamics.

In each panel in figure one, time is on the x -axis to portray that we are investigating these inferences over time. Each slice contains an observation of y , such that at time t we observe y_t and at $t + 1$ we observe y_{t+1} . What differentiates the panels – the inferences – is the pattern of relationships we investigate – and we add complexity as we move from A to D . For example, researchers do not include lag effects when they are interested in relationships over time (panel A), but they do include a lag effect when they study change or dynamics (panels C and D). We will devote a section to each of these inferences below, but we first describe some preliminary pieces about code and data that we refer to repeatedly in this paper.



Introduce data sets and generic variables

We will use two generic variables – affect (x) and performance (y) – throughout this paper. These variables will hopefully provide continuity across the inferences and also provide an illuminating backdrop after we refer to x or y generically. Moreover, we use code examples in each section that refer to data sets that contain measures of affect and performance on 50 simulated subjects across five time points.

These data are contained in two data sets: `long_df` and `wide_df`. The raw data are the same, but their formatting differs because different estimation techniques require different data structures. Structural equations modeling (SEM) requires wide data, whereas HLM requires long data. The first data set, `long_df` contain the data in long form,

affect	performance	id	time
10.269606	17.23310	1	1
9.370015	22.81949	2	1
10.868660	17.64258	3	1
11.727196	20.56741	4	1
10.024188	12.08548	5	1
10.368025	13.17514	6	1
8.690796	12.76671	7	1
10.738622	13.62823	8	1

where `id` refers to a person identifier, `time` refers to the observation period, and scores on `affect` and `performance` are listed in their respective columns.

The second data set, `wide_df` contain the data in wide form,

id	affect.1	performance.1	affect.2	performance.2	affect.3	performance.3
1	10.269606	17.23310	9.945866	13.653924	9.059233	20.944278
2	9.370015	22.81949	10.461612	10.886965	10.093910	16.578068
3	10.868660	17.64258	9.403230	9.386411	10.066253	10.834513
4	11.727196	20.56741	11.263258	20.491540	9.009344	8.547953
5	10.024188	12.08548	8.854671	16.052982	9.927885	16.759775
6	10.368025	13.17514	11.084624	13.839404	9.776743	26.595386
7	8.690796	12.76671	8.471005	13.229533	9.857223	10.831559
8	10.738622	13.62823	8.426258	16.364850	10.535407	8.794605

where `id` is defined above and now `affect` and `performance` are given new columns at each measurement period – such that, as an example, person one reports 10.3 for affect at time one and 9.9 for affect at time two (the data continue for five time points). Again, we will refer to these variables and data sets as we unpack each section, but remember that the values within each data set are the same – the only difference is their format.

Introduce Code and Its Use

Finally, we will also present code snippets that estimate models related to each inference. Code is typically published in methods literature to demonstrate how to estimate models, but it can also be used as a tool – a language – to build a greater understanding of the phenomenon (nature of code cite). We would like to use it for both reasons. Our goal is to provide readers with code for estimating models, but also allow them to see the inferences represented in various ways – words and code – to help clarify what they represent.

The code snippets will take consistent forms throughout. HLM models will be expressed as follows:

```
hlm_model <- lme(  
  
  code  
  more code  
  
  data = long_df  
  
)
```

168 where `hlm_model` is an object that stores the results of our model, `lme` is a function call to a
169 linear mixed-effects regression (HLM), and within that we specify our effects and reference
170 our data. In the inference sections, `code` and `more code` will be replaced by the effects we
171 estimate, and `data` will always reference `long_df` because HLM requires long formatted data.
172 Finally, after storing our results in the object `hlm_model` we can actually view them with:

```
summary(hlm_model)
```

173 Similarly, SEM models will be expressed as:

```
sem_string <- '  
  
  code  
  more code  
  
'  
  
sem_model <- sem(sem_string,  
                 data = wide_df)
```

where `sem_model` is an object that stores the results of our SEM model and we refer to the `wide_df` data set because SEM requires wide data. Notice that in the SEM code snippet we first create a string object, `sem_string` to specify our effects. Again, the `code` and `more code` will be replaced by actual effects when we get to our inferences. Just like the HLM code, we then view our SEM results with:

```
summary(sem_model)
```

In summary, the style of code snippets just presented will be used throughout each inference section. What will change are the `code` and `more code` pieces, and in those areas we will impute effects specific to each inference. If you wish to run these models on your own computer, you will also need to load their packages in your `r` script with `library(nlme)` for HLM and `library(lavaan)` for SEM (and install them with `install.packages()` if you have not done so already).

We now turn to the inferences.

Relationships

Inference 1

What is the relationship between two or more variables across time?

Explanation

A common inference in our longitudinal literature is the relationship between an outcome (y) and one or more predictors (x_p) over time. As shown in figure one, researchers observe y and one or more predictors at each time point, and are then interested in the immediate effect of the predictors on y . Although there are multiple slices in our figure,

typically the effect of x on y is treated as stable over time and therefore the analysis returns an estimate of a single parameter (e.g., a single beta weight). This parameter is essentially a summary statement of the immediate effect of x on y at any point in time. In other words, researchers observe x and y at every t from time t to $t + 5$, as an example, and then report a statement of the effect of x_t on y_t , or the expected immediate effect of x on y at any possible moment.

Although the effect (i.e., the parameter relating x to y) is treated as stable over time, the values on x and y – the raw data – are typically allowed to vary. When the values of x (potentially) change at each observation, the analysis is referred to as a time-varying covariates analysis – whereas a time-invariant analysis would be one where the raw data on x does not change at each observation (e.g., gender).

To clarify, consider this inference with respect to our generic variables: affect x and performance y . Researchers would collect performance and affect data on multiple people at each observation over several time points. Affect may vary at each observation – it may be 5 at time t and 9 at time $t + 1$ – so this analysis is referred to as a time-varying covariates analysis. Researchers are then interested in the stable, immediate influence of affect on performance. That is, they are interested in the effect of affect_t on performance_t at any potential t , where, on average, they expect the effect of affect on performance to be close to their parameter value.

There is a distinction with how we use the term “stable” that merits more explanation. In a relationships inference, “stable” means that we expect the parameter value relating affect to performance to be the same at each moment. In other words, the relationship between affect and performance will be the same at each t – high values of affect will result in high values of performance (if the parameter is positive) and low values of affect will result in low values of performance. “Stable” in this inference context does not mean that affect has a lasting impression on performance, or that affect at time t influences

performance at some later time. This distinction is a difficult one, but it represents a major difference between making a relationships inference versus some of the others we have yet to explore. A relationships inference, therefore, is concerned with the average influence over time, or what we expect the immediate effect of x on y to be at any given moment.

Literature Examples and Hypotheses

There are many examples in our literature that are interested in relationships over time. When a researcher is interested in making a relationships inference, they propose a hypothesis of the form: x predicts y (given some direction, positive or negative). Using our generic variables, we would propose:

Affect positively (or negatively) predicts performance over time.

For example, Barnes, Schaubroeck, Huth, and Ghumman (2011) predict a negative relationship between poor sleep and cognitive self control. Similarly, Chi, Chang, and Huang (2015) hypothesize that daily negative mood negatively relates to daily task performance.

Code

We gain even more clarity on this inference when we consider the code used to estimate models. A typical SEM model would be estimated with something similar to the following code.

```
sem_string <- '  
  
    performance.1 ~ b1*affect.1  
    performance.2 ~ b1*affect.2  
    performance.3 ~ b1*affect.3
```

```
performance.4 ~ b1*affect.4
performance.5 ~ b1*affect.5
'
sem(sem_string, data = wide_df)
```

where this code snippet is identical to our introductory SEM code but we have replaced `code` and `more code` with actual effects we wish to estimate. In this case, we regress performance at time t on affect at time t and estimate `b1` – the parameter relating affect to performance over time. The analysis will return one number for `b1` because, again, we are treating this as a stable estimate over time.

The HLM equivalent would be:

```
lme(

  fixed = performance ~ affect,
  random = ~1|id,
  data = long_df

)
```

where we again replace `code` and `more code` from the introductory HLM snippet with a regression of performance on affect. Notice that we do not need to type the performance on affect regressions at each time point as we did with the SEM code. Typically, in SEM software you type out the entire model, whereas HLM packages use condensed code. There are two other new pieces of code: `fixed` and `random`. These commands specify how we want HLM to estimate the parameters we are interested in, but at this point we do not unpack them further – we will return to what they mean in the full modeling section at the end of

the paper.

We will devote an entire section to the statistical properties of HLM and SEM below, what is important here is our regression of performance on affect. In both HLM and SEM we estimate a stable parameter relating affect at time t to performance at time t – in SEM software we explicitly identify a parameter (**b1**) whereas HLM software typically does so automatically.

Relationships Inference 1 Summary

- Hypothesis:

- x relates to y over time.

- Parameters From SEM or HLM:

- beta coefficient relating x to y at each time point.

Growth

We now move to our second inference panel, B and explore a variety of inferences related to growth.

Inference 1

What is the level of a construct at a given point in time?

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