Process Cookbook

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Abstract

Begin here...

Keywords: ....

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Process Cookbook

Take aways from last time:

- Change hook
  - Not a "this is what true process is" paper. An organizing paper on the inferences people make and the models they use with longitudinal data.
- Change structure
  - Start early with Xu and DeShon figure to organize everything
  - Use generic variables throughout
  - Data structures issues at end

Hook

The story:

- People want us to do stuff with longitudinal data, to make inferences over time. But this literature can be confusing. We could use some organization.

New researchers are increasingly asked to collect longitudinal data and study how things happen over time. They are advised to because the organizational and psychological processes we study "are not static but instead develop, change, and evolve over time" (Pitariu & Ployhart, p. 405) and "many, if not most, of the psychological phenomena in which we are interested are…sequences of events and event reactions that play out within each person's stream of experience" (Beal, 2015, p. 5). If a researcher 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 phenomeon 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 patters "with longitudinal methods" (p. 329). Not only do longitudinal data collections help the researcher observe relationships over time, many argue that it helps refine and strengthen 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 – and suggest to newcomers that their designs ought to entail repeated assessments.

To satisfy these calls, a newcomer might look to our existing literature for examples of how others understand the patterns they observe in longitudinal designs; this literature is not hard to find. Empirical studies commonly employ repeated measures and the number of time points they use appears to be growing. Words such as "dynamic," "change", and "process" are becoming more prevalent in our literature. Event-sampling methods, which collect repeated observations by necessity, are becomming one of the most popular data collection techniques (Beal, 2015). Finally, a quick skim over the latest issues of top organizational journals reveals that many new studies employ longitudinal designs.

Although our researcher would find some similarities across this literature, she would be confronted by many more areas of disconnect. Some studies use hierarchical linear models (HLM), whereas others employ latent growth curves – even when the underlying questions that they examine are the same. Some make inferences about change, whereas others are interested in dynamics or growth – even when the models they apply are identical. Some propose hypotheses with lags, whereas others do not – even when both collect data across the same number of time points and interval spacing. All of these authors examine patterns in longitudinal data, but it can be unclear how they fit together across their seemingly unrelated hypotheses, models, and inferences. What, then, is a new researcher interested in making inferences with respect to their longitudinal data to do?

Our goal is to organize the common inferences made with longitudinal data so that researchers have a clear sense of what hypotheses they can propose, models they can use, and inferences they can make given their data structure and research question. Our literature is starting to accumulate great examples of the types of inferences we can make with longitudinal data, but their similarities and strengths can sometimes go unnoticed due to the different language used by separate content and statistical modeling areas. Two studies may be interested in the same type of question or inference but apply different models to their data or describe their results with dissimilar variable names. Rather than miss the common ground between these two, we want to provide a framework for seeing how both provide similar types of knowledge. On the other hand, just because two researchers study something over time does not mean they provide the same type of information – and we want to help researchers avoid misconstrued similarities. Moreover, there are small differences in how we conceptualize and model longitudinal data that result in vastly different inferences. In this paper, therefore, we want to organize the inferences researchers make with longitudinal data.

Below, we discuss four common longitudinal research areas: 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 discuss each stream in depth, provide examples from the literature, point researchers to potential models, and acknowledge the pitfall and limitations of each approach.

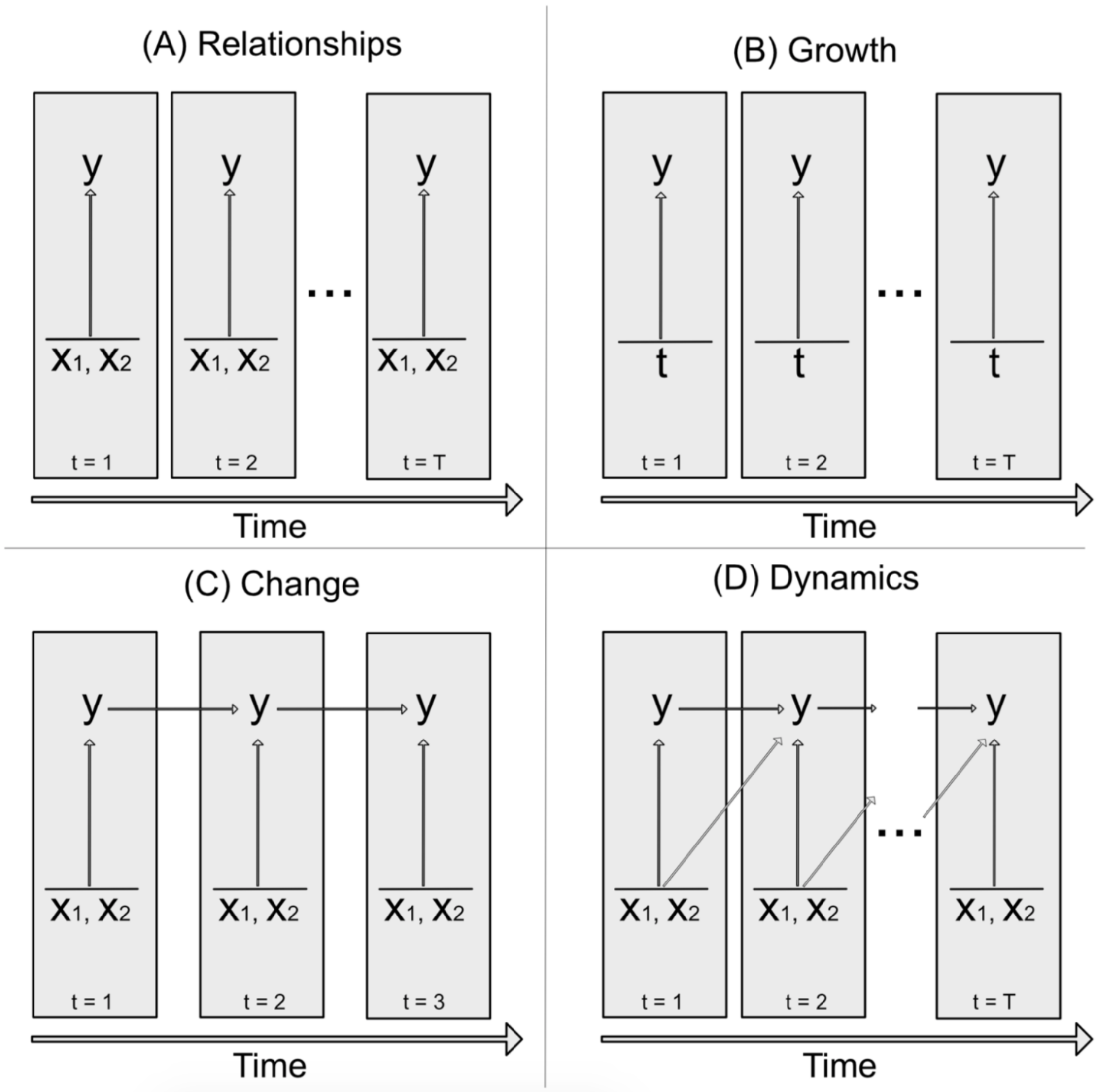
Intro

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 a collection of observations of one unit over time – a distinction that focuses on the amount of people in our study. 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 each i at each t.

Introduce framework

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



Discuss each briefly

Provide generic variable names to use throughout

Examples

Relationships (Goran, Mike, Rick do not read past here, this is the same as last time…not updated yet)

Inference 1

The relationship of one or more predictor variables with a response variable over time.

Examples.

Hypotheses.

Barnes, Schaubroeck, Huth, and Ghumman (2011) and Chi, Chang, and Huang (2015) present hypotheses that are consistent with a relationships inference. Barnes et al. (2011) predict a negative relationship between poor sleep and cognitive self control. Similarly, Chi et al. (2015) hypothesize that daily negative mood negatively relates to daily task performance.

Longitudinal Data Structure.

Researchers that infer relationships over time either a) measure their variables at the same time points or b) treat the data as if they were measured as so by the constraints of their analysis. Barnes et al. (2011) give an example of the former; they measure sleep and cognitive self control every morning for five consecutive days (study 4). Chi et al. (2015), as an example of the latter, measure negative mood in the morning and task performance in the afternoon – but these variables are treated as if they were taken at the same time (e.g., day 4) when entered into their analysis (described later).

There is no limit to the number of possible time points, but studies of this type typically collect between three and ten repeated measurements. Our examples above measure their variables once per day, but other frequencies could also be used. Methods literature typically recommends that researchers maintain the same interval between each measurement across their study, but this can be difficult when studies last longer than a week. For example, Chi et al. (2015) take their measurements for ten work days. In the middle of those assessments, however, their sample employees go home for the weekend and are not measured. The space, therefore, between t and $t + 1$ is not the same across their analysis. Finally, our organizational literature almost always takes measures on more than one unit across time.

Models.

Both Barnes et al. (2011) and Chi et al. (2015) use hiearchical linear modeling (HLM) – also known as multi-level or random coefficient models – to estimate the parameters that generate their observed data. Random coefficient models assume that their random effects are distributed $N(\gamma, \sigma^2)$ – but this statement is easier to understand with a contrast. Imagine that everyone in the sample receives their own X_t on Y_t effect and we then summarize those effects by taking their average. HLM, conversely, estimates one X_t on Y_t effect across units (people) but does so by imposing a normality constraint. Finally, Barnes et al. (2011) and Chi et al. (2015) use models that fall into the broader time-varying analysis class because their measurements of X are allowed to vary over time. In time-invariant analyses, conversely, values of the covariate remain stable (e.g., gender).

Pitfalls and Recommendations. What can go wrong. Recommendation. Why.

Growth

Inference 1

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

Examples.

Hypotheses.

There are few (if any) studies that make direct predictions about construct levels at certain time points. Almost every longitudinal study, however, estimates an intercept term to approximate the answer. These terms are then discussed in the context of broader growth inferences that we discuss below.

Longitudinal Data Structure.

This inference requires several repeated measures on one variable. For example, Zhu, Wanberg, Harrison, and Diehn (2016) measure work adjustment once a month for nine months (among expatriates) and Jones et al. (2016) measure concealing behaviors (among pregnant women) every week – but it is not clear for how long they do so.

Models.

Zhu et al. (2016) use HLM to estimate their parmaters, whereas Jones et al. (2016) do so in a structural equation modeling framework. As stated, researchers are interested in an intercept estimate for this inference, and although they can place it on any time point, researchers typically use their first observation. In SEM, the intercept is a latent variable regressed on either an observed indicator (again, usually the first observation) or its latent equivalent. Jones et al. (2016), for example, regress their latent concealing behaviors intercept term on the latent variable for concealing behaviors at time one. In HLM, the investigator first creates a variable that represents time and then regresses the outcome on this time indicator to estimate an intercept term. For example, Zhu et al. (2016) regress work adjustment on time using HLM to estimate its initial level.

Pitfalls and Recommendations. What can go wrong. Recommendations. Why.

Inference 2

What are the patterns of a trajectory or trajectories across time? How does the construct change over time?

Examples.

Hypotheses.

Zhu et al. (2016) predict that expatriate work adjustment follows a positive trajectory, increasing over the time of the assignment. Similarly, Jones et al. (2016) hypothesize that concealing behaviors will have negative slopes over time.

Longitudinal Data Structure.

As with our previous inference, the only requirement here is a repeated assessment on one variable over several time points – both Zhu et al. (2016) and Jones et al. (2016) meet these requirements.

Models.

Researchers use slope terms in their models for making inferences about trajectory patterns. In HLM, the same procedure we described above – regressing the outcome on time – also provides a slope estimate. Typically researchers do not allow their slope estimates to vary over units, but the models can easily support random slope terms. Zhu et al. (2016), for example, estimate a random slope effect by regressing work adjustment on time. In SEM, a latent slope term is regressed onto all time points except for the time point that was used by the latent intercept term. Jones et al. (2016) regress a latent concealing behaviors slope term on latent concealing behaviors at all time points beyond t_1.

Researchers may also be interested in curvilinear slopes. The only additional requirement for doing so is to create other time indicators with respect to the higher order polynomial. Zhu et al. (2016), for example, included linear, quadratic, and cubic time variables to estimate different slope curves. Note that these are still "linear" processes because they are linear in parameters.

Pitfalls and Recommendations. What can go wrong. Recommendations. Why.

Inference 3

Are there between person differences in trajectories or levels?

Examples.

Hypotheses.

Similar to our first growth inference, researchers rarely make a direct prediction about between person differences in trajectory or level, but it is almost always included as part of a larger growth analysis.

Longitudinal Data Structure.

We now require repeated observations on multiple units to examine between person (unit) differences. For example, Zhu et al. (2016) collect data from 179 expatriates across nine consecutive months.

Models.

Models that estimate intercept or slope terms also estimate a variance on those terms, and these are then subjected to significance tests. When the variance on the intercept is significant, that is taken to mean that there are between unit differences in intercept (levels), whereas significant variance estimates on the slope terms indicates between unit differences in slope (trajectory). Zhu et al. (2016) use HLM to estimate the variance on their intercept and slope terms and find evidence of between person differences in work adjustment intercept (level) and slope (trajectory).

Pitfalls and Recommendations. What can go wrong. Recommendations. Why.

Inference 4

How is the level of a construct related to the trajectory of the same or different constructs? What is the correlation between intercept and slope terms?

Examples.

Hypotheses.

Schaubroeck, Lam, and Peng (2016) predict that initial levels of peer leader's transformational leadership will positively relate to the slope of employee beliefs. Zhu et al. (2016) hypothesize that initial level of expatriate work adjustment is negatively related to the speed of change in work adjustment. Notice that the first prediction is about how the level of one construct is related to the slope of another, whereas the second focuses only on a single variable. Although it is uncommon in our literature, developmental researchers will also predict associations between slope and the final – rather than initial – observation.

Longitudinal Data Structure.

Data structures that researchers use to examine this inference are consistent with what we have already reviewed. Schaubroeck et al. (2016) measured transformational leadership and employee beliefs at three time points. Their time two assessment was 10 weeks after their first observation, whereas their final measurement was taken 10 months after their second observation. That is, the data structure for their respective time points were t, $t + 10$, and $t + 40$. As stated above, Zhu et al. (2016) collected data once a month for nine months.

Models.

Both HLM and SEM provide estimates of the covariance between the intercept and slope terms discussed above, and this covariance indicates the association between level and trajectory. For example, Zhu et al. (2016) report a negative covariance estimate betwen the initial level of expatriate work adjustment (intercept) and its linear trajectory over time (slope). As stated, researchers can also examine this association but among the level of one variable and the trajectory of a different variable. Schaubroeck et al. (2016) report an estimate of the relationship between transformational leadership intercept and employee beliefs slope. It is often helpful to generate predicted values using the analysis estimates and then plot the levels and trajectories to interpret them appropriately.

Pitfalls and Recommendations. What can go wrong. Recommendations. Why.

Inference 5

What inter-individual characteristics relate to intra-individual differences in level or slope?

Examples.

Hypotheses.

Inferences of this type take the form of stable unit effects and their relationship with trajectory or level. Li, Burch, and Lee (2017) predict a positive relationship between job strain and job complexity trajectory. Zhu et al. (2016) hypothesize that the trajectory of expatriate work adjustment is positively related to perceived career instrumentality. Finally, Jones et al. (2016) make two inferences of this type: contextual support is a) negatively related to average levels of concealing but b) positively related to the slope of concealing.

Longitudinal Data Structures.

We discussed the data structures for Zhu et al. (2016) and Jones et al. (2016) above. Li et al. (2017) use a similar design but their data are collected once per year. Job complexity is measured once every year for three years, and job strain is measured once at the final time point (year 3).

Models.

Both Li et al. (2017) and Zhu et al. (2016) use HLM to estimate their parameters, whereas Jones et al. (2016) do so with SEM. In these models, the intercept or slope terms discussed above are regressed onto the inter-individual characteristic. For example, Li et al. (2017) report the estimate of job strain predicting job complexity trajectory and Zhu et al. (2016) do the same but for career instrumentality and job complexity trajectory. In the SEM framework, Jones et al. (2016) report estimates of contextual support predicting concealing slope and intercept. Note that these models fit into the broader time-invariant analysis class that contrast with the time-variant covariates analyses discussed earlier.

Pitfalls and Recommendations. What can go wrong. Recommendations. Why.

Change

Inference 1

How are the changes of one variable associated with changes in another over time?

Examples.

Hypotheses.

Change inferences are similar to relationship inferences in that they relate a predictor to a response at the same time point, but the researcher now wants to know whether the predictor is associated with an increase or decrease of the outcome. For example, Johnson, Lanaj, and Barnes (2014) predict that, within individuals, exhibiting daily procedural justice behavior is associated with an increase in resource depletion. Similarly, Lanaj, Johnson, and Lee (2016) hypothesize that, within individuals, transformational leadership is associated with a decrease in negative affect.

Longitudinal Data Structures.

Johnson et al. (2014) measured justice behavior and resource depletion in the afternoon of 10 consecutive workdays. Lanaj et al. (2016) measured their variables at different frequencies. They measured transformational leadership and negative affect in the afternoon of 15 consecutive workdays, but they also took an additional measurement of negative affect every morning – creating a data structure of three variables: negative affect from t to $t + 15$, transformational leadership from t to $t + 15$ and morning negative affect from t to $t + 15$. That is, they essentially doubled the time points of negative affect – from t to $t + 30$ by measuring it twice as frequently.

Models.

Johnson et al. (2014) and Lanaj et al. (2016) employ HLM change models that are consistent with our literature's preference for using partialed values of the outcome variable rather than difference scores. In models of this type, researchers regress their outcome on the predictor at the same time point and the prior value of the outcome variable. For example, Johnson et al. (2014) regressed resource depletion at time t on 1) procedural justice behavior at time t and 2) resource depletion at time $t-1$; they then report the relationship between justice behavior and resource depletion change. Similarly, Lanaj et al. (2016) regress negative affect at time t on 1) transformational leadership at time t and 2) negative affect at time $t-1$ (i.e., morning negative affect) and report the association between transformational leadership and affect change. Note that, due to the different data sampling strategies, Johnson et al. (2014) reports change from the prior day, whereas Lanaj et al. (2016) report change from the morning to afternoon.

Pitfalls and Recommendations. What can go wrong. Recommendations. Why.

Dynamics

The core concept is: how are prior states related to future states?

Inference 1

How is one variable related to its future self?

Examples.

Hypotheses.

Longitudinal Data Structures.

Models.

Pitfalls and Recommendations.

Inference 2

How is one variable related to a different variable in the future?

Examples.

Hypotheses.

Gabriel, Diefendorff, Chandler, Moran, and Greguras (2014) hypothesize that perceived P-O fit is positively related to subsequent positive affect.

Longitudinal Data Structure.

Gabriel et al. (2014) measured perceived P-O fit and positive affect five times per day for 10 consecutive work days.

Models.

Researchers that use models related to this inference regress their outcome at time t on a prior value of the independent variable. Gabriel et al. (2014) do so using HLM and regress perceive P-O fit at time t on 1) positive affect at time $t-1$ and 2) perceived P-O fit at time $t-1$.

Pitfalls and Recommendations. What can go wrong. Recommendations. Why.

Inference 3

Directionality – what is the relationship direction among a set of variables?

Examples.

Hypotheses.

A directionality inference is typically explored using a pair of dynamic hypotheses. For example, Hardy, Day, and Steele (2018) predict that 1) prior self efficacy negatively relates to subsequent meta cognition and 2) prior meta cognition positively relates to subsequent self efficacy. Similarly, Matthews, Wayne, and Ford (2014) contrast two theories, one that predicts that work-family conflict is negatively related to subsequent well-being, whereas the other predicts that well-being is negatively related to work-family conflict.

Longitudinal Data Structures.

Hardy et al. (2018) measured self efficacy and meta cognition after five evenly spaced computer game trails – although they also measured baseline self efficacy. Matthews et al. (2014) assessed work-family conflict and well-being concurrently at three points in time: t, $t+1$, and $t+7$ where the intervals are months – meaning that the final survey was assessed six months after the survey before it.

Models.

Both Hardy et al. (2018) and Matthews et al. (2014) use an SEM approach to estimate their parameters, but Matthews et al. (2014) restrict their model to a path analysis. Their modeling strategies are the same as those just presented, but they examine them as a set to explore the relationship direction among their variables. Matthews et al. (2014) find significant effects in both directions – WFC predicting subsequent well-being and well-being predicting subsequent WFC – and therefore suggest that the relationship works in both directions. Hardy et al. (2018) also report the estimates of self efficacy predicting subsequent meta cognition and vice versa, but only find significant effects for the latter. They conclude that "self-regulatory processes (i.e., exploration and meta cognition) positively influenced subsequent self-efficacy... In contrast, we only found limited support for the notion that self-efficacy significantly influences subsequent self-regulated learning processes" (p. 24).

Pitfalls and Recommendations. What can go wrong. Recommendations. Why.

Inference 4

Reciprocal – Is the pattern of relationships reciprocal, such that one variable influences another, and this latter variable then goes back to influence the first?

Examples.

Hypotheses.

Kaltiainen, Lipponen, and Holtz (2017) present a set of hypotheses to explore reciprocal dynamics among justice perceptions and trust. They predict that "process justice perceptions and cognitive trust have positive reciprocal relations over time. Specifically, planning stage (time 1) process justice (cognitive trust) perceptions will have a positive relationship with subsequent post-merger (time 2) cognitive trust (process justice) perceptions, which in turn will have a positive relationship with later post-merger (time 3) process justice (cognitive trust) perceptions" (p. idk).

Longitudinal Data Structure.

They assess cognitive trust and justice perceptions once a year for three years.

Models.

Kaltiainen et al. (2017) evaluate a number of models but find best fit for a model that includes reciprocal relationships among justice and trust. In that model, trust at time t is regressed on trust at time $t-1$ and justice at time $t-1$, and justice at time t is regressed on trust at time $t-1$ and justice at time $t-1$. They find significant cross-lag effects for trust on justice at all times but only one significant cross-lag effect of justice on trust, and ultimately conclude that "the justice $\Rightarrow$ trust $\Rightarrow$ justice reciprocal relationship was supported but the trust $\Rightarrow$ justice $\Rightarrow$ trust relationship was not supported as the relationship between justice at time 2 and cognitive trust at time 3 was not statistically significant" (p. 14).

Pitfalls and Recommendations. What can go wrong. Recommendations. Why.

Inference 5

Mediation – one variable influences an outcome through an intermediate variable

Things to notice and questions

1) Not going example by example, I am combining them.

    - Originally I thought it would be more clear this way, but I could be wrong. I do not have enough examples to pair every inference with its own unique empirical example.

2) Pitfalls and recommendations after each inference (as I did here...) or after each entire inference section (i.e., one for relationships, one for growth, etc.)?

3) "We" or "they" phrasing?

    - I.e., "we as a field typically do this..." or "researchers tend to do this..."
    - Not for stylistic reasons but for authoritative reasons.

4) Several issues that came up while writing the data structures sections

    - 1) They are repetitive
    - 2) Each example has their own issue (e.g., spacing between t and t + 1 isn't consistent, or the variables were measured at different frequencies). If I bring them up out of the blue it is really easy to lose the reader.
    - Solutions
        - I could write one data structure piece per inference section rather than one per inference
        - I could skip data structures in the inference examples – just provide hypotheses and models – and then give them their own section later
        - I could give pictures like figure 1 in Xu and DeShon in each inference example section and then give data structures and issues their own section later. That is, in the examples I simply speak about hypotheses and models

as if every study measured their variables from t to $t + 10$ on the same interval. Then, at the end I come back with data collection problems/discrepancies I noticed in the articles. I like this option.

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