Equilibria in Personality States:
A Conceptual Primer for Dynamical Analyses

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18 Abstract

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20 We provide a basic, step-by-step introduction to the core concepts and mathematical
21 fundamentals of dynamic systems modeling through applying the Change as Outcome model,
22 a simple dynamical systems model, to personality state data. This model characterizes
23 changes in personality states with respect to equilibrium points, estimating attractors and their
24 strength in time series data. Using data from the Personality and Interpersonal Roles (PAIRS)
25 study, we find that mean state is highly correlated with attractor position but weakly
26 correlated with attractor strength, suggesting strength provides added information not
27 captured by summaries of the distribution. We then discuss how taking a dynamic systems
28 approach to personality states also entails a theoretical shift. Instead of emphasizing
29 partitioning trait and state variance, dynamic systems analyses of personality states
30 emphasize characterizing patterns generated by mutual, ongoing interactions. Change as
31 outcome modeling also allows for the effects of personality development after significant life
32 changes to be conceptualized in more nuanced ways, separating effects on characteristic
33 states after the significant change and how people are drawn towards those states (an aspect
34 of resiliency). Estimating this model demonstrates core dynamics principles and provides
35 quantitative grounding for measures of “repulsive” personality states and “ambivert”
36 personality structures. Supplementary materials: <https://osf.io/dps4w>.

Personality psychology has done important and lasting work in understanding the origin and structure of traits. Nevertheless, researchers have repeatedly stressed the need for a deeper understanding of the processes that generate these traits (Baumert et al. 2017, Fleeson & Jayawickreme 2015; John & Srivastava, 1999; Fleeson, 2001; 2004; Benet-Martinez et al., 2015; Mischel & Shoda, 1995). Processes inherently unfold over time, and so studying personality processes requires theorizing about and modeling changes over time (Vazire & Sherman, 2017). Understanding the characteristic patterns of change that emerge from different components interacting over time is the core goal of dynamic systems theorizing and methods, and researchers have repeatedly suggested that dynamic systems can give insight into personality processes (e.g., Mischel & Shoda, 1995; Read & Miller, 2002; Read, Droutman, & Miller, 2017; Sosnowska, Kuppens, De Fruyt, & Hofmans, 2019; Mayer, 2015; Endler & Magnusson, 1976). We believe that the field of personality psychology can enhance both its explanatory and predictive potential through the systematic integration of ideas from dynamic systems research.

Like the PersDyn approach of Sosnowska and colleagues (2019; this issue), our approach includes core explanatory concepts from dynamic systems, including equilibria, attractor states, repeller states, phase space, and perturbations. Our goals are complimentary to those of Sosnowska and colleagues: we would like to see people consider personality through the lens of dynamic systems, an approach that has been extraordinarily fruitful in allied disciplines (Beer, 1997; De Bot, Lowrie, & Verspoor, 2007; Otto & Day, 2011; McElreath & Boyd, 2008; Rabinovich, Varona, Selverston, & Abarbanel, 2006; Van Geert, 2008). Researchers have invoked the high level theoretical concepts from dynamics to explain personality for decades (e.g., Endler & Magnusson, 1976; Magnusson, Anderson, & Törestad, 1993; Ford & Lerner, 1992; Lucas, 2007), but a frequent difficulty we encounter when trying to discuss these ideas with researchers less familiar with dynamic systems

modeling is vagueness and trepidation about understanding core dynamics constructs at the concrete level of modeled data. We address this lack of clarity by introducing readers to the Change as Outcome model (Butner et al., 2014), a simple dynamic systems model that can be estimated using regression. We explain core dynamic systems constructs in detail by considering the specifics of this model, breaking down each component of the equations used to estimate it, and providing visualizations to guide intuition.

The ideal audience for this manuscript is a psychologist with limited training in dynamic systems, but who would like to gain some intuition about the “nuts and bolts” of applying dynamic systems to personality psychology means. Our approach is not intended to be at odds with or superior to other personality dynamics approaches; rather, we believe it “pairs well” with them, particularly the article on PersDyn in this special issue (Sosnowska et al., this issue) in that it intends to provides a strong theoretical fundament and step-by-step primer of how to “become a dynamic systems thinker” in the domain of personality – and then lays out what implications this can have for the field of personality and personality development.

There are many statistical models used to estimate change over time in psychological data, including latent change scores (McArdle, 2009; McArdle & Grimm, 2010); dynamic structural equation modeling (DSEM; Asparouhov, Hamaker, & Muthen, 2018), statistically estimating differential equation models (DeBoeck & Bergeman, 2013), Bayesian hierarchical process modeling (Oravecz, Tuerlinckx, & Vandekerckhove, 2016), among others. Some models of personality dynamics are even instantiated as neural networks (e.g., the Cue-Tendency-Action model; Brown, 2017; Revelle & Condon, 2015). We chose to present the Change as Outcome model, a relatively simple model that can be estimated in a linear regression framework, specifically because it is easier to illustrate and understand dynamics using this model. We do not attempt a direct quantitative comparison of these modeling

strategies, nor do we claim that this is the most sophisticated contemporary approach for modeling personality dynamics—although, because of the close “proximity” of the two articles within the special issue, we do provide a direct comparison with the parameterization of PersDyn in an appendix. Our goal is decidedly to illustrate, in the most clear and immediately applicable way, the mathematical and conceptual core of a dynamic systems approach, rather than to evaluate which of the employable statistical dynamic systems technique fits data best.

Core Concepts in Dynamic Systems

Core concepts from the dynamic systems literature—such as equilibria, attractors, repellers, topologies, and perturbations—allow personality researchers to think in a nuanced way about patterns of change over time. We believe these concepts are necessary for more fully understanding personality processes, and that dynamic systems theory is particularly well-suited to understanding the reciprocal way person factors and situation factors interact and feed off each other to generate specific patterns of behavior.

Our approach in this manuscript is inherently exploratory. Some researchers have developed formal models of personality and underlying processes, which translate “top down” theoretical intuitions into quantitative simulations (e.g. Read & Miller, 2002; Smaldino, Lukaszewski, Von Rueden, & Gurven, 2019). To complement these top-down approaches, we estimate here parameters from observed data, hoping that this “bottom up” approach will spur further theorizing about dynamic processes underlying personality.

Our approach is also inherently person-centered, or idiographic, in that different models are estimated for each participant in a study. The importance of person-centered analysis has been stressed in personality research for decades, and we will not reiterate these

arguments in detail (Molenaar, 2004; Molenaar & Campbell, 2009; Pelham, 1993; Barlow & Nock, 2009; Fisher, Medaglia, & Jeronimus, 2018). Briefly, the approach stresses that processes may differ between people, and therefore the interrelationships between variables might also differ between people. For example, for some people socializing in a group might elicit positive emotions (like excitement) while for others it might elicit negative emotions (like anxiety). The association between the variables “being around others” and “emotional valence” would therefore differ substantially across people. Trying to summarize a whole group of people by saying “being around others leads to positive emotion” would ignore the underlying differences in processes across individuals. Even worse, a variable-centered analysis might average out these opposing effects and lead researchers to conclude that socializing has no influence on emotions—though that conclusion might not hold for any single individual in the sample. Person-centered approaches therefore begin by analyzing the relationships between variables within a single person, and only then try to form aggregates or clusters that capture regularities in differences in processes.

In this manuscript, we begin by describing the Change as Outcome model, drawing primarily on the description provided by Butner and colleagues (2014). We identify its key features and how to interpret them in the context of personality state variables. We then describe ways in which this model should influence personality theory and reorient our thinking. Next we describe how to implement the model in a linear regression framework, providing accompanying R code in Supplementary Materials. We then provide summaries of a series of Change as Outcome models run on a large sample of participants, demonstrating how parameters estimated from these models differ from those estimated from more traditional approaches. Finally, we discuss implications for this approach moving forward.

State Personality

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138 Researchers employing the Whole Trait approach to personality construe trait levels
139 as features of the distribution of experienced personality states (Fleeson, 2004; Fleeson &
140 Jayawickreme, 2015). Over the course of a week, for example, one person might be very
141 extraverted at times—perhaps on a Friday night—and less extraverted at other times—
142 perhaps on a Monday morning. From the perspective of Whole Trait Theory personality is
143 the overall density distribution of these states, which can be represented quantitatively using
144 different moments of the distribution such as mean, standard deviation, skewness, and
145 kurtosis. An example of a time series of state extraversion measures, and the resulting density
146 distribution, are given in Figure 1A and 1B. Data are taken from the Personality and
147 Interpersonal Roles Study (PAIRS), where participants completed a series of three items
148 related to extraversion four times per day, approximately four hours apart (further details of
149 data are given below).

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151 Figure 1: Converting Personality State Measurements to a Density Distribution

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153 A: Time Series with Mean and Standard Deviation Overlaid

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156 B: Density Distribution with Mean and Standard Deviation Overlaid

Note: The solid line overlaid on both plots represents the mean of the distribution. Dotted lines represent the mean plus and minus one standard deviation.

However, characterizing a series of measurements taken over a period of days, weeks, or months merely by a state density distribution completely ignores the temporal ordering of the data. All information about which state came before or after any other is lost in conversion. From a dynamic systems perspective, this information about how the states change is vital for understanding the process that generated the data.

We can introduce changes to our representation of personality states by plotting the value of the personality state along the x -axis, as above, against the *change in personality state* along the y -axis. Butner and colleagues (2014) describe this as the “hidden dimension” of change over time. This scatterplot allows us to see the typical level of change associated with a particular state. This is a visualization of a Change as Outcome model (cf. Fig. 2).

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172 Figure 2: Identification of an Attractor Point in a Change as Outcome Model

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174 A: Theoretical Change as Outcome Model

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176 B: Change as Outcome Model Plotted for One Participant

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Values above zero on the y-axis correspond to increases in personality state. So if a point is in the upper left quadrant of the plot, this indicates that when the state is low (to the left on the x-axis), the expected change in the next time point will be positive (up on the y-axis). Points in this quadrant indicate that low states tend to move back towards a higher equilibrium over time. Points in the lower right quadrant of the plot indicate that when a state is high (to the right on the x-axis) the expected change will be negative (down on the y-axis). The tendency is for high values to move back towards a lower equilibrium. An example of this kind of plot using real data is given in Figure 2A.

One way to visually explore the tendency of an individual to increase or decrease at a particular state is to add a loess regression line to the plot. Loess is a form of local regression that tracks the shape of the data without making any assumptions about the underlying relationship between plotted variables (e.g., linear relationship, quadratic, etc.). The loess line displays the trend to increase or decrease across all possible state values. An example of plotting the Change as Outcome model based on real data with a loess line is given in Figure 2B.

The line $y = 0$ takes on a special significance in this plot. When the expected change in a state is zero, this indicates an equilibrium point. Since the expected change is zero (i.e. we neither expect an increase or decrease from the current to the consecutive state), the person is expected to stay in this state unless some unexpected force moves her away from it. Of course, many forces throughout someone's day—both in the form of external features of a situation and internal changes in cognitions and emotions—may jostle the person from this theoretical resting point, but an equilibrium is important because it can indicate the location of an *attractor* within the *structure* (*topography*) of the system.

An attractor is a technical term used in the dynamic systems literature, and is one of two kinds of equilibria that can occur in a one-dimensional system (a system that is tracking just one state at a time). An attractor is a point that a system is drawn towards. We would interpret it in this case by saying that whenever something pushes this system (the person in their environment) away from the attractor point, the natural tendency is to return to it.

The representation of this individual's measurements using a Change as Outcome model gives different measures from a density distribution. Instead of a mean, we obtain an equilibrium point. This is the state towards which the system naturally moves over time, and it has a different theoretical interpretation, and may differ empirically, from the mean of the distribution. Instead of a standard deviation, we can estimate the strength of the attractor. This is the speed with which the system returns to the attractor. A system (person in their environment) with a stronger attractor will return to that point more quickly. These features enrich our picture of personality states, complimenting quantities already incorporated in Whole Trait Theory.

We identify the kind of equilibrium point by estimating the local behavior around it. Examining the local slope—the slope around an equilibrium point in the Change as Outcome model—gives us insight into both the strength and type of the equilibrium point. If the local slope around the equilibrium is negative, as in Figure 2B, this indicates an attractor. Starting at the equilibrium point, as the state increases a small amount, the subsequent predicted change is to decrease—meaning the system will move back towards the equilibrium. As the state decreases a small amount, the subsequent predicted change is to increase—again moving the state back to its equilibrium.

If the local slope around the equilibrium point is positive, this indicates the equilibrium point is a repeller. A repeller is a point that the system tends to move away from. As the state increases a small amount, the subsequent predicted change is to increase

further—meaning it moves further away from the equilibrium point. As the state decreases a small amount, the subsequent predicted change is to decrease further—again moving away from the equilibrium. In the dynamic systems literature, this is sometimes referred to as an unstable equilibrium, because while no change is expected when the system is in *exactly* at that state, any perturbation will push the system away from that equilibrium. This makes it unlikely that the system will land in the unstable equilibrium in the first place. A useful metaphor is balancing a pencil on its point; while it is theoretically possible to do so, any tiny movement will tend to push it away from this balanced equilibrium state.

Next consider the angle of the slope. If the slope is very steep—either in the positive or the negative direction—this means that the attractor or repeller is very strong. Strength is defined here in terms of rate of change: stronger means that the state changes more quickly. This can again be understood visually on the Change as Outcome figure. Consider an attractor with a steep versus shallow slope, as in Figure 3. If the slope is steep, this indicates that when the state increases a small amount, the subsequent predicted decrease is larger. The person returns to the equilibrium value more quickly. If the slope is shallow, a small increase in state leads to only a small decrease in the next time point. The person returns to the equilibrium value more slowly. (A special case occurs when the absolute value of the slope is greater than one: the person increases so much that she overshoots her equilibrium point. For such cases, a specialized model such as a damped oscillator might be appropriate (e.g., Chow, Ram, Boker, Fujita, & Clore, 2005). This case has not been observed in any of the hundreds of personality state time series we have analyzed.) Note that other dynamic models have slightly different interpretations of equilibria: in Revelle and Condon's (2015) model they represent the balancing of opposing forces, and in Sosnowska and colleagues' (this issue) model, equilibria can only be attractors and they represent a person's baseline state.

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254 Figure 3: Visualizing Attractor Strength

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256 A: Strong Attractor, as Indicated by Steep Local Slope Around the Equilibrium Point

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258 B: Weak Attractor, as Indicated by Shallow Local Slope Around the Equilibrium Point

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Note: Change is in per hour metric. The y-axes are scaled based on the data, so the top plot indicates a large amount of expected change (~ 0.5 change for a one-point increase or decrease) while the bottom plot indicates a small amount of expected change (~0.001 change for a one-point increase or decrease). In both cases, a linear model (as opposed to a loess smooth) was plotted, because a linear model was found to fit the data well.

Theoretical Importance of a Single Attractor Model

It is tempting to think of this attractor as an ideal or desired personality state, but this agentic language is not quite accurate. In our interpretation, the person is just one part of the system; the environment and responses elicited by the person are also part of the system. Saying that the system is “drawn towards” an attractor does not necessarily mean that the individual is considering their ideal state and taking steps to adjust their behavior to reach the situation. This is different from the conceptualization of personality states in Whole Trait Theory, which suggests these states vary due to people pursuing different goals (McCabe & Fleeson, 2012; Prentice, Jayawickreme & Fleeson, 2019). Goals are typically conceived of as internal and conscious, while system dynamics do not necessarily need to be either.

For example, an individual might resist going out to meet friends—and indeed might tell themselves or others that their goal is to have a “quiet night”—but nonetheless end up finding themselves out with friends and in a high extraversion state. In the dynamic systems perspective, this is because of the continuous feedback between person and situation. The social situation might slowly edge the person towards higher extraversion—and internal factors, such as liking conversations with friends, might edge the person towards being pulled into these social situations. The extraversion therefore emerges naturally through system

dynamics, without a plan to satisfy a need for connection; indeed it can emerge in opposition to a conscious plan to stay in.

This explanation also does not mean that the situation controls a person's state, in the sense of a "strong situation" (Cooper & Withey, 2009). The situation does not "want" a person to act in any particular way, although it does have an influence on personality state. There is continuous feedback between person and situation, and so some people who are naturally "energized" by social interaction might end up having a synergistic reaction that leads to high extraversion. Other people might be naturally stressed by social interaction and so be pushed towards a low extraversion state. The attractor is therefore distinct from either goal pursuit or strong situational influences; it is a description of the expected behavior of the *person in the situation*—with the situation, in this case, representing the typical places and events that a person encounters in their daily life. This is the set of situations (or niche) the person has created for themselves in their day-to-day life.

This shift to thinking in terms of person vs. situation to the *person in situations* is one of the most important points to understand about this perspective. Theoretically, the attractor is generated by the continuous, ongoing interactions between both changes in the person and in the situations she encounters in her everyday life. Disentangling these to describe a behavior as X% caused by the situation and Y% caused by the person cannot capture the true complexity of the idiosyncratic origin of the behavior. In fact, the analytic paradigm is shifted from trying to divide causes of behavior into person, situation, and person x situation interaction to something new: trying to understand the behavior of the person in the situation as a single coherent entity (the system). That is, we want to characterize the consistent patterns of the person/situation system, the idiosyncratic changes, and potential modifiers of this system-level pattern.

Imagine a person laughs at a friend's joke. In the moment, both the situation—the joke—and the person—her sense of humor—influence the behavior. But the dynamic system approach invites us to consider the causal history of this event. The friend's decision to tell the joke was in part caused by knowledge of the person's (good) sense of humor—so the situation was elicited by previous personality states. The person's sense of humor was also influenced by her exposure to her friend's jokes—so personality was caused by previous situations. The history of the previous interactions between the components of the system influence the current behavior of the system.

Given that earlier interactions between system components influencing the current state, the state can take radically diverging paths. A person who has joked with a friend a lot in the past can end up laughing a lot more at a given joke due to their shared history of interactions, while that same joke would barely warrant a smile with a different friend. One hallmark of complex systems (a subset of the broader field of dynamic systems) is dependency on initial conditions, so that the ultimate trajectory of a state can diverge broadly based on small differences, i.e. the butterfly effect (Lorenz, 2000). Disentangling the proportion of variance explained for these mutually influencing, continually interacting components is impractical, and in some cases impossible. Instead, dynamic systems researchers focus on characterizing the behavior of the system as a whole; in this case, the typical trajectory of interactions of the person with her funny friend.

Identifying an attractor in personality states is an example of identifying a system-level characteristic. The attractor is a pattern that is created by the continuous interactions between person and situation. Changes to either have the potential to alter the underlying dynamics, as do changes in the way they interact, thus, they might change location and strength of the attractor. For example, a person who becomes more responsive to her situation (e.g., becoming sensitized to others noticing her) might change her extraversion dynamics

without fundamentally changing her extraversion levels; similarly, a social situation that is suddenly more responsive to the person's extraversion (e.g. she ends up at the center of attention in a group) could change the dynamics, even if the characteristic ways that people respond to extraversion (e.g. talking more to people in extraverted states) have not changed. Fundamentally, then, the dynamic systems approach to personality states is about shifting the focus of a model from *decomposing* person-situation influences to *characterizing* how person and situation work together to determine a person's state. Distinct from the largely static, multiplicative way person by situation interactions have been modeled previously, it emphasizes that the components of the system are continuously interacting and so any particular summary snapshot of person and situation will not give a definitive answer to the question of what caused a particular behavior.

Variability and Error in the Change as Outcome Model

Variability and error in the Change as Outcome model—as in many dynamic systems—is characterized in terms of natural *perturbations*. The system that governs change in personality state over time—the personality state system—is taken to have a characteristic internal dynamic which guides its evolution over time. Left unperturbed, the system would change in a purely deterministic fashion, moving towards an attractor and then remaining at that point (ignoring the more complex idea seen in multi-dimensional systems that cycles of change can themselves be attractors). However, systems in the real world are constantly being influenced by idiosyncratic internal and external events that have not been modeled. Personality states influence themselves, such that they will tend to move in a characteristic way towards an attractor, but the many internal and external idiosyncrasies occurring in a person's life “perturb” the system, pushing it away from its dominant pattern.

Perturbations can be thought of as idiosyncratic events and reactions, which are modeled as essentially random deviations from the dominant trajectory that reveal its topology. Consider a person whose attractor state for extraversion is 3.3, and whose current state is at this attractor. The person gets called unexpectedly into a meeting, which pushes her extraversion state up to 4 as she responds to the situation. If she has no further external perturbations—no more pokes from new, unexpected situations—she will eventually go back to her normal job tasks and return to her attractor state of 3.3. This will be more or less rapid based on the strength of the attractor.

Given how frequently situations change and influence us, perturbations to the system are likely to occur frequently. So the personality state system is continually trying to move towards its attractor point, but unexpected forces are continually pushing it in unexpected directions. Measurements of personality state capture the system responding to its own dynamics and to idiosyncratic pushes. Error in the Change as Outcome model can be thought of as these perturbations.

Perturbations can be thought of as representing concrete entities; a specific perturbation might be running into an old friend, or becoming engrossed in a book and ignoring social opportunities. These are specific events, but researchers can understand that no model can account for every possible event without becoming unworkably complex. The Change as Outcome model—as any dynamic model of a real-world process—divides our representation of the world into events that are part of a characteristic, repeating pattern and those events that are deviations from the pattern. Perturbations are error terms in a model, while characteristic changes are meaningful terms (e.g., regression coefficients—see below for details of specifying models).

Since the person-situation distinction is such a persistent conceptual frame in psychology, it is worth emphasizing that perturbations are not the “situation part” of a

Change as Outcome model. Perturbations are the part of the observations that cannot be explained with reference to the characteristic pattern captured in the model. The characteristic pattern includes both person and situation influences, so the “situation part” is split into characteristic recurring parts and unexpected, non-recurring parts. Perturbations can also come internally from within the person. For example, feeling tired, appraising a situation as threatening, or an internal change in hormone or neurotransmitter levels can all be conceived of as perturbations if they are not part of the person’s characteristic pattern of state changes. While it is easy to think of perturbations in terms of external events, it is more accurate to think of them as unmodeled portions of an observation.

More Exotic Topologies

While the simplest case—and the case encountered in the vast majority of personality state time series we have analyzed—is a topology where there is a single attractor point, more complex topologies are possible. Consider the Change as Outcome plot in of the participant in Figure 4. The loess regression crosses the $y = 0$ line in three places. Since each time the regression crosses this line indicates an equilibrium point, the data suggest that this participant has three different equilibria.

Figure 4: An Example of a Three-Equilibrium Topology

As described above, the local slope of the line around an equilibrium point determines the type of equilibrium: an attractor or a repeller. In the figure above, two equilibrium points—one around $x = 2.4$ and one around $x = 3.3$ —have negative local slopes. These are attractor states. When this individual's state extraversion is close to 2.4, it will be drawn to this value; when the individual's state extraversion is close to 3.3, it will be drawn to this higher attractor value. The prior state of the system therefore dictates where the system will naturally be drawn: to a low or high attractor state.

The slope around the equilibrium point at approximately $x = 2.8$ is positive, indicating that this is a repeller. If an individual has a personality state variable of exactly 2.8, then the modeled dynamics of the situation suggest that they will remain at exactly that state. However, as soon as there is any perturbation—they move a little bit above or below 2.8—then they will continue to move away from the repeller point. If they are pushed from 2.8 to 2.9, then they will increase in state extraversion until they reach the attractor at 3.3. If they

are pushed from 2.8 to 2.7, then they will continue to decrease in state extraversion until the reaches the attractor at 2.4.

Overall, the dynamics of this system suggest that the individual has two characteristic levels of extraversion, and will move from one to the other whenever his state extraversion crosses a dividing threshold around 2.8. In our exploration of personality state time series, multiple equilibria in a single topology like this was rare. However, this form of modeling allows for the identification of unusual, person-centered topologies that can potentially be theoretically and practically informative. For example, in popular culture, the term “ambivert” is sometimes used to describe a person who can be characterized by introverted and extroverted tendencies at different times. The Change as Outcome model suggests that “ambiverts” can be characterized in a formal way by examining the number of attractor points in personality state topology; the dynamics illustrated in Figure 4 define the individual as an ambivert. This form of modeling may prove useful in characterizing the personality state dynamics of specific kinds of people—for example, people building new habits—or people in specific kinds of situations—for example, people with very different social roles at home versus at work. Furthermore, the existence of “ambiverts” emphasizes that the equilibrium approach has the potential to expand current theoretical possibilities.

Identifying Equilibria in Personality State Data

Dynamic systems are specified by an equation or a system of equations that describe how a state variable changes over time. To analyze the system, researchers use the equations to identify the points at which no change is expected. These are the equilibrium points. The equations are also used to determine the behavior of the system around these equilibrium points. The visual exploration of dynamics described previously relates the current state of

the system (plotted along the x -axis) to change in the next state (plotted along the y -axis). A simple mathematical representation of this relationship takes a form familiar to researchers who have used regression analysis:

$$\Delta_x = m * x + b$$

In this equation, the change in x is represented by the delta symbol. This is analogous to the outcome or criterion variable in a regression. Change is being predicted by x , the state variable, times a regression coefficient—here written as m —and an intercept—written as b . This equation indicates that the current state has a linear relationship with change.

Specifying a linear relationship is significant. In our visual exploration, we examined places where the loess line crossed the line $y = 0$, which here correspond to $\Delta = 0$ (no change). A straight line can only cross the line $\Delta = 0$ once, so a linear regression model *assumes* that there is only one equilibrium point. To model a system with more than one equilibrium point, a different mathematical description must be used. For example, Butner and colleagues (2014) discuss how a cubic regression equation—with x^2 and x^3 terms—allows for the possibility of three equilibrium points. However, we will focus on the simple linear case in this manuscript, as our analyses suggest that it is appropriate to capture changes in personality states in the majority of participants we have analyzed.

In our linear regression model, the value of m in this equation indicates the strength of the relationship between x and Δ . If m has a large value (either positive or negative), this indicates that the current state has a strong influence on change. This corresponds to *strength* of an attractor or repeller. For example, if m is very small, this would indicate that the current state does not have a very strong influence on the next state. Although there may be an attractor, the person is not moving very quickly towards that point.

The sign of m indicates the behavior expected around the equilibrium point. If m is negative, it indicates that when the value of x increases, there tends to be a negative change— at the next time point, x will decrease. This suggests that there is a value towards which x will return. The equilibrium point will therefore be an attractor. On the other hand, if m is positive, then increases in x are associated with further increases in the next time point. This suggests that there is increasing movement away from a point. The equilibrium point will therefore be a repeller.

In a system with only a single equilibrium point it is rare for that point to be a repeller. Having just a single repeller suggests that there is just one characteristic pattern: the system is driven as far as possible from a specific value. Conceptually, this is a poor match for the analysis of personality states. It would suggest that, absent perturbations, the individual would continually be pushed towards the extreme ends of the scale. We would suggest that, if a researcher fits a linear Change as Outcome model to personality state data and finds a positive value of m , it should give pause. It may be that this is not an appropriate characterization of the data, and other functional forms (such as a cubic polynomial expansion) should be explored.

The specific location of the equilibrium point can be identified through an algebraic manipulation of the linear regression specified above. An equilibrium point is defined as the point at which the expected change is zero. We therefore want to find the value of x that leads change to be equal to zero. We do this by setting $\Delta = 0$ and solving for x . The steps of the algebraic manipulation are given below:

$$0 = m * x + b$$

$$-b = m * x$$

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$$\frac{-b}{m} = x$$

Through this algebra, we can see that the value of x at which there is no expected change is given by $-b/m$. This is the location of the equilibrium point. When m is negative, we can see that the value of the equilibrium point will ultimately be positive. It will therefore typically be a value in the range of the response scale used by the participants. When m is positive, the value of the equilibrium point will be negative, which is outside the range of the response scale. This is another reason why finding that m is positive in a linear change-as-outcome model suggests a problem with the model. If the model is going to characterize the data well, its major topological features should be in the range of allowable responses. We present a summary of dynamic systems terms introduced in this manuscript below, in Table 1:

Table 1: Core Dynamic Systems Concepts in Change as Outcome Model

Concept	Definition
Equilibrium	States at which a system is not expected to change. In a one-dimensional system, equilibria can be an attractors or repellers.
Attractor	State towards which a system is drawn over time. Can be one of multiple equilibria, so that the system is only drawn to this state locally, but in other parts of the state space the system is drawn toward other states.
Attractor Strength	Speed with which a system is drawn towards a particular attractor. A stronger attractor is one the state is drawn to more quickly.
Repeller	State a system is pushed away from over time. Can be one of multiple equilibria, so that the system is only pushed away from this state locally.
Repeller Strength	Speed with which a system is pushed away from a particular repeller. A stronger repeller

is one the state is pushed away from more quickly.

Topology

Representation of the characteristic patterns of change estimated in a model, with indications of the expected direction of change at each location.

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511 *Uneven Sampling*

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513 Researchers using experience sampling methods *only* to characterize the mean and
514 standard deviation of a state need to be concerned with collecting an adequate sample of
515 points to accurately represent a person's typical experiences. In this traditional analysis, the
516 rate of sampling is of secondary interest, because the relation between consecutive time
517 points is not being modeled. Dynamic systems analyses, on the other hand, account for the
518 temporal sequence of measurements. Researchers interested in using these analyses should be
519 more concerned with sampling rate.

520 First, sampling rate dictates what kind of patterns can be observed. If an individual's
521 conscientiousness rises and falls every 30 minutes but this person only reports on their
522 conscientiousness level every 4 hours, then it will be impossible to capture the true process.
523 Important points at which the state changes simply are not measured. The resulting problem
524 is referred to as *aliasing* in time series literature, and it occurs when a continuous-time signal
525 is sampled less frequently than twice the rate of the highest frequency component of interest
526 (Hinich & Wolinsky, 1988). Formal tests can be performed to determine if aliasing has
527 occurred in a data set (Hinich, 1982).

528 Determining the proper sampling rate for a particular process might be addressed
529 empirically, by sampling a person's personality states at incredibly high rates—for example,
530 every five minutes—and then determining from these measures how frequently the state

needs to be assessed to capture the patterns of change. Methods developed for use in historical data can help determine if higher frequency sampling is needed (Nason, Powell, Elliott, & Smith, 2017). However, in the case of personality states, this would create a prohibitively high burden on the participant. The participant would be so busy filling out surveys, she would not be able to experience life naturally (however, analyses using passive mobile sensing for imputation of “in-between” states may be able to help address these concerns; e.g. Ghahramani et al., 2018).

We therefore suggest that determining the proper sampling rate is primarily a theoretical issue. The researcher should consider beforehand what the likely time scale of their process of interest is. If we were interested in the way a person’s conscientiousness changes in a fast-paced, highly variable environment, we would choose to assess this state more often. Our hypothesis would have an inherent time scale; we would be interested in the way rapid shifts in work tasks influence conscientiousness. On the other hand, if we were interested in the way the development of a habit—occurring over the course of months—changes conscientiousness, we would sample less frequently. Our hypothesis about the role of a habit (such as daily meditation) on conscientiousness has a longer time scale.

The second major concern with sampling rate is related to the ability to make fair comparisons between change scores. An individual increasing in conscientiousness by one point after 2 hours is different from that same individual increasing by one point after 6 hours. When plotting raw change scores, both these changes will appear identical. Yet if we assume that the change from one point to the next is linear—and it is difficult to do otherwise, when no points are sampled in between—then the first change is relatively rapid while the second is relatively slow. We therefore suggest converting the change scores to a common metric, such as change per hour. In our example, the first change score would be transformed from one point to 0.5 points per hour, while the second change score would be

transformed from one point to 0.17 points per hour. This allows for a fairer comparison in change points, and is useful when conducting secondary data analysis. However, this conversion is not a substitute for higher quality data with a consistent sampling rate and good participant compliance. Addressing these issues at the point of planning and data collection as opposed to in modeling afterwards will lead to more accurate results.

Empirical Example

To demonstrate this approach, we used data from Wave 1 of the Personality and Interpersonal Roles (PAIRS) study (Vazire et al., 2015). This study includes a time-based experience sampling design, and has been published on extensively (Beck & Jackson, 2018; Colman, Vineyard, & Letzring, 2017; Edwards & Holtzman, 2017; Finnigan & Vazire, 2017; Solomon & Vazire, 2014; Sun, Schwartz, Son, Kern, & Vazire, 2018; Sun & Vazire, 2018; Wilson, Harris, & Vazire, 2015; Wilson, Thompson, & Vazire, 2017). Detailed documentation of the study is available on the Open Science Framework (OSF): <https://osf.io/dps4w>.

Participants. Participants were 434 undergraduate students from Washington University in St. Louis, and of these only participants who completed at least 25 measures of a given construct were included in these analyses.

Procedure. The data analyzed were from an ESM survey emailed to participants at 12 PM, 3 PM, 6 PM, and 9 PM for 15 days. Participants were asked to respond to Big Five Inventory (BFI; John & Srivastava, 1999) questions describing their state in the last hour. Items corresponding to extraversion, agreeableness, neuroticism, and conscientiousness (but not openness) were used. Data on openness was not collected in this wave. Two items for each

trait—except neuroticism, which had three—were used, rated on a 5-point Likert scale. Moreover, agreeableness items were only assessed when participants were in social situation leading on average to less measurement point for agreeableness than for extraversion, neuroticism, and conscientiousness. Change as Outcome models for each trait were estimated separately.

Analysis Strategy. We used a two-step approach to estimating equilibria. First we conducted an exploratory analysis, estimating a loess regression line connecting state to change per hour. We then identified the number of equilibria by identifying the number of times the loess regression crossed the line $y = 0$ (computationally this can be done by comparing each successively estimated point in the loess to determine if they have opposite signs). We then grouped the participants according to the number of equilibria points. We estimated models using polynomial expansions to capture the number of equilibria seen in the loess regression. For example, if one equilibrium was found, a first-order equation was used; if three equilibria were found, a third order equation was used. The values of the equilibria points and the strengths of attractors and repellers were estimated for all individuals.

Results. The distribution of equilibria points observed varied in expected patterns across the four personality states assessed. Of the total 422 time series estimated, one-attractor topologies were found for 412 agreeableness time series, 403 conscientiousness time series, 406 extraversion time series, and 368 neuroticism time series. We found 14 extraversion ambiverts (people with two extraversion set points), 8 agreeableness ambiverts (people with two agreeableness set points), 17 conscientiousness ambiverts (people with two extraversion set points), and 46 neuroticism ambiverts (people with two neuroticism set points). There were a few cases with two set points, where using one extreme end of the rating scale was a

repeller. In the neuroticism data, there was one case with three attractors and two repellers—a “tri-vert”—and one case with two attractors and two repellers. This suggests that topologies with multiple features are uncommon, but likely to be present in a large sample of participants. They occur most commonly for neuroticism, perhaps indicating that many college students have periods of high anxiety and low anxiety in response to shifting demands of classes and internal self-evaluations.

Only topologies with a single attractor were considered in the following analyses, as these are quantitatively comparable to each other. Equilibria tended to be highest for agreeableness, a desirable personality state, and lowest for neuroticism, an undesirable personality state. The locations of the equilibria were highly correlated with the means of the distributions ($r = .95$, $t(783) = 83.36$, $p < .001$) but were only weakly related to the standard deviations of the distributions ($r = -.30$, $t(783) = -8.82$, $p < .001$). Also of note is the relatively small variability in equilibria for agreeableness, compared to other traits. Many participants had equilibrium points around agreeable states from 4 to 5, while extraversion equilibria were more evenly distributed between 2 and 4 and neuroticism equilibria were distributed between 1.5 and 3.5. This may be due to a self-perception gap, where individuals see themselves as more agreeable than others do (Sun & Vazire, 2019).

The strength of the attractors formed distinctive clusters for all traits: one large group of people had very weak attractors, while another group had stronger attractors. Attractor strength was weakly related to the mean ($r = -.10$, $t(783) = -2.75$, $p = .006$) and standard deviation ($r = .05$, $t(783) = 1.37$, $p = .170$) of response distributions. Attractor location and strength were also weakly related ($r = -.11$, $t(783) = -3.21$, $p = .001$). People with weak attractors are those who are not very strongly drawn to their equilibria or strongly and continuously pushed away from their equilibria, suggesting that perturbations have longer lasting effects on the personality system. These people might be flexible, less reactive to the

situation, or face more open-ended situations. Another large group of people do tend to consistently return to their equilibria, suggesting a more active person-situation regulatory processes or a more structured everyday life. Figure 5 displays the distributions of attractor points and equilibria for participants with just one attractor in their topology.

Figure 5: Distributions of Attractor Points and Strengths for Participants with One Attractor Topologies

A:

B:

Note: All attractors and attractor strengths are calculated based on the change-per-hour metric.

The correlations among estimated topological features are provided in Table 2 below.

Note that the position and strength of the attractors for each trait are only very weakly correlated. On the other hand, the strength of the attractors were relatively highly correlated. This suggests that the tendency to return to a baseline state quickly may be a generalized tendency among individuals.

655 Table 2: Associations Among Topological Features

656 *Means, standard deviations, and correlations with confidence intervals*

657

Var.	<i>M</i>	<i>SD</i>	1	2	3	4	5	6	7
1. Ext: Pos.	2.81	0.58							
2. Ext: Str.	-0.13	0.12	-.05 [.19, .08]						
3. Agr: Pos.	4.00	0.47	.20** [.07, .33]	-.02 [.16, .12]					
4. Agr: Str.	-0.13	0.13	-.07 [.21, .06]	.83** [.78, .87]	-.01 [.14, .12]				
5. Neu: Pos.	2.17	0.59	-.19* [.33, -.04]	-.03 [.19, .12]	-.21** [.35, -.07]	-.10 [.25, .05]			
6. Neu: Str.	-0.09	0.10	-.07 [.22, .08]	.89** [.85, .92]	.04 [.11, .19]	.81** [.75, .86]	.06 [.09, .20]		
7. Con: Pos.	2.89	7.81	-.05 [.18, .09]	-.10 [.23, .04]	.17* [.03, .30]	-.09 [.22, .05]	-.15 [.30, .00]	-.08 [.23, .07]	

8.									
Con:	-0.12	0.11	-.04	.89**	-.07	.83**	-.05	.86**	-.10
Str.									
			[-.18, .10]	[.86, .91]	[-.20, .07]	[.78, .87]	[-.20, .10]	[.81, .89]	[-.23, .03]

Note. *M* and *SD* are used to represent mean and standard deviation, respectively. Values in square brackets indicate the 95% confidence interval for each correlation. * indicates $p < .05$. ** indicates $p < .01$. Agr = Agreeableness, Ext = Extraversion, Neu = Neuroticism, Con = Conscientiousness, Pos = Position, Str = Strength.

Alternate Regression Models for Capturing Topologies

We have discussed in detail the use of a simple linear regression to characterize personality state topology. However, as discussed, linear regression assumes that (i) there is only a single attractor, and (ii) the strength of the attractor is the same for all states. Using polynomial expansions of the state variable as further predictor terms is one approach that loosens the first restriction and allows for multiple attractors. The typical approach to determining the necessity of higher order terms in a model is to conduct hierarchical regression, where a significance test determines if including the additional term increases the fit of the model (Aiken, West, & Reno, 1991). This approach has been proposed to determine if a model allowing for more equilibria is warranted (Butner et al., 2014). In the context of one participant's measurements on a 5 or 7-point Likert scale, we have seen few cases when the addition of a higher order term was supported by such a significance test. Further, significance tests of higher order regression coefficients are likely to be underpowered given typical time series for a single individual (assuming regression coefficients of the size seen in our data set; see Jayasuriya, 1996). We therefore advocate for a qualitative assessment of model fit as a first step in analysis. Further development of this method may yield greater insight into optimal solutions for identifying the number of equilibria to include in a model.

The second assumption of the linear model, that the attractor has the same strength when an individual is at any state, can be loosened using regression splines. Regression splines are a series of two or more regression lines that have been joined. These splines allow for the slope of a regression to change in different regions of a predictor variable. For example, the slope of the line relating conscientiousness to change might be very steep when state conscientiousness is low; when state conscientiousness is high, however, the slope might be less steep. Similarly, we might model attractor strength differently when the state is above or below the attractor point.

A comparable approach was taken by John Gottman and colleagues when modeling the affective states of husbands and wives during interactions (Cook et al., 1995; Gottman, Swanson, & Murray, 1999; Gottman, Swanson, & Swanson, 2002). Each husband and each wife was assumed to have a typical pattern of change for positive affect (when the valence score was above zero) and a different pattern of change for negative affect (when valence was below zero). While a regression spline approach does not appear common when analyzing unidimensional systems, it would be possible to specify different slopes above and below a particular knot point—or to allow a machine learning algorithm like Multivariate Adaptive Regression Splines to use pre-specified criteria for identifying an optimal knot point.

We recommend a two-step process for estimating models. We first suggest an exploratory approach, where a localized regression is fit to the data and the adequacy of a one-equilibrium model with a relatively constant slope is assessed qualitatively. We then suggest estimating this model in all time series for which it is relevant. If this model appears inadequate, we suggest exploring other functional forms, including a higher order polynomial or a spline regression.

Measurement Error

While our emphasis in this manuscript is on developing a non-technical introduction to what a Change as Outcome Model provides theoretically, a similar framework has developed in the structural equation modeling (SEM) literature under the name Latent Change Scores (McArdle, 2009; Ferrer & McArdle, 2010; McArdle & Nesselroade, 2014). This approach estimates a latent variable that represents change in a state over time and can be implemented in a multivariate framework with latent change in two or more variables estimated simultaneously. However, this approach has also been geared primarily towards researchers estimating longitudinal models using a few time points, and is less commonly applied to data collected in intense bursts (such as ESM data). For example, Kevin Grimm and colleagues (2013) estimated a latent change score and latent acceleration factor as a method for modeling non-linear development in math scores, measured annually at eight grade levels. Additionally, Latent Change Score models are typically variable-centered, as opposed to person-centered. One advantage of the modeling technique advanced in the PersDyn article in this issue is that their dynamic model accounts for measurement error. A version of the Change as Outcome model in an SEM framework, possibly using Latent Change Scores, is an area for future research.

Summary and Future Directions

The number, location, and strength of attractors and repellers are quantitative properties estimated by the Change as Outcome model that characterize system dynamics. These are core concepts from the literature on dynamic systems originating outside of psychology, and we believe they can provide new insight into personality states. These concepts, and the dynamic systems perspective more broadly, requires some re-orientation on

ways of conceptualizing data. We summarize some key principles of dynamic systems below, but we would encourage researchers interested in these ideas to read more general treatments of dynamic systems in psychology (e.g., Vallacher, Read, & Nowak, 2017; Richardson, Dale, & Marsh, 2014).

What is Important About Personality States?

The Change as Outcome model characterizes personality states in terms of equilibria and their strengths, adding the concepts of prior state and system topology to our explanatory toolbox. The Change as Outcome approach explicitly links current state to the next state by modeling change. Each new state is determined in part by the previous state. The system topology is a way of characterizing characteristic person-situation patterns, which suggests that there are meaningful person-situation patterns to be picked up on in the data. Each new state is determined partly by these recurring person-situation patterns in daily life, and in part by unique natural perturbations.

Implications for Personality Development

The Change as Outcome model can be used to describe several different ways personality dynamics can change in response to external events. These changes can represent taking on a new role, such as becoming a parent or a manager in a company; undergoing a major life event, such as moving to a new city or dealing with the death of a loved one; or even the results of personality change through therapy (Roberts et al., 2017; Roberts & Mroczek, 2008; Hudson & Fraley, 2015). Traditional analyses would suggest that these significant changes could be modeled as changes in the mean or standard deviation of the

distribution of personality states; for example, a large meta-analysis recently found that therapy appears to make people less neurotic (Roberts et al., 2017). In the dynamic systems framework we present here, however, significant changes can be thought of as shifting the person's underlying personality state topology. If repeated measurement burst designs were used, development in these dynamic traits of personality states could be tracked across the lifespan (Ram & Gerstorf, 2009).

In the Change as Outcome model significant life events, which influence personality development (e.g., Specht, Egloff, & Schmukle, 2011), can have several different effects. They can change the *location of an attractor state*. For example, a person's characteristic neuroticism score might be lowered from 3.5 to 2. This can be seen in Figure 7A. They might also change the *strength of an attractor*. For example, a person might be drawn more quickly back towards a neuroticism state of 2.8. This could be treated as a form of resiliency, or the ability to bounce back to a healthy pattern after a perturbation. This can be seen in Figure 7B. Finally, the intervention could fundamentally change the *features in the topology*. A person could shift from having attractors at states 4.5 and 1.8 to just having an attractor at state 2.8. This can be seen in Figure 7C. Change as outcome modeling therefore gives a richer conceptual vocabulary and mathematical tools that can be used to describe how significant events change people's personalities. For example, while grieving an individual might not increase in neuroticism (e.g., mean-level change), but might return to their baseline level of neuroticism more slowly than before they experienced the death of a friend (e.g., a heightened vigilance). Therapy or recommendations to deal with this situation might therefore focus on strategies for returning to baseline—as opposed to strategies for shifting the baseline.

Figure 7: Hypothetical Personality Development Effects of Significant Life Events

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783 A: Shift in Attractor Location

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785 B: Shift in Attractor Strength

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789 C: Shift from Complex to Simple Topology

Towards a Multivariate Approach

Current research in personality dynamics often centers around discussions of network models, which typically represents correlations among many variables as a series of edges connecting variables to each other (conceptualized as nodes). These models emphasize the “system” aspect of dynamic systems, with development centering around capturing the specifics of the interrelationships between every measured variable (Epskamp, Borsboom, & Fried, 2017). However, network models are not inherently “dynamic”—in the sense that they can be estimated on data that was all collected at the same time (e.g., cross-sectional networks; Costantini et al., 2015). This is because network models were developed as an alternative to latent variable models, so the problem they were introduced to solve is not one of how best to think about change over time, but how best to think about the interrelationships between many variables (Schmittmann et al, 2013). However, many psychologists may be surprised that dynamic systems researchers in other fields often consider capturing the patterns of change to be of primary interest, and often limit their

investigation to just one or two variables changing over time (Otto & Day, 2003; McElreath & Boyd, 2003; Nowak, 2006). Psychologists using typical ANOVA and regression models can estimate three, four, five-way or even higher order interactions, but are often discouraged from trying to estimate these complicated effects due to difficulty of interpretation and instability of estimates; similarly, students learning dynamic modeling are often encouraged to consider change in only a handful of state variables at a time.

When systems are more complex, researchers are encouraged to consider modeling “combined” variables (e.g., a ratio between two quantities of interest) or to consider certain variables to be fixed for the purposes of analysis (e.g., the carrying capacity or overall population size of an environment in population biology models). Even one dimensional dynamic models can have interesting dynamics that yield scientific insight (May, 2004). In psychology, for example, the Haken-Kelso-Bunz (HKB) model of motor coordination has a single state variable, the relative phase angle of two people performing a rhythmic action together (Haken, Kelso, & Bunz, 1985). This single dimensional model combines information about two people acting together in a single quantity—the relation between two oscillating movements, such as fingers or hammers being swung back and forth—and yet has been the basis for decades of motor dynamics research.

Our modeling approach begins by capturing change in just one personality factor at a time, primarily for didactic purposes. Understanding system dynamics one at a time provides an opportunity to illustrate the core constructs in a relatively straightforward way. However, a two dimensional extension of the Change as Outcome model has been used in prior research (Butner, Berg, Baucom, & Wiebe, 2014), and we think it is plausible that personality states may interact with each other over time. However, there are many other kinds of dynamics possible when two states interact—including limit cycles, saddle points, spiral attractors and repellers, and torus (or donut-shaped) relationships. Future manuscripts will discuss a two-

dimensional extension of this approach, providing space and detail for describing these more complex relationships.

Limitations and Areas for Future Research

There are many open areas in dynamic systems theory and modeling being addressed by thoughtful and innovative researchers; we cannot feasibly address all these open areas in this manuscript. Work in measurement and psychometrics of experience sampling data is sorely needed, but our modeling strategy is largely orthogonal to this concern. If a new personality state scale with better psychometric properties were developed this year, all of our discussion would still apply—we would just encourage researchers to use this better scale (e.g., Zimmerman et al., 2019).

Another issue raised by early reviews of our work is the question of whether personality states themselves can be thought of as continuous—i.e. that they exist at all times and can be measured at any given moment—or whether another conceptualization is needed. For example, perhaps only certain relevant states exist in a given moment (e.g. state extraversion only “exists” in situations relevant to socializing). Continuity of states is a fundamental assumption shared by almost all contemporary approaches to personality dynamics. While we would be interested in theoretical re-conceptualizations of personality states, and in how to interpret self-reported personality states under the assumption that personality was not continuous, defending this core assumption of the personality dynamics literature is beyond the scope of this manuscript. We take it as given that an individual does have an underlying personality state incorporates content like thoughts, emotions, and situational awareness that change continuously over time, and that researchers can assess its current status at any given moment (with few exceptions, e.g., while sleeping, while performing another task like driving that requires full concentration). The modeling strategy

857 we present may need to be modified or dropped for researchers making alternate
858 assumptions.

859 Another criticism is that changes in personality states are non-linear and highly
860 reactive to situations. For example, state extraversion might jump quickly after a person goes
861 to party, and stay high—instead of increasing continuously while at the party. Only
862 measuring state extraversion an hour before the party and then three hours later towards the
863 end of the party would miss the shape of this change; the consistent high extraversion at the
864 party just wouldn't be measured. This is a common issue faced by all modeling strategies
865 using time series data: was the data sampled at a rate that can provide an adequate picture of
866 the process the researcher is interested in? (See the earlier section on sampling rate). This is
867 an open question in personality state research, because extremely high frequency personality
868 state data (e.g. every five or ten minutes) is not typically available. If the appropriate data for
869 addressing these rapid fluctuations in personality became available, we would still advocate
870 for a dynamic systems approach, as the feedback loops common to dynamic systems
871 modeling are well-suited to represent non-linear changes. However, more sophisticated
872 models might be indicated to capture that pattern.

873 We have also prepared a thorough comparison of our model to the PersDyn model
874 presented in this issue in an appendix. Briefly, the Change as Outcome model allows
875 equilibria to be either attractors or repellers, allows for multiple equilibria to be present in a
876 person's personality system, and uses a "purely idiographic" approach by not allowing data
877 from other participants to influence the estimation of parameters for a specific participant.
878 PersDyn models personality variability separately from attractors, includes a measurement
879 model, and is estimated in continuous time. Our approach is therefore better suited to
880 introduce dynamic systems ideas, but the PersDyn model is more sophisticated in several
881 ways.

Implications for the Person-Situation Debate

Researchers in the allied disciplines of personality and social psychology generally agree at a broad level that both the person and the situation are responsible for determining any given behavior. The systems level view presents a way of doing this without emphasizing person *versus* situation. It suggests instead that we need to characterize the patterns emerging from the continuous, ongoing interactions of person and situation—the coherent entity that we describe as the system. The interactions described in a dynamic systems approach are different from those in a typical ANOVA or regression analysis, because the assumption underlying these traditional analyses is that an outcome—for example, a behavior being predicted—is a linear combination of main effects and interactions that are clearly separable. Interactions in a dynamic system, however, are assumed to involve ongoing non-linear feedback loops. Situations change personality states, which in turn change situations, so that there is no clear break point at which we can separate out their influences into person + situation + person x situation interaction. The estimated effects of each factor would change from moment-to-moment as the ongoing feedback alters the relationship between parts of the system. The dynamic person–situation system is the underlying fundamental unit of analysis.

To adequately characterize these interactions, we need to consider the role of time in understanding behavior. The history of a dynamic system helps to constrain and determine its current behavior; people’s current behavior is similarly guided by their own “history” of lived experiences as well as their expected and imagined future. For example, a person that has been in a satisfying relationship for the last years and who can expect to return to their partner at the end of the day might act very differently in a romantic setting than a single person would. The focus of dynamic systems analysis is on understanding how small,

907 repeated interactions can lead to broad patterns that can be characterized by a model. People
908 are constantly interacting with their physical and social environments such that most medium
909 scale behaviors psychologists are interested in understanding—from conversations to
910 attitudes to identity—will necessarily be the result of some combination of person and
911 situation. A useful dynamic systems model of personality state change will capture the
912 important patterns in these medium scale behaviors, and provide insights for how the system
913 as a whole can move towards adaptive or maladaptive outcomes.

914 We believe the Change as Outcome model will be particularly useful when applied to
915 analyze time series of personality state data. Yet we hope that it also contributes to the
916 broader conversation about how best to develop an integrated understanding of the ways in
917 which person variables and situation variables jointly influence behavior. Taking a dynamic
918 systems approach has the promise of yielding a deeper philosophical and quantitative
919 unification of person and situation.

920

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Appendix A: Detailed Comparison of Change as Outcome and PersDyn Models

In this issue, Sosnowska and colleagues present Bayesian Hierarchical Ornstein-Uhlenbeck Modeling (BHOUM) as a parameterization of their PersDyn model. The PersDyn model and our model both draw on core concepts from dynamic systems, such as attractors, that have been discussed for decades by several research groups in personality psychology (e.g. TESSERA, Wrzus & Roberts, 2017; CAPS, Mischel & Shoda, 1995; Magnusson & Torestad, 1993). The manuscript by Sosnowska and colleagues presents a high level overview of the current status of an active research program aimed at integrating dynamic systems thinking into personality psychology, with a prior theoretical manuscript laying out the conceptual foundations of this approach (Sosnowska et al., 2019). Integrating dynamic systems thinking into personality psychology is also our goal, and we believe their manuscript is a significant contribution in this area. That said, there are several differences in the details of our approaches worth noting.

First, we describe the attractor location in the context of the broader category of equilibria. Equilibria in a one-dimensional system can include either attractors—points a system is drawn towards—and repellers—points a system is drawn away from. The BHOUM model used for PersDyn takes the following form:

$$d\theta(t) = B(\mu - \theta(t))dt + \sum dW(t)$$

The term $B(\mu - \Theta(t))$ indicates that change is proportional to deviation from the mean, so the model always assumes people are drawn back to their average personality state. That is, the model assumes people have a single attractor state, and precludes the possibility of repeller states or multiple equilibria. Our analyses suggest that this simplifying assumption is generally warranted with personality state data; we rarely encountered time series in which an individual's dynamics could not be adequately captured using just a single attractor. However, we believe that providing examples of repellers and systems with multiple equilibria is helpful when considering what insights the dynamic systems perspective can provide. Further, we believe there may be sub-populations where topologies with multiple equilibria are common, such as individuals with certain personality disorders or whose lifestyle involves intense differences across tasks—such as emergency responders.

Additionally, we opt for a “pure idiographic” approach to personality dynamics in this manuscript, meaning that we estimate models separately for each individual. Hierarchical modeling, which is used in PersDyn, takes into account data from the broader population when estimating parameters for the individual. This can be thought of as a kind of regularization; the parameters estimated for each individual—such as attractor strength and location—are biased towards the mean of the group. Further, in a hierarchical model all participants need to have the same parameters; there cannot be individual differences in the number of equilibria points. By estimating separate models for each individual, we allow for the possibility that some people will differ in the *structure* of their change over time. We also allow each person to be independent from all others, without assuming that people's attractor and attractor strength parameters are drawn from common underlying distributions. It may be that only certain groups of people come from a common distribution, while other groups come from different distributions. While a

hierarchical model with a common structure appears empirically adequate in the data we have examined so far, it is worth examining this assumption in future research using the conceptual tools provided in this manuscript.

This manuscript also presents details on how major life changes might shift personality dynamics. Although the PersDyn model has not yet addressed the role of major life changes on personality dynamics, we believe that this description is largely consistent with the way that PersDyn models personality dynamics. The exception, as above, is that PersDyn currently only allows for topologies with a single attractor. This means that the BHOUM model could not capture life changes that add or subtract equilibria to personality topology. We suspect that this will only be important in special cases, perhaps in response to stress or trauma, but believe these kinds of changes are worthy of future empirical attention.

The PersDyn model also includes several important distinctions not present in our work. First, BHOUM is a continuous time model, meaning it is technically modeling the derivative of the outcome variable with respect to time. This allows the BHOUM to deal with the unequal spacing of ESM data by incorporating a time-varying term associated with both the change and the error process. Continuous time models can lead to less biased estimates of continuously varying processes than discrete time models, like vector autoregression (de Haan-Rietdijk et al., 2017). Our own approach to dealing with uneven spacing by creating a change score is more similar to latent change score modeling, an alternative statistical model (McArdle, 2009). We find the Change as Outcome model more intuitively accessible for introducing constructs, but a review of the statistical fit of the most advanced modeling techniques might ultimately suggest a continuous time model is necessary to reduce bias in parameter estimation.

PersDyn involves a third core construct beyond attractor location and attractor strength: level of variability. This natural level of fluctuation has had an important role in prior theorizing, particularly in Whole Trait Theory (Fleeson & Jayawickreme, 2015). Currently, our model treats variability not accounted for by attractor location and strength as part of the model residuals—which we describe as perturbations. We are still determining if there is an important role for variability in personality states in a future iteration the Change as Outcome model.

The PersDyn model is also currently able to handle two-dimensional systems using the BHOUM parameterization, and the manuscript points to further modeling techniques for including more dimensions. Our modeling technique focuses on the one-dimensional case, although there are clear extensions that could allow us to model higher dimensional cases. In this regard, the PersDyn model has already given more thought to this more complex case, and we look forward to seeing the details of a two (or more) dimensional model being implemented.

Further the PersDyn model includes a measurement model in its estimation. In the interests of keeping our explanation and modeling simple and easy-to-follow, we have not included a measurement model in our current estimation. However, this is clearly an area in which Change as Outcome modeling will need to progress in the future, and an area that has been given more thought by the researchers using the PersDyn approach. The incorporation of personality variability as a core construct and use of a measurement model capture an underlying difference in our goals in our manuscripts: Sosnowska and colleagues are presenting the most up-to-date thinking on a new theoretical model, while we are attempting primarily to illustrate several core concepts from dynamic systems to an audience looking for an entrance point to dynamic system thinking.

1018 There is also an important theoretical distinction between the way that we conceptualize
1019 dynamic systems models. Sosnowska and colleagues interpret attractor strength as representing
1020 an aspect of an individual's regulatory strength, suggesting it is an internal property of the
1021 individual. We would interpret it as consistency of patterning in the person-situation system.
1022 That is, the demands of a person's daily life (e.g. a demanding work schedule) can pull them
1023 back towards a particular state as quickly as their internal need to be in that state (e.g. a strong
1024 achievement motivation).

1025 More broadly, we believe that dynamic systems models—and the Change as Outcome
1026 model in particular—call for a reconceptualization of the person-situation dichotomy in
1027 psychology. Dynamic systems approaches emphasize that there is continuous feedback between
1028 aspects of a system, such as person and situation. Experience sampling data measuring
1029 personality states is always made when an individual is in (or just was in) a particular situation,
1030 so from a dynamic systems perspective we believe these measurements should be conceptualized
1031 as the joint product of both person and situation. That is, if my state extraversion at one time
1032 point is 3.8, this measurement was influenced both by the situation I was just in (e.g., I may have
1033 been talking to colleagues), and by my own internal processes (e.g., I become more extraverted
1034 when around colleagues).

1035 Given this theoretical commitment, we understand dynamic models to be capturing the
1036 consistent patterns in the way one person's personality state changes over time. For example, the
1037 attractor locations and strengths estimated in the Change as Outcome model should be thought of
1038 as a quantitative summary of the consistent, dominant pattern of person-situation influences on
1039 personality states. These patterns are like a temporal version of Mischel and Shoda's situation-
1040 behavior profiles (Mischel, Shoda, Mendoza-Denton, 2002). Instead of situating personality in

the consistent part of a situation-behavior graph, the Change as Outcome model situates dominant personality dynamics in the consistent feedback between person and situation in the individual's daily life.

Like all statistical models of human behavior, there is necessarily a residual error term in the Change as Outcome model. This residual error is the part of the observation that is not modeled by the other estimated terms. Given that the estimated terms are capturing the broad, consistent pattern of personality state fluctuations, the residual error must therefore contain information about the “random” or surprising and idiosyncratic thoughts and events that influence personality states. That is, error is not just imprecise measurement—we assume that it represents the substantive concept of natural perturbations. These perturbations are also influenced by both person and situation. They can represent idiosyncratic reactions to normal events, normal reactions to surprising events, or some mix of these.

Estimating dynamic models therefore suggests an important distinction not commonly discussed in personality: that between consistent patterns and idiosyncrasies. Person and situation are assumed to influence both patterns and idiosyncrasies through continual coupling and feedback. In dynamic systems modeling, the complex interplay of person and situation in determining behavior can effectively be bracketed and treated (perhaps just temporarily) as “irreducibly complex.” Instead, dynamic modeling suggests that we can gain traction by addressing a different distinction: consistent patterns versus idiosyncrasies. We suggest that this conceptual metaphor will be a more fruitful way to think about patterns of behavior than the traditional distinction of “some is caused by the person, other parts are caused by the situation.” This theoretical commitment is not shared by many prior conceptualizations of personality

dynamics. Table A1 presents key differences between our model and the PersDyn model, including theoretical interpretations.

Table A1: Comparison of Change-as-Outcome (COM) Model and PersDyn Model

<i>Construct</i>	PersDyn	Change as Outcome
<i>Modeling of Time</i>	Continuous	Change-per-hour
<i>Interpretation of Parameters</i>	Internal, as features of the individual	System-level, as features of consistent person-situation interactions
<i>Equilibria</i>	Discusses only attractors, one kind of equilibria	Includes attractors, repellers, and the possibility of multiple equilibria in a single model
<i>Attractors</i>	Included	Included
<i>Repellers</i>	Not included	Included
<i>Multiple Equilibria</i>	Not included	Included
<i>Effects of Interventions / Life Changes on Dynamics</i>	Not included	Included
<i>Estimation technique</i>	Bayesian	Frequentist (could be implemented in Bayesian framework in future iterations)
<i>Level of Analysis</i>	Combined between and within (multi-level)	Purely idiographic, within person, allowing for unique person-level dynamics
<i>State Variability</i>	Included	Part of perturbation term and not clearly distinguished
<i>Including more than one state</i>	Modeling approach discussed; not demonstrated	Modeling approach discussed; not demonstrated
<i>Measurement model</i>	Included	Not included