1   Process Cookbook

2   . . .[1]

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4   Author Note

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6   Correspondence concerning this article should be addressed to ..., ... E-mail: ...

7 Abstract

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.

32 • Much of this work is not easily accessible to researchers with the usual methodological

33 and statistical background obtained from doctoral level training in management.

34 • We provide recommendations.

35 **Thoughts from last meeting**

36 **A no argument but describing paper.**

37 • We care about longitudinal data

38 • Our literature now contains a lot of cool examples and inferences

39 • We are going to describe them

40 • This paper is for newcomers who want some examples and for longitudinal modelers

41 who want other options to augment what they are doing

42 Organizational researchers are increasingly interested in longitudinal data structures.

43 These data align with the processes we study, which "are not static but instead develop,

44 change, and evolve over time" (Pitariu & Ployhart, p. 405) or are "sequences of events that

45 play out within each person's stream of experience" (Beal, 2015, p. 5). If researchers can

46 collect longitudinal data, they are then in a better position to understand patterns over

47 time. Bell and Kozlowski (2003), for example, state that "longitudinal designs. . . will be far

48 more revealing of the team phenomeon under investigation" (p. 59). Similarly – in their

49 review of emotional labor – Grandey and Gabriel (2015) suggest that future researchers

50 may be much better equipped to demonstrate emotion regulation patters "with

51 longitudinal methods" (p. 329). Not only do longitudinal data collections help researchers

52 observe relationships over time, many argue that doing so helps improve our theories. For

53 instance, Pitariu and Ployhart (2010) suggest that collecting longitudinal data, observing

54 change, and testing dynamic models "stimulates greater refinement in our existing theories"

55 (p. 411), and Grandey and Gabriel (2015) urge for greater theoretical development of

56 emotions by studying their "reciprocal and unfolding. . . processes. . . through momentary

57 assessments or lagged effects" (p. 322). These quotes reveal our field's emphasis on

58 collecting longitudinal data to sufficiently observe a process and build better theory.

59   A greater emphasis on longitudinal data is also apparent in our empirical literature,

60 where collecting repeated measures is now common. For instance, Jones et al. (2016)

61 observed the work attitudes of pregnant women in their second trimester every week until

62 they gave birth. (**???**) assessed job satisfaction across three time points that were each

63 separated by six weeks. Matthews, Wayne, and Ford (2014) studied work-family conflict

64 across several months. Meier and Spector (2013) examined counterproductive work

65 behavior over five waves. Hardy, Day, and Steele (2018) investigated self-regulation over 20

66 lab trials. Gabriel, Diefendorff, Chandler, Moran, and Greguras (2014) measured fit and

67 affect five times per day for 10 consecutive work days. Finally, Johnson, Lanaj, and Barnes

68 (2014) observed justice behavior and resource depletion across 10 consecutive workdays.

69   Armed with repeated observations, these studies then explore a variety of interesting

70 inferences. Hardy et al. (2018) propose and find support for growth trends in

71 self-regulation, metacognition, and performance. Jones et al. (2016) conclude that

72 concealing behaviors among pregnant women lead to greater subsequent physical health.

73 Johnson et al. (2014) establish that "justice is dynamic: The frequency of actors' justice

74 behaviors varies day to day" (p. 10), and these daily fluctuations predict daily changes in

75 depletion. Finally, Meier and Spector (2013) suggest that the effects of work stressors on

76 counterproductive work behaviors are not substantially different across different time lags.

77   Moreover, we find different types of sophisticated modeling strategies throughout.

78 Meier and Spector (2013) present a sequence of path models that test increasingly longer

79 time lags. Hardy et al. (2018) and Jones et al. (2016) employ bivariate cross-lagged latent

80 growth curves, an approach similar to the latent change model used by (**???**). We also find

81 complex hierarchical linear models in various event-sampling studies (e.g., **???**; Rosen,

82 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. Somtimes 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.

109   **Intro**

110 **Define longitudinal**

111   This paper is exclusively devoted to the inferences we make with repeated

112 observations, so we begin by identifying a few labels and definitions. Authors typically

113 identify a "longitudinal" study by making a contrast with respect to either a) research

114 designs or b) data structures. Longitudinal *research* is different from cross-sectional

115 research because longitudinal designs entail three or more repeated observations (Ployhart

116 & Bliese, Singer & Willett). We therefore emphasize differences on the number of

117 observations when we distinguish longitudinal from other types of research. Longitudinal

118 *data* are repeated observations on several units (i.e., N or $i > 1$), whereas panel data are

119 observations of one unit over time – a distinction that focuses on the amount of people in

120 our study (given repeated measures). Most organizational studies collect data on more

121 than one unit, therefore our discussion below focuses on longitudinal research with

122 longitudinal data, or designs with $N > 1$, $t >= 3$, and the same construct(s) measured on

123 (potentially) each i at (potentially) each t.

124 **Introduce framework**

125   Presenting the entire inference and modeling literature that uses longitudinal data

126 would be impossible. Instead, we focus on four related streams that we feel can be

127 organized using a framework proposed by Xu and DeShon. Figure one shows each inference

128 we will discuss in this paper: relationships, growth, change, and dynamics.

129   In each panel in figure one, time is on the x-axis to portray that we are investigating

130 these inferences over time. Each slice contains an observation of y, such that at time t we

131 observe y_t and at $t + 1$ we observe y_{t+1}. What differentiates the panels – the inferences – is

132 the pattern of relationships we investigate – and we add complexity as we move from A to

133 D. For example, researchers do not include lag effects when they are interested in

134 relationships over time (panel A), but they do include a lag effect when they study change

135 or dynamics (panels C and D). We will devote a section to each of these inferences below,

136 but we first describe some preliminary pieces about code and data that we refer to

137 repeatedly in this paper.

138
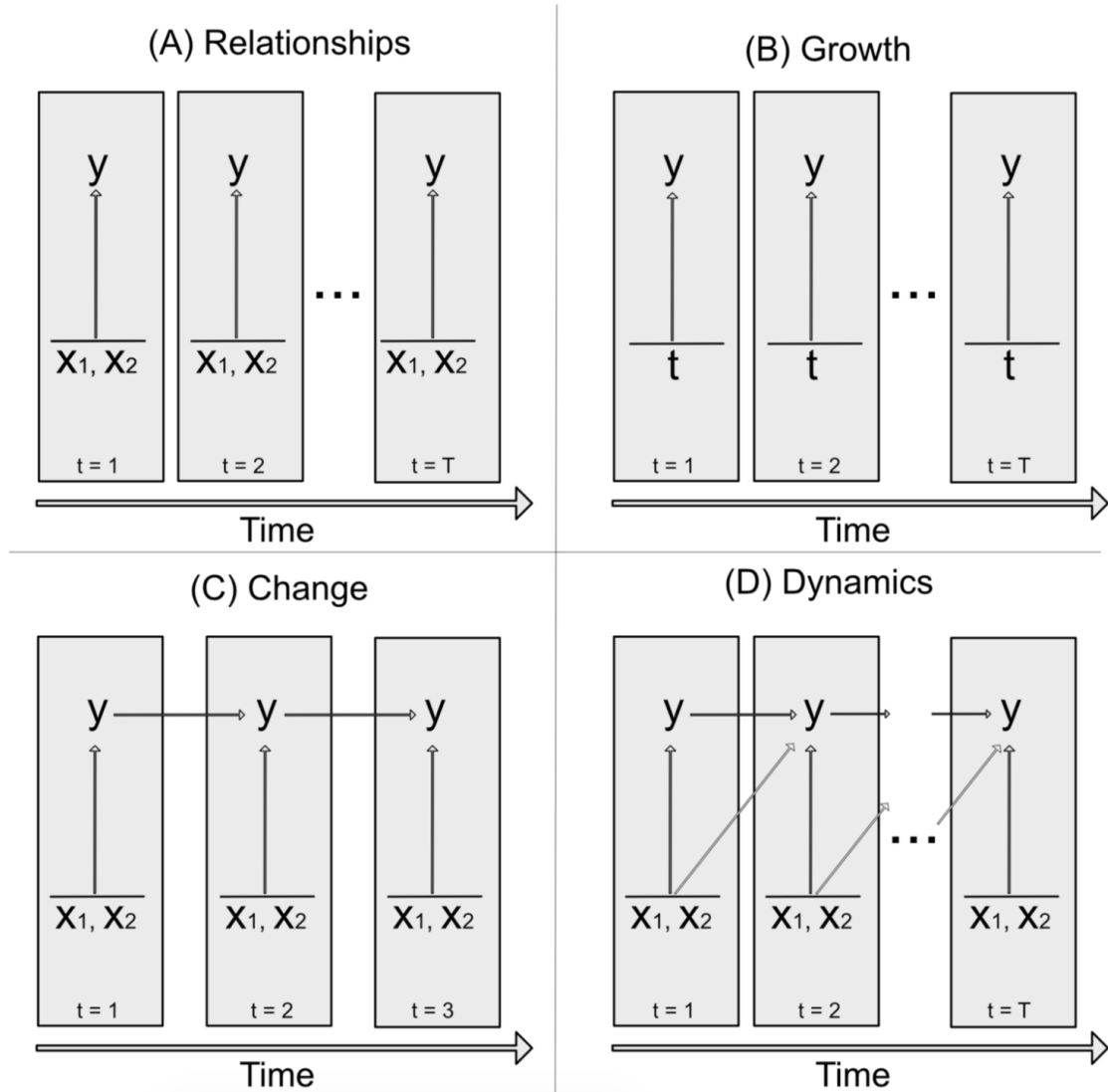
139 **Introduce data sets and generic variables**

140   We will use two generic variables – affect (x) and performance (y) – throughout this

141 paper. These variables will hopefully provide continuity across the inferences and also

142 provide an illuminating backdrop after we refer to x or y generically. Moreover, we use

143 code examples in each section that refer to data sets that contain measures of affect and

144 performance on 50 simulated subjects across five time points.

145   These data are contained in two data sets: `long_df` and `wide_df`. The raw data are

146 the same, but their formatting differs because different estimation techniques require

147 different data structures. Structural equations modeling (SEM) requires wide data, whereas

148 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

150 where `id` refers to a person identifier, `time` refers to the observation period, and scores on

151 `affect` and `performance` are listed in their respective columns.

152   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


)
```

¹⁶⁹ where `hlm_model` is an object that stores the results of our model, `lme` is a function call to

¹⁷⁰ a linear mixed-effects regression (HLM), and within that we specify our effects and

¹⁷¹ reference our data. In the inference sections, `code` and `more code` will be replaced by the

¹⁷² effects we estimate, and `data` will always reference `long_df` because HLM requires long

¹⁷³ formatted data. Finally, after storing our results in the object `hlm_model` we can actually

¹⁷⁴ view them with:

```
summary(hlm_model)
```

¹⁷⁵ Similarly, SEM models will be expressed as:

```
sem_string <- '


    code

    more code



'


sem_model <- sem(sem_string,

                data = wide_df)
```

¹⁷⁶ where `sem_model` is an object that stores the results of our SEM model and we refer to the

¹⁷⁷ `wide_df` data set because SEM requres wide data. Notice that in the SEM code snippet we

¹⁷⁸ first create a string object, `sem_string` to specify our effects. Again, the `code` and `more`

¹⁷⁹ `code` will be replaced by actual effects when we get to our inferences. Just like the HLM

¹⁸⁰ code, we then view our SEM results with:

```
summary(sem_model)
```

¹⁸¹   In summary, the style of code snippets just presented will be used throughout each

¹⁸² inference section. What will change are the `code` and `more code` pieces, and in those areas

¹⁸³ we will impute effects specific to each inference. If you wish to run these models on your

¹⁸⁴ own computer, you will also need to load their packages in your `r` script with

¹⁸⁵ `library(nlme)` for HLM and `library(lavaan)` for SEM (and install them with

¹⁸⁶ `install.packages()` if you have not done so already).

¹⁸⁷   We now turn to the inferences.

<div align="center">

Relationships
</div>

¹⁸⁸

¹⁸⁹ **Inference 1**

¹⁹⁰   What is the relationship between two or more variables across time?

¹⁹¹ **Explanation**

¹⁹²   A common inference in our longitudinal literature is the relationship between an

¹⁹³ outcome (y) and one or more predictors (x_p) over time. As shown in figure one, researchers

¹⁹⁴ observe y and one or more predictors at each time point, and are then interested in the

¹⁹⁵ immediate effect of the predictors on y. Although there are multiple slices in our figure,

¹⁹⁶ typically the effect of x on y is treated as stable over time and therefore the analysis

197 returns an estimate of a single parameter (e.g., a single beta weight). This parameter is

198 essentially a summary statement of the immediate effect of x on y at any point in time. In

199 other words, researchers observe x and y at every t from time t to $t + 5$, as an example, and

200 then report a statement of the effect of x_t on y_t, or the expected immediate effect of x on y

201 at any possible moment.

202   Although the effect (i.e., the parameter relating x to y) is treated as stable over time,

203 the values on x and y – the raw data – are typically allowed to vary. When the values of x

204 (potentially) change at each observation, the analysis is referred to as a time-varying

205 covariates analysis – whereas a time-invariant analysis would be one where the raw data on

206 x does not change at each observation (e.g., gender).

207   To clarify, consider this inference with respect to our generic variables: affect x and

208 performance y. Researchers would collect performance and affect data on multiple people

209 at each observation over several time points. Affect may vary at each observation – it may

210 be 5 at time t and 9 at time $t + 1$ – so this analysis is referred to as a time-varying

211 covariates analysis. Researchers are then interested in the stable, immediate influence of

212 affect on performance. That is, they are interested in the effect of affect_t on performance_t

213 at any potential t, where, on average, they expect the effect of affect on performance to be

214 close to their parameter value.

215   There is a distinction with how we use the term "stable" that merits more

216 explanation. In a relationships inference, "stable" means that we expect the parameter

217 value relating affect to performance to be the same at each moment. In other words, the

218 relationship between affect and performance will be the same at each t – high values of

219 affect will result in high values of performance (if the parameter is positive) and low values

220 of affect will result in low values of performance. "Stable" in this inference context does not

221 mean that affect has a lasting impression on performance, or that affect at time t influences

222 performance at some later time. This distinction is a difficult one, but it represents a major

²²³ difference betweeen making a relationships inference versus some of the others we have yet

²²⁴ to explore. A relationships inference, therefore, is concerned with the average influence over

²²⁵ time, or what we expect the immediate effect of x on y to be at any given moment.

²²⁶ **Literature Examples and Hypotheses**

²²⁷ There are many examples in our literature that are interested in relationships over

²²⁸ time. When a researcher is interested in making a relationships inference, they propose a

²²⁹ hypothesis of the form: x predicts y (given some direction, positive or negative). Using our

²³⁰ generic variables, we would propose:

²³¹ ***Affect positively (or negatively) predicts performance over time.***

²³² For example, Barnes, Schaubroeck, Huth, and Ghumman (2011) predict a negative

²³³ relationship between poor sleep and cognitive self control. Similarly, Chi, Chang, and

²³⁴ Huang (2015) hypothesize that daily negative mood negatively relates to daily task

²³⁵ performance.

²³⁶ **Code**

²³⁷ We gain even more clarity on this inference when we consider the code used to

²³⁸ estimate models. A typical SEM model would be estimated with something similar to the

²³⁹ 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)
```

240 where this code snippet is identical to our introductory SEM code but we have replaced

241 `code` and `more code` with actual effects we wish to estimate. In this case, we regress

242 performance at time t on affect at time t and estimate `b1` – the parameter relating affect to

243 performance over time. The analysis will return one number for `b1` because, again, we are

244 treating this as a stable estimate over time.

245   The HLM equivalent would be:

```
lme(


  fixed = performance ~ affect,

  random = ~1|id,

  data = long_df


)
```

246 where we again replace `code` and `more code` from the introductory HLM snippet with a

247 regression of performance on affect. Notice that we do not need to type the performance on

248 affect regressions at each time point as we did with the SEM code. Typically, in SEM

249 software you type out the entire model, whereas HLM packages use condensed code. There

250 are two other new pieces of code: `fixed` and `random`. These commands specify how we

251 want HLM to estimate the parameters we are interested in, but at this point we do not

252 unpack them further – we will return to what they mean in the full modeling section at the

253 end of the paper.

254   We will devote an entire section to the statistical properties of HLM and SEM below,

255   what is important here is our regression of performance on affect. In both HLM and SEM

256   we estimate a stable parameter relating affect at time t to performance at time t – in SEM

257   software we explicitly identify a parameter (`b1`) whereas HLM software typically does so

258   automatically.

Relationships Inference 1 Summary

259

- Hypothesis:

260

  - x relates to y over time.

261

- Parameters From SEM or HLM:

262

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

263

<div align="center">

Growth

</div>

264

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

266   related to growth.

Inference 1

267

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

269   **References**

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