A person-centered approach in developmental science

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PERSPECTIVE

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A person-centered approach in developmental science: Why this is the future and how to get there

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Abstract

This paper argues for a person-centered approach in developmental science and presents theoretical and empirical techniques to help shift the focus to the individual. The need for a person-centered approach is urgent, because of widespread nonergodicity in developmental psychology: traditional between-individual, group-level statistics often cannot be used to understand individuals over time. Evidence for nonergodicity has been gathered in domains such as personality, emotions, identity, performance and intelligence. This highlights a mismatch between our typical research methods—group-level analyses—and a core aim of developmental science: understanding the development of individuals. The implications are profound. Without insights into within-individual processes, our understanding of development remains incomplete and perhaps even incorrect, which could hinder the design of effective interventions. Many of our developmental theories might need to be adjusted to accurately capture individual-level development. The theory of complex dynamic systems and person-centered simulations offer promising avenues to do this. In addition, many promising person-centered analysis techniques, that typically use long time series of data, are available to enhance our understanding of individual-level development. Together, these person-centered theoretical and empirical tools have the potential to help shift developmental science towards an understanding of development that genuinely reflects individual processes.

Highlights

- The problem of nonergodicity in psychological science is widespread, this highlights a need for a person-centered approach to development.
- Creating individual-level theoretical models is a difficult challenge, but complex dynamic systems theory and simulations can help.
- Person-centered analytical techniques presented in this paper can answer questions on individual development, by investigating the shape of individual trajectories, within-individual dynamics and nonlinear developments.

1 | INTRODUCTION

'One model to rule them all.' This sums up a common goal in developmental science: finding one model, to explain the behaviour of all individuals. But is it realistic? Does a population-level model allow us to understand the various individuals within that population? In this paper, I will argue that the answer is often likely to be no. If we want to understand the development of individuals, a person-centered approach is essential in both our theoretical models and empirical analyses.

2 | WHY IT IS DIFFICULT TO USE GROUP-LEVEL FINDINGS TO UNDERSTAND INDIVIDUALS

Nearly two decades ago, Molenaar's (2004) groundbreaking paper demonstrated that we often cannot use traditional group-based statistics to understand individual development over time. Molenaar argued that this approach is only valid when some very strict 'ergodicity' assumptions are met, which are typically unrealistic for psychology. Simply put, these assumptions are (1) that any one human is the same as the next human (referred to as 'homogeneity') and (2) that any one human will remain the same in the future (known as 'stationarity'). When these assumptions are not met, our commonly used between-individual models on a group-level cannot accurately describe individuals over time.

For developmental psychologists, the second assumption of 'stationarity' is particularly strange. After all, developmental psychologists often study how humans change over time, how they develop their cognitions, identity, relations, emotions and so on. To assume that humans remain static is, for developmental phenomena, quite absurd. Thus, almost by definition, it seems that the stationarity assumption, and thus ergodicity, is unrealistic for developmental processes.

Moreover, there is mounting evidence that the first ergodicity assumption, homogeneity, is frequently violated, as individuals can vary greatly. Of course, it is widely understood that individuals can have variations in attributes, such as IQ and personality scores, around a certain mean. However, the lack of homogeneity refers to a different form of variation: a statistical model computed for a single individual over time can be vastly different from that of another individual. This hampers the ability of one single group-level model to accurately describe various individual processes. It might be tempting to think that a group-level model is just an average, and so naturally, individuals will deviate from it. But it is not that straightforward. Hamaker (2023) demonstrated that a between-individual correlation can be markedly different from the average of within-individual correlations. This suggests that group-level models might not even capture the average within-person process accurately, emphasising that between-individual models can be fundamentally different from within-individual ones.

Hamaker (2012) elegantly illustrates this phenomenon through a well-known thought example involving typists. Imagine a random sample of people in which, at the group-level, there is a distinct between-person negative correlation between typing speed and errors: those who type faster tend to make fewer errors. This can be attributed to varying levels of typing expertise—experienced typists can type quickly with minimal errors, whilst novices are slower and more error-prone. Interestingly, when you zoom in on the individual level, the relationship is reversed—there is a positive correlation within individuals. In other words, as a person types progressively faster, they tend to make more errors. This example highlights the possibility that a relation on an individual level can be the opposite of this same relation on a group level.

Whilst this thought example is quite dramatic, illustrating a between-person relationship that is the opposite of the individual-level relationship, such discrepancies may not always be so big for real-world developmental phenomena. However, the truth is, we are largely in the dark on the extent of such discrepancies, mainly because the within-individual or person-centered approach is not yet commonly adopted, and the ergodicity assumptions are rarely tested. That said, over the past two decades, a growing body of longitudinal research employing a person-centered approach has emerged, and their results are cause for considerable worry. There is empirical evidence for nonergodicity in a range of areas critical to developmental psychology, including personality, emotions, identity, performance and intelligence.

Let me provide a brief overview of a few longitudinal studies that highlight a lack of homogeneity, and thus non-ergodicity, in these domains. First, a lack of homogeneity has been observed in personality structures. Molenaar and Campbell (2009) analysed data from a study by Borkenau and Ostendorf (1998) that illustrates this nicely. Typically, group-level analyses reveal a five-factor personality structure known as 'the big five'. However, when analysing intensive longitudinal data of a single individual, the number of personality factors varies, with some individuals exhibiting a 'big three' or 'big two'.

Nonergodicity has also been observed in emotion dynamics. Using time-series data of over a hundred individuals with each a hundred time points, Fisher et al. (2018) demonstrated that the relationship between several emotions and behaviours (e.g., fear and avoidance) is much more varied at the individual level compared to the group level. For instance, whilst only positive correlations are found between fear and avoidance using between-individual models on a group level, on an individual level, correlations are much more varied, and a small portion of individuals even exhibits a negative correlation. This means that some persons are more likely to approach a situation when experiencing fear—something that the between-individual models do not capture at all. Indeed, the average between-individual correlation was in all cases very different from the average of within-individual correlations, and the within-individual correlations varied greatly from one another, demonstrating a lack of homogeneity.

Similarly, in the realm of identity development, van der Gaag et al. (2016) found that correlations between exploration and commitment vary greatly on a within-individual level. Some individuals showed positive correlations, whilst others showed negative correlations. This finding contrasts previous group-level studies that typically present a single between-individual correlation to describe the entire population. Importantly, there was again a discrepancy shown in within-individual and between-individual results: previous group-level studies showed a positive correlation between in-depth exploration and commitment, whilst on an individual-level these same correlations tended to be negative—thus the opposite—again demonstrating a lack of homogeneity and thus nonergodicity.

Finally, there are also indications of nonergodicity in cognitive development and sports performance. Schmiedek et al. (2020) discovered that the existence of one intelligence '*g*' factor, which is a well-established between-person finding, is much less prominent within individuals. This suggests that the hierarchical model of intelligence may not accurately describe the structure of intelligence within individuals. Additionally, in the field of sports performance, Neumann et al. (2022) revealed that the relationship between load (the pressure an athlete experiences) and recovery (the time the athlete takes to recover) varies greatly at the individual level compared to the between-individual relationship found on a group level. This led Neumann et al. to conclude that processes of load and recovery are nonergodic.

In sum, the substantial variation in within-individual models and the contrasts with between-individual models, as empirically demonstrated in these developmental phenomena, challenges the validity of applying the between-person effects found in group-level statistics to make claims about individual development. Such violations of the ergodicity assumptions for identity, intelligence, emotions, personality and performance, imply that at least in these domains we likely cannot rely on between-person models to understand, predict or explain individual-level behaviour. And, considering how fundamental this ergodicity issue is, it is plausible that nonergodicity extends to many other domains of developmental psychology, and psychology in general, as well.

The widespread nonergodicity in developmental phenomena highlights the importance of aligning our analytical approach with our intended inference. If our goal is to make claims about individual development, then our unit of analysis needs to be the individual, not the group. This means developing individual-level theoretical models, conducting longitudinal studies on individuals and explicitly testing ergodicity assumptions. Whether we truly want to spend considerable effort to do this, depends on whether we consider individual-level knowledge to be essential. And I firmly believe that it is indeed essential, for at least two reasons.

3 | WHY WE NEED MORE KNOWLEDGE ABOUT INDIVIDUALS

One could firstly argue, like Molenaar (2004) did, that our knowledge of development will remain incomplete if we do not have knowledge of within-individual processes. I would go a step further and argue that much of the theoretical knowledge that we now have in psychology is based on group-level empirical studies whilst making individual-level theoretical claims. Indeed, the empirical base of individual-level theoretical claims could be shaky, if not non-existent, if it turns out that the ergodicity assumption is violated. Therefore, I believe that we are in dire need of checking to what extent ergodicity is a problem for each phenomenon in developmental psychology. And if we do these ergodicity checks and find that is indeed a problem for a certain phenomenon, then we need to take action to make sure that we generate individual-level theory to complete and perhaps correct our current knowledge. This means that we need to make sure to disentangle the between-person, group-level effects from the within-individual processes in our theory and root knowledge of individuals in theoretical models and empirical studies that take a person-centered approach.

Secondly, I would argue that taking a person-centered approach is not only a fundamental necessity to complete and perhaps correct our knowledge of psychological development but it also has important practical value. Of course, the group-centered approach has already brought us many relevant insights that we can use in practise. For instance, this type of knowledge is very useful to help us identify individuals at risk, such as children who are likely to develop mental disorders in adulthood, or adolescents who have an elevated risk for school drop-out. Yet it does little to inform us on how to intervene, as interventions typically take place on an individual level, between client and therapist, or student and teacher. This is where individual-level knowledge would be a very welcome addition to our existing group-level knowledge base. If individuals can differ greatly in their psychological models, then for some it may help to do intervention A, whilst for others intervention B works better. Some studies, such as the HowNutsAreTheDutch project (van der Krieke et al., 2016), have attempted to create such individual models to understand under which circumstances individuals experience psychopathology symptoms, and under which circumstances they feel good. Such individual-level models could result in more effective intervention strategies tailored to the needs of the individual. This person-centered approach has already been proposed as a highly promising and necessary way forward in clinical psychology (Hayes et al., 2019; Lundh & Falkenström, 2019; Wright & Woods, 2020), and I think it is a promising avenue for developmental science as well.

Thus, in my view, we do very much need individual-level knowledge, to create better theories of development and to be better able to inform practise. Unfortunately, the nonergodicity problem implies that currently, we may have little knowledge that we can validly apply to individual-level developments. And although this may be a discouraging realisation, there is also reason to be optimistic about our path forward. There are many interesting and feasible approaches to generate individual-level theory and conduct person-centered empirical studies.

4 | PERSON-CENTERED THEORY DEVELOPMENT

The nonergodicity problem suggests that many of our developmental theories might need adjustments to more accurately reflect individual-level developments. But creating individual-level theory is no easy task. As the above empirical studies demonstrate, individual processes over time can be highly varied. Thus, individual-level theory needs to be able to handle this variation, as well as the inherent complexity and uncertainty of individual trajectories over time. Complex dynamic systems (CDS) theory offers a metatheoretical framework capable of addressing these challenges. By drawing on its theoretical principles, we can construct individual-level theoretical models for specific developmental phenomena. In addition, if we formalise and simulate these theoretical models, we ensure that they are well-designed, logically consistent, and closely aligned with observed phenomena.

4.1 | Complex dynamic systems theory as a metatheory of human development

When viewed as a complex dynamic system, individual development cannot be separated from time (Kunnen et al., 2019; Smith & Thelen, 2003; van Geert, 2011), it is always history dependent. This simply means that you are not a completely different person from one moment to the next, your current developmental or psychological state depends on your previous state—in CDS terms this is called ‘iterativity’. This may seem obvious, but many of our between-individual statistical models do not automatically include this. Consequently, theoretical models that are informed by such group-level statistical models, tend to have features that are peculiar on an individual level. For example, many psychological models look something like the model in Figure 1a. The model may for example represent the phenomenon that if individuals feel depressed (x) or worried (z), they tend to sleep badly (y). And then the model stops. But in real life, an individual wakes up sleep deprived the next day, which may cause them to feel even more depressed and worried, thus over time, y will affect x and z as well. Thus, when applied to the individual, psychological models should look more like the model in Figure 1b, where each variable is expected to affect itself at the next point in time, and is also expected to affect other variables at the next time point. If we take an individual perspective, we are forced to think about, and quantify, such effects of history dependence.

This history dependence or ‘iterativity’ in development has consequences for our understanding of the stability of certain behaviours, and the mechanisms that explain this stability. Iterativity allows us to form certain habits. Habits are basically a relatively stable set of behaviours, thoughts or emotions that we are drawn to—in CDS terms this is called an ‘attractor state’ (van Geert, 2011). Put simply, habits are formed when we do something in a certain way because we have successfully done it like that many times before. Or, put more accurately, they emerge because certain behaviours, thoughts, emotions or other variables interact with each other, and over time these interactions form stable patterns (Lichtwarck-Aschoff & van Geert, 2004). Such patterns, habits, or ‘attractor states’, can be important predictors for the future: you are much more likely to behave in your habitual way than to behave in a novel way.

Borsboom (2017) suggested that such stable patterns of interaction between behaviours, thoughts and emotions, are better able to explain psychological disorders than the latent disease model: instead of an underlying disease causing psychopathology symptoms, it is proposed that psychopathology symptoms cause each other through their interaction. For example, depression can be described as an attractor state that results from a self-reinforcing pattern: a lack of sleep gives rise to a negative mood, which increases worry, causing furthermore sleep problems—and the pattern repeats. Its result is a stable, dysfunctional pattern of interacting symptoms that has emerged

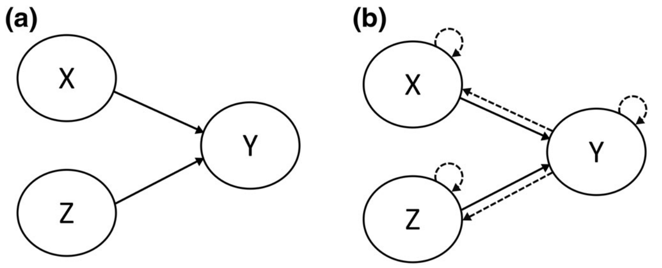

FIGURE 1 A simple group-level model is shown in (a), with two independent variables *X* and *Z* that have a certain relationship with the dependent variable *Y*. In (b) this same model is shown but then applied to an individual over time, the added effect of time dependency is illustrated with dashed arrows. Specifically, in each time step all variables are to some extent affected by their own previous value (curved dashed arrows) and the previous values of the other variables (straight dashed arrows).

because the symptoms cause each other. The pattern keeps itself alive without any particular input from the environment, nor any underlying latent variable that causes it—this is called 'self-organisation' in CDS terms. Including these mechanisms of self-organisation in our theoretical models can have interesting implications for intervention. For example, we should perhaps not treat psychopathology by trying to heal an underlying mental disease but try to sever the connection between symptoms that the individual experiences (Borsboom, 2017).

As a consequence of this tendency of individuals to form patterns, habits or attractors, it is unlikely that development is typically gradual and linear but is rather characterised by 'wobbles, humps and sudden jumps' (van Dijk & van Geert, 2007). Individuals can spend a long time in a stable state where nothing changes much; they follow their normal, stable patterns of behaviour, emotion and thought. Then something may happen that disrupts the status quo, for example growth in some domain, or a profound change in the environment—the latter is called a 'perturbation' in CDS terms. During such times, the quiet stability can suddenly be replaced by a turbulent period, characterised by much variability. Eventually, the individual will settle in a new stable state again.

This may sound like development is a very unpredictable process, but the theory of CDS actually claims that sudden, nonlinear changes can be predicted to some extent. They are likely to be preceded by early warning signals, such as critical slowing down (Scheffer et al., 2012) or periods of increased variability (van Dijk & van Geert, 2007). In practise, however, applying such early warning signals as predictors of change can be challenging. Their effectiveness depends strongly on the specific system under investigation and they are particularly sensitive to noise and sampling frequency (Dablander et al., 2023). Despite these challenges, there have been successes. For instance, increases in instability have been identified as predictors of a new level of functioning during psychological treatments for mood disorders (Olthof et al., 2020).

These principles of complex dynamic systems have proven useful in informing many specific person-centered theories in several subfields of developmental psychology (for many examples see Kunnen et al., 2019). For instance, it has been used to understand the shape of transitions in adolescence and to predict the moment of these transitions (Hollenstein & Tsui, 2019). And to develop a theory on mental health that has the potential to be more useful in practice (Borsboom, 2017; Schiepek et al., 2019). It was used to reconceptualise the longstanding assumption on self-esteem, that it is not just a trait that characterises someone, but a state that emerges out of individual–context interaction on a moment-by-moment basis (de Ruiter, 2019; De Ruiter et al., 2017). When applied to morality, it was used to predict that individuals have several levels of morality that become active in certain situations, challenging the classical view of consecutive stages of moral reasoning (Kaplan, 2019). Attractor principles were also used to predict the pivotal role of identity integration in constraining everyday life experiences (Van der Gaag et al., 2020). Moreover, CDS theory predicted, and this was subsequently shown, that classroom interactions change from rigid to flexible over the course of a teacher intervention (Menninga et al., 2021). Thus, CDS theory has been proven useful for developing theory on the 'how' of development, creating practically relevant theory, reconceptualising long-standing models and generating novel predictions (van der Gaag et al., 2019).

As such, the metatheory of complex dynamic systems can be a valuable tool for theory development in developmental science, but there are limits to using it only in a verbal theory. There are many ways to precisely define and specify a complex system, which results in various behaviours. One CDS does not behave exactly the same as the next one. For example, a system may flexible or rigid, have a high or low likelihood of sudden transitions etc. (e.g., Scheffer et al., 2012). Thus, whilst complex dynamic systems theory is a valuable prototype theory to borrow person-centered theoretical principles from, generally more steps need to be taken to tailor it to a specific developmental phenomenon. Simulations can be helpful to do just that.

4.2 | Simulations to create solid person-centered theory

Calls for the formalisation of psychological theory through simulations have become more numerous recently (Borsboom et al., 2021; Oberauer & Lewandowsky, 2019; Robinaugh et al., 2021; Smaldino, 2017, 2020). This is in part because there's a growing consensus that the current state of psychological theory is less than ideal. In fact, Oberauer and Lewandowsky (2019) have argued that the replication crisis in psychology is at its core a 'theory crisis', rooted in poorly defined theory and an often weak link between theory and empirical studies. Whilst they argue that this largely stems from discovery-oriented research using theory-testing tools, the ergodicity problem may also contribute. If past inferences have indeed incorrectly translated between-individual phenomena to individual-level theory, whilst the ergodicity assumptions do not hold, then it is likely that the overall quality of psychological theory has suffered.

A good way to develop high-quality individual-level theory is to formalise it. Simply put, formalising a person-centered theory typically means writing down the assumed mechanisms of individual development as a set of equations or rules, and then simulating these to see how they play out over time. The simulation results can be used to generate hypotheses, or can be compared to real empirical data. Formalisation tightens the link between theory and empirical findings because the generated hypotheses are directly derived from the theory, which is not necessarily the case with verbal theories—there the link between theory and hypothesis can be rather weak (Borsboom et al., 2021; Oberauer & Lewandowsky, 2019). Indeed, many have suggested that formalising theory is an essential step forward in psychological science to make sure that our psychological models are specific and internally consistent and that the hypotheses derived from them are firmly grounded in theory (e.g., Borsboom et al., 2021; Frankenhuis, 2019; Frankenhuis & Tiokhin, 2018; Haslbeck, Ryan, et al., 2021; Oberauer & Lewandowsky, 2019; Robinaugh et al., 2021; Smaldino, 2017, 2020).

Borsboom et al. (2021) proposed a systematic method to formalise theory. The process begins by identifying a robust phenomenon—a general, stable finding (for example, high comorbidity between anxiety and depression). The next step is to create a 'prototheory', which consists of a few broad rules that are assumed to explain the phenomenon. Striking a balance between complexity and simplicity is crucial in this step—the theory needs to be as basic as possible whilst still sufficiently explaining the phenomenon of interest. The prototheory is then formalised in a set of equations or rules suitable to construct simulations. The simulation results are then analysed to evaluate the theory's merit. Borsboom et al. (2021) noted that developing a prototheory is the least methodologically developed step. It is indeed perhaps the most difficult step, as researchers grapple with defining the core assumptions and must determine essential elements to include in the model. To help with this, Borsboom et al. suggest 'analogical abduction': to steal principles from other successful theories, perhaps in other fields. For psychological development, a suitable theory to abduct principles from is CDS theory (see the previous section). For example, the principle of iterativity (history dependence) is one core assumption that would be crucial to make in any person-centered theoretical model.

Formalising and simulating theory is always a good idea to enhance its quality, but it is even more important when the theory is both person-centered and incorporates principles from CDS. When we model individuals over time, include their history dependence and multiple interacting elements, it becomes nearly impossible to verbally predict how their development will play out in the long run. To further complicate matters, individuals typically differ from each other, and we may want to reflect this in our models. This results in even more possible outcomes, which hampers our ability to use our logic and imagination to understand which phenomena will be produced by the theoretical model. This is where simulations come in. Computers can generate millions of hypothetical trajectories stemming from our person-centered theory, offering insights beyond our intuitive grasp. As such, simulations allow us to comprehend the long-term consequences that result from our hypothesized mechanisms development.

There are already a few examples in psychology where a person-centered simulation approach has successfully been applied, leading to novel hypotheses.[1] One such example is a simulation of intelligence (Van Der Maas et al., 2006). This simulation model is based solely on interactions between cognitive processes during development but can explain the emergence of a manifold intelligence structure, without having to assume an underlying latent '*g*' factor. Another example is a simulation of major life decision-making (van der Gaag et al., 2020). This simulation model predicts that differences between individuals, such as how selective they are and how they tend to explore, will determine the shape of decision-making processes and decision quality. It shows for example that patterns of ruminative exploration emerge spontaneously amongst picky individuals who tend to explore much in depth—a new, more parsimonious view on existing theories that typically conceptualise ruminative exploration as a qualitatively different type of exploration. These examples demonstrate that simulation models allow us to form parsimonious, precisely defined theories that are rooted in within-individual processes, which may lead to novel insights.

Not only can simulations offer us precise and parsimonious individual-level theories but they can also tackle the ergodicity issue in a powerful way when we combine them with empirical data. Currently, simulation models often serve as thinking tools, ensuring the logical coherence of our theoretical models and verifying if our assumptions produce plausible developmental trajectories. But obviously, combining such formal theory development with empirical testing is an important advancement and the next logical step in the field. Haslbeck, Ryan, et al. (2021) introduce a promising method to do this. Their approach involves fitting a statistical model to both simulated and empirical data, and then comparing the outcomes. If any discrepancies are found, an explanation needs to be sought, potentially leading to theory adjustments. Although this method still needs to be developed further, Haslbeck, Ryan, et al. (2021) already give a useful example that demonstrates the power of this approach. They first generated time-series data from a formalised person-centered theoretical model. They then applied a between-individual, group-level statistical model to a cross-sectional sample of this simulated data. Thus, the simulation showed which group-level effects would be produced by the individual-level theoretical model. If the empirical group-level effects are similar, this provides preliminary evidence for the within-individual theoretical model. Crucially then, this method offers a unique advantage: it bridges the gap between individual-level theory and group-level empirical models. And it does so without violating any ergodic principles. This means person-centered simulations enable us to harness the extensive between-individual data already available in psychology to start validating theories focused on individual development.

Thus, simulations emerge as a promising way forward to create solid person-centered theories. For those eager to learn more about the practicalities of simulations, Smaldino (2020) offers an accessible beginner-level tutorial on formalising and simulating models. Borsboom et al. (2021) provide a comprehensive framework for constructing formal theory grounded in observed phenomena and empirical data. If you are still doubting the importance of this approach, Robinaugh et al. (2021) articulate the many ways formal theory can enhance theory construction, and Oberauer and Lewandowsky (2019) emphasise the role of theory in generating solid hypotheses and safeguarding against questionable research practises.

5 | PERSON-CENTERED EMPIRICAL APPROACHES

Besides advances in person-centered theory formation, there are now many tools to empirically analyse data from a person-centered perspective, both qualitative and quantitative methods. Qualitative approaches adopt a person-centered lens by design, analysing the data of each individual separately. Such studies are invaluable for creating individual-level theory and deepening our understanding of the nuances behind quantitative findings. However, quantitative approaches remain indispensable as well, as they can be used to study many individuals and compare them easily. Luckily, quantitative methods can also easily be applied in a person-centered approach.

In the following, I will name a few of these quantitative methods that I find the most useful or promising. I want to add a quick disclaimer that this list is by no means exhaustive and that I am no statistician. Moreover, as person-centered empirical techniques are rapidly developed, this list may soon be outdated. Nevertheless, I believe that a succinct, non-technical overview of some main person-centered empirical methods from the perspective of a user may help you select and apply some of these in your own work. Therefore I present to you an informal overview of person-centered analytical techniques, that typically make use of intensive longitudinal, quantitative data.

The way I see it, person-centered analytical techniques can answer questions on three important aspects of individual development. Firstly, it may be interesting to investigate the general shape of developmental trajectories and individual differences in these shapes. This may answer questions such as 'at what stage during childhood does cognitive ability X develop?' Secondly, delving deeper, we can analyse the relationships between variables within an individual that shape these trajectories. A question that can be answered here might be 'does teacher autonomy support help to foster cognitive ability X?' Thirdly, it may be valuable to explore the non-linear dynamics of longitudinal trajectories, to for example answer questions like 'does cognitive ability X exhibit attractor states and what are their characteristics?' The subsequent sections will categorise analytical techniques based on these three types of questions. However, note that many analytical techniques are not limited to answering only one type of question - a single method can often be adapted to serve multiple objectives.

5.1 | Investigate the shape of development

Investigating the shape of individual trajectories in developmental psychology presents unique challenges. Averaging many longitudinal trajectories is a common practice, and this may be fitting but can also be misleading, depending on the data. There might be instances where the average trajectory is flat and gradual (such as in Figure 2a) and this accurately reflects the typical development of individuals in the sample. In such cases, presenting an average trajectory is fitting to describe the individual development in question. However, there are also situations where the average does not accurately represent an individuals' experience, for example, if the individual trajectories exhibit much variability (as in Figure 2b). Here, an average trajectory might give a misleading impression of smooth and gradual development when, in reality, it is volatile and fluctuates considerably. Moreover, it is possible that some individuals follow a volatile trajectory, whilst others exhibit a smooth and gradual path, suggesting the presence of subgroups in the data. When visually presenting this data, it is important to avoid misleading representations and keep the complexities of individual development visible. Similar considerations come into play when we aim to analyse the shape of development. We must decide whether our data are best represented by a single smooth, general trend, or if it might be more accurately represented by other trajectory markers, such as variability, and potentially by identifying subgroups.

First, if you believe that the individual trajectories in your data can be accurately described by a general, average trend with individual variations around it, then a simple multilevel model might be the best choice. Whilst multilevel models are versatile and can handle a range of complex analyses (see also Hoffman & Walters, 2022), they are also well-suited for analysing simple developmental trends. This typically involves applying a linear model to the longitudinal data of all individuals in the dataset (though other slope shapes, such as curvilinear, are also possible), whilst allowing both the intercept and slope to vary across individuals, by incorporating 'random effects'. These individual models then inform an overarching, group-level model, represented by the 'fixed effects'. The fixed effects shed light on the average trajectory of the entire sample, illuminating the general trend of development, whilst the random

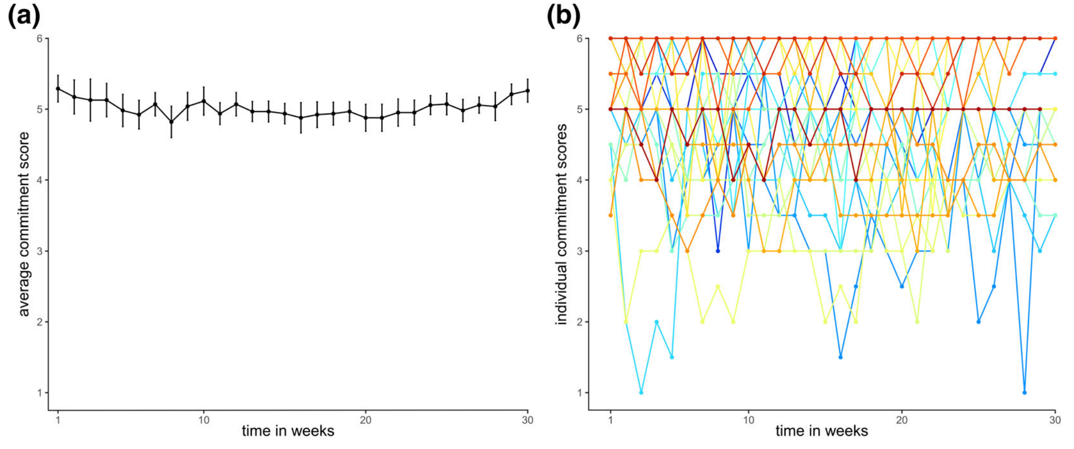

FIGURE 2 (a) The average trajectory of educational commitment over 30 weeks amongst first-year psychology students, including within-subject confidence intervals for each measurement point. (b) The raw data of the individuals, each colour represents a different individual (figures based on data from Van der Gaag et al., 2019). Comparing the graphs leaves us to wonder: is any individual trajectory accurately described by the average trajectory?

effects capture individual variations around this average. Whilst the fixed effects often receive primary attention, it is important to highlight the variability between individuals to uphold a person-centered perspective. This focus on individual trajectories can be preserved by reporting the distribution of the random effects and by visualising not just the general trend but also the individual trajectories and their models.

Secondly, if you think that the data may be best described by different subtypes of trajectories, or if non-standard characteristics such as variability of an individuals' trajectory seem important, clustering the individuals could be beneficial. Techniques like latent class growth models (e.g., Jung & Wickrama, 2008) can help discover different subtypes in longitudinal trajectories. However, in their standard form, these models come with assumptions that might not always be realistic for your data or theory, such as the notion that development is gradual and linear. For a more flexible approach that allows other assumptions, one might consider general clustering methods like k-means (e.g., Tan et al., 2005) or customised growth mixture models (e.g., Muthen & Asparouhov, 2008). With these methods, it is easier to select intriguing markers of development as a basis for clustering. One can for example select the variability of a trajectory,[2] changes in this variability, a count of abrupt changes in the trajectories, or even more complex trajectory markers such as early-warning signals of a shift to a new attractor state (e.g., Olthof et al., 2020). After forming clusters based on these markers, the different trajectory types can be visualised and related to various outcomes. For example, using this method, it was discovered that much stability in educational commitment predicts persistence in education, whilst much variability is a warning of potential dropout (Van der Gaag et al., 2019). Thus, this method helps researchers to discover the ways that individuals might vary in their shape of development and allows them to predict different outcomes based on these shapes.

5.2 | Analyse within-individual dynamics

Whilst we have discussed techniques to describe the shape of individual developments, there are also many methods to analyse the within-individual dynamics, that is, the linear relationships between variables that shape these individual trajectories. Perhaps the simplest method is to calculate a within-individual correlation (e.g., Neumann et al., 2022). Essentially, you just compute a simple correlation as you would normally do, but apply it to the time-series data of one individual, and repeat this for every individual. However, this method violates the assumption of independent observations, leading to potential exaggerations or underestimations of the correlations. A recent solution, the repeated measures correlation, addresses this by not relying on the independence assumption (Bakdash & Marusich, 2017). This technique is both intuitive and easy to apply. Yet, like all correlations, it does not account for overlapping variance.

Beyond these basic correlational techniques, there exists a range of advanced person-centered methods that can include multiple variables and disentangle their overlapping variance (for a comprehensive overview, see Hamaker et al., 2015). A prominent example is vector autoregressive (VAR) modelling. This method essentially captures the dynamic interplay between the time series of multiple variables within an individual. VAR is similar to the concept of within-individual correlations: it reports relationships between variables based on intensive longitudinal data for each individual. However it adds that overlapping variance is separated. In essence, a VAR model resembles a simple linear regression model, but it is applied to individual time-series data and includes temporal dependencies. This results in models uniquely tailored to each individual, enabling claims about the dynamics between variables on an individual basis.

In some cases, it might be interesting to investigate how within-individual dynamics change over time, for example comparing individual dynamics before and after an intervention. One way to do this is by segmenting the longitudinal data into sections, like pre- and post-intervention, and then generating a VAR model for each segment. More advanced methods, such as time-varying vector autoregressive models (TV-VAR) are being developed and offer the potential to model individual change processes with greater precision (e.g., Bringmann et al., 2018; Haslbeck, Bringmann, et al., 2021). However, these typically require more data points than standard VAR models and can be difficult to interpret (Bringmann, 2021). Despite these challenges, such novel tools promise to provide nuanced insights into the changing dynamics of individual development over time.

Having a bunch of individual-level models still leaves us with the problem of drawing a general conclusion that extends beyond ‘everyone is different’. For this, multilevel modelling techniques are again helpful. They can estimate the dynamic interplay between variables within each individual and simultaneously estimate a general, group-level model based on these dynamics. A notable contribution in this area is dynamic structural equation modelling (DSEM) introduced by Asparouhov et al. (2018) (see also McNeish & Hamaker, 2020 for an accessible introduction). DSEM is a multilevel modelling framework specifically designed to handle time-series data of individuals. VAR models can be incorporated in the multilevel framework of DSEM, thus estimating not only individual-level VAR models but also an overarching group-level VAR model. However, a pitfall to using multilevel techniques such as this, is the potential overemphasis on the mean-level model: researchers may be enticed to focus predominantly on average, group-level results, whilst sidelining variations between the individual models. Moreover, multilevel models typically assume that the various within-individual relations are normally distributed, ignoring the potential existence of subgroups. To gain more insight into the individual differences, it is crucial to also include information on the individual models, for example by visualising them, even though this requires taking some extra (manual) steps.

Visualising differences in the coefficients of within-individual models can be very informative to get an idea of the extent of the variation between individuals, and to identify possible subgroups. You can use classic distribution graphs like boxplots or histograms to depict individual model coefficients (the betas), regardless of whether they are generated with multilevel or VAR models. However, richer visualisation techniques are also available in R (R Core Team, 2020). For instance, violin plots (Adler & Kelly, 2020), bean plots (Kampstra, 2008), pirate plots (Phillips, 2017), and raincloud plots (Allen et al., 2021), these do not only illustrate distributions but also highlight individual data points, means, and confidence intervals. It is also possible to visualise the within-individual relationships between variables as a network, this is often done in combination with VAR models (Bringmann, 2021).[3] Whilst generating such visualisations typically requires a bit of programming skill in for example R or Python, the learning curve is manageable. With resources like generative AI and online tutorials, even novices can become reasonably proficient programmers in weeks or even days—an investment that may pay off for a very long time.

Whilst these visualisations can offer valuable descriptive insights into individual differences and similarities in within-individual dynamics, it can also be helpful to quantify these differences and similarities. One method that achieves this is the group iterative multiple model estimation (GIMME) approach (Gates & Molenaar, 2012; Wright et al., 2019). Unlike multilevel modelling, GIMME adopts a bottom-up approach. It does not assume the individual models to be normally distributed, which ensures that individual model estimates are not constrained by a group-level model. GIMME can also identify subgroups of individuals with similar types of models. Moreover, it can pinpoint group-level effects, which are not defined as a between-individual relationship determined on a group level, but rather defined as a within-individual relationship that is shared by a majority (typically >75%) of individuals. When such an effect is identified, it indicates a large extent of ergodicity: one pattern can be generalised to most individuals.

This already touches on the idea that a part of the data may be ergodic, whilst another part may be nonergodic, and it may be key to distinguish these parts (Voelkle et al., 2014). When a phenomenon is largely ergodic, group-level methods can provide valid insights into individual-level behaviours (von Oertzen et al., 2020). Thus, determining the extent of ergodicity may be important, as it may reveal that not all phenomena require continued intensive longitudinal study. von Oertzen et al. (2020) present a promising new approach to test the extent of nonergodicity: ergodic subspace analysis, which separates the variance between individuals over time from the variance within individuals. Although this ergodic subspace analysis may be a bit technical in execution, there is an R package and code available (see von Oertzen et al., 2020). If we quantify the extent of nonergodicity for each phenomenon, this will ultimately help us to discover which of our group-based theories can be applied to individuals, and which will need to be revised or extended to include within-individual development.

5.3 | Explore nonlinear development

A potential downside to the analytical techniques mentioned so far, is that they typically assume linearity in the relation between, and changes in, variables. This assumption might not always align with the theory that you aim to investigate. For instance, if you hypothesise that a particular variable exhibits intrinsic, nonlinear dynamics rather than merely fluctuating around an average, dynamic linear modelling might be a more suitable approach. This method offers more flexibility than for example vector autoregressive modelling, allowing you to assume that a variable fluctuates nonlinearly (Campagnoli et al., 2009; for an applied example see van der Gaag et al., 2017). Although this technique can incorporate some nonlinearities, the equations that it uses are still mostly linear—for a full nonlinear approach, other techniques are more helpful.

A perhaps quite intuitive nonlinear technique is the state space grid (Hollenstein, 2007; Meinecke et al., 2019). This allows you to visualise patterns of interactions on a grid. It is often used for observational, categorical data, enabling researchers to discern patterns, such as how frequently a specific action by person A is followed by a particular reaction from person B. It has been used in several studies focused on interactions, for example, to understand changes in classroom interactions before and after an intervention (Menninga et al., 2021). Its main strength is descriptive, it can effectively illustrate key process properties over time. For instance, it can visualise the presence of certain attractor states, or shed light on the stability and variability in interactions.

Recurrence quantification analysis is a deeper, albeit more complicated, technique to analyse nonlinear patterns in individuals or dyads (Heino et al., 2021). Simply put, it can find patterns in the data by quantifying how often certain scores or categories of behaviour, re-occur. Consequently, it can pinpoint habits or attractors within individual behaviours (Heino et al., 2021) or within dyadic interactions (Cox et al., 2016). For example, it has been employed to discern shifts in the flexibility of parent–child dialogues (Cox & van Dijk, 2013) and to measure the synchronisation between a child's gestures and speech during tasks of varying complexity (De Jonge-Hoekstra et al., 2021).

Deciding between linear and nonlinear techniques hinges on the nature of the process you are examining. Is it best described as linear, or nonlinear? Whilst sometimes this choice can be guided by theory, it can also be investigated empirically, with local linear models (Toonen et al., 2016). This method operates on the premise that even if a developmental process is inherently nonlinear, each small part of it can nonetheless be described by a linear model. If these linear models, derived from all the small parts, are highly similar, then a linear model for the entire process is appropriate. Conversely, if these models are highly dissimilar, then a nonlinear approach fits better. Employing this technique requires many data points for each individual (e.g., Toonen et al., 2016). Despite this challenge, it might be valuable to do this in at least a few studies, as understanding whether a developmental phenomenon is linear or nonlinear can guide more accurate analyses in future research.

6 | CONCLUSION

In conclusion, the ergodicity issue poses major challenges to developmental science, making it difficult to generalise findings from group-level data to individual developmental trajectories. Considering the fundamental nature of the ergodicity problem and the empirical findings that support it, we cannot keep assuming that our group-level models can be translated to knowledge on the individual's development. We must at least check the ergodicity assumption before assuming it to be so, because so far nonergodicity seems to be the norm rather than the exception. If non-ergodicity is indeed as widespread as it seems to be, then our theories of development may in the best case be over-generalising and in the worst case be plainly incorrect when applied to individuals. Therefore, it is essential that we develop individual-level theory and conduct person-centered empirical studies.

The advancements in both theory development and empirical approaches described in this paper offer promising avenues to do just this. By drawing from complex dynamic systems theory and utilising simulations, we can create theoretical models truly rooted in individual dynamics, and generate novel hypotheses. When we combine simulations with empirical analyses, we can bridge the divide between individual-level and group-level knowledge. On the empirical side, many person-centered analysis techniques, both linear and non-linear, have emerged. These techniques enable us to investigate individual trajectories and their dynamics, revealing unique patterns often obscured in between-individual, group-level analyses. These person-centered theoretical and empirical techniques can substantially help fill the current gaps in our understanding of within-individual processes.

As such, person-centered approaches are not just alternative methods; they represent an important shift in how we understand development. By embracing this shift, we can navigate the challenges posed by ergodicity, refine our theories to truly reflect individual development, and ultimately design interventions and educational strategies tailored to the unique development of each individual.

AUTHOR CONTRIBUTIONS

Mandy A.E. van der Gaag: Conceptualization; investigation; visualization; writing – original draft; writing – review and editing.

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PEER REVIEW

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DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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ENDNOTES

[1] In many other scientific fields, such as biology and physics, it is very common use simulations to develop theory on processes over time. For a taste, have a look at the website jondarkow.com (Darkow, 2022), it has many interesting simulations to try out online, such as predator–prey and strange attractor models.

[2] Preferably a measure that is well able to capture fluctuations in individual trajectories, such as RMSSD (Von Neumann et al., 1941), as a standard deviation can underestimate these (Kunnen, 2011).

[3] Interestingly, such individual network visualizations may have important practical applications, they can for example be used to guide individualized interventions (see for example Heininga & Kuppens, 2021).

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