Inferences With Longitudinal Data

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Abstract

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Keywords: ….

Word count: 95

Inferences With Longitudinal Data

There is now a common understanding that the phenomena organizational researchers study unfold over time. Beal (2015), for example, states that psychological phenomena are "sequences of events and event reactions that play out within each person's stream of experience," and "describing these within-person processes is fundamental to understanding" (p. 5). Similarly, Pitariu and Ployhart (2010) note that the processes we study "are not static but instead develop, change, and evolve over time" (p. 405). Moreover, organizations are systems with many connected parts, and systems are inherently dynamic. Studying these systems and processes, therefore, requires paying attention to how things happen over time; doing so puts us in a better position to capture the sequence, understand it, and can lead to new and interesting insights (Kozlowski & Bell, 2003).

This sentiment is reflected in our empirical literature, where repeated assessments are 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. Meier and Spector (2013) examined counterproductive work behavior over five waves. Hardy, Day, and Steele (2018) investigated self-regulation over 20 lab trials. Finally, Johnson, Lanaj, and Barnes (2014) observed justice behavior and resource depletion across 10 consecutive workdays.

Armed with repeated observations, there are then different research questions that we can explore. Jones et al. (2016) ask about trend: they want to determine if the trajectories among certain variables increase or decrease over time. Johnson et al. (2014) about change: they are interested in how changes in one variable relate to changes in another across time. Hardy et al. (2018) inquire about dynamic relationships, where prior values on one variable predict subsequent values on another, and this second variable then goes back to predict the first at a later point in time. Finally, Meier and Spector (2013) examine how effect sizes change when they vary the time lag between their independent and dependent variable.

Researchers then evoke statistical models that are determined by their research questions. 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 Ritter, Matthews, Ford, and Henderson (2016) We also find complex hierarchical linear models in many event-sampling studies (e.g., Koopman, Lanaj, & Scott, 2016; Rosen, Koopman, Gabriel, & Johnson, 2016).

The spine of an investigation, finally, is to interpret the model and make an inference regarding the original question. Jones et al. (2016) infer negative slopes for concealing behaviors and positive slopes for revealing behaviors. Johnson et al. (2014) state that justice behaviors fluctuate day to day and predict changes in depletion. Hardy et al. (2018) find support for dynamic relationships between self-efficacy, metacognition, and exploratory behaviors. Finally, Meier and Spector (2013) suggest that the effects of work stressors on counterproductive work behaviors are not substantially different across different time lags.

None of these inferences perfectly discovers the data generating mechanism. Rather, each asks an interesting and important question about how DVs relate to IVs. Only with lots of asking about lots of different patterns of relationships across the variables could we piece together one (of many) possible representation(s) of the data generating process – hopefully having a good theory to guide the way.

We want to link inferences to models in this paper so that researchers know which of the many models they can use when they are interested in one of the many possible inferences in a longitudinal investigation. As should be clear to anyone reading our literature, there is great excitement for the utility of longitudinal studies; they can pose interesting questions and discover patterns that would otherwise be impossible to capture in a static investigation. We bring attention to the span of questions available so that researchers can fully appreciate and take advantage of their data. Although the inferences concern trajectories or relationships over time, their small differences have large implications for what we take away from them – what we ultimately conclude. Moreoever, there are many inferences, many models, and different models can be used to understand or explore the same inference. In this paper, we provide readers with a specific model for each inference so that they can be sure that the model they evoke is appropriate for the research question that they are interested in. In summary, this paper exposes researchers to the span of inferences they may investigate when they collect longitudinal data, links those inferences to models, and parses some of the modeling literature that may be difficult to consume for researchers with only graduate level training in statistics.

Below, we do these things.

Longitudinal Definitions

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 & Vandenberg, 2010). 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 $N > 1$, $t >=$ 3, and the same construct(s) measured on (potentially) each i at (potentially) each t.

Framework

Relationships. Growth. Change. Dynamics. These are umbrella research foci, each has its own sub-inferences and models.

Relationships

General discussion.

Inference 1

A stable x relates to y.

Model. .

```
'
perf.1 ~ b1*gender
perf.2 ~ b1*gender
perf.3 ~ b1*gender
perf.4 ~ b1*gender


'
```

Inference 2

A fluctuating x relates to y.

Model. .

```
'
perf.1 ~ b1*affect.1
perf.2 ~ b1*affect.2
perf.3 ~ b1*affect.3
perf.4 ~ b1*affect.4

'
```

Growth

General discussion.

Inference 1

There is growth (positive or negative) in a given variable. Other terms: trend, slope, some call this change; we won't.

Model. .

```
'
latent_perf_slope =~ 0*perf.1 + 1*perf.2 + 2*perf.3 + 3*perf.4

'
```

Inference 2

There are inter-individual differences in growth.

Model. .

```
'
latent_perf_slope =~ 0*perf.1 + 1*perf.2 + 2*perf.3 + 3*perf.4


'
```

Inference 3

There is a relationship between growth (slope) and level in a given variable.

Model. .

```
'
latent_perf_level ~~ latent_perf_slope


'
```

Inference 4

There is a relationship between a stable x and growth in y. There are inter-individual characteristics that relate to inter-individual differences in slope.

Model. .

```
'
latent_perf_slope ~ b1*gender


'
```

Could also do this for level.

Inference 5

There is a relationship between a fluctuating x and y after partialling the growth in y. Or, there is growth in y after partialling the relationship between a fluctuating x and y.

Model. .

```
'
latent_per_slope =~ 0*perf.1 + 1*perf.2 + 2*perf.3 + 3*perf.4


perf.1 ~ b1*affect.1
perf.2 ~ b1*affect.2
perf.3 ~ b1*affect.3
perf.4 ~ b1*affect.4


'
```

Growth 2.0

Above, we examined growth in y and how it related to correlates or predictors – but those predictors/correlates were assumed to have no growth. There is also a class of models for examining relationships between two variables where both are assumed to grow.

Inference 1

There are correlated slopes among two growth curves.

Model. .

```
'

latent_perf_slope ~~ latent_affect_slope

'
```

Change

General Discussion.

Inference 1

x is associated with a change in y: an increase or decrease.

Model. .

```
'

perf.2 ~ b1*affect.2 + g1*perf.1
perf.3 ~ b1*affect.3 + g1*perf.2
perf.4 ~ b1*affect.4 + g1*perf.3

'
```

Dynamics

General discussion.

Inference 1

There is autoregression in a variable, a relationship between prior and future values.

Model.

```
'
perf.2 ~ g1*perf.1
perf.3 ~ g1*perf.2
perf.4 ~ g1*perf.3

'
```

Inference 2

There are cross-lag effects, where one variable relates to another at a different point in time.

Model.

```
'


perf.2 ~ b1*affect.1
perf.3 ~ b1*affect.2
perf.4 ~ b1*affect.3

'
```

Inference 3

There is a relationship direction among a set of variables. Either both variables predict each other, neither predict the other, or the relationship occurs in one direction.

Model. .

```
'


perf.2 ~ b1*affect.1
perf.3 ~ b1*affect.2
perf.4 ~ b1*affect.3

affect.2 ~ b2*perf.1
affect.3 ~ b2*perf.2
affect.4 ~ b2*perf.3


'
```

Inference 4

There is a reciprocal relationship, or feedback, where one variable subsequently relates to another, and this second variable then relates to the first at an even later point in time.

Model. .

```
'


perf.2 ~ b1*affect.1
perf.3 ~ b1*affect.2
```

```
perf.4 ~ b1*affect.3


affect.2 ~ b2*perf.1

affect.3 ~ b2*perf.2

affect.4 ~ b2*perf.3


'
```

Summary List of Inferences

Relationships

Inference 1

A stable x relates to y.

Inference 2

A flucuating x relates to y.

Growth

Inference 1

There is growth (positive or negative) in a given variable.

Inference 2

There are inter-individual differences in growth.

Inference 3

There is a relationship between growth (slope) and level in a given variable.

Inference 4

There is a relationship between a stable x and growth in y. There are inter-individual characteristics that relate to inter-individual differences in slope.

Inference 5

There is a relationship between a fluctuating x and y after partialling the growth in y. Or, there is growth in y after partialling the relationship between a fluctuating x and y.

Inference 6 (growth 2.0)

There are correlated slopes among two growth curves.

Change

Inference 1

x is associated with a change in y: an increase or decrease.

Dynamics

Inference 1

There is autoregression in a variable, a relationship between prior and future values.

Inference 2

There are cross-lag effects, where one variable relates to another at a different point in time.

Inference 3

There is a relationship direction among a set of variables. Either both variables predict each other, neither predict the other, or the relationship occurs in one direction.

Inference 4

There is a reciprocal relationship, or feedback, where one variable subsequently relates to another, and this second variable then relates to the first at an even later point in time.

References

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