Contemporary Methodological Considerations for Key Issues in Research on Personality Disorder Development

Abstract

In the present paper, we aim to contribute to further progress in the field of personality disorder (PD) development by highlighting several recent methodological innovations related to (1) the measurement of personality pathology, (2) the modeling of typical features of personality pathology, and (3) the assessment of processes that characterize PD development. For each of those issues we discuss key points of attention and methodological strategies, illustrated with recent publications in the PD research field as potential resources for future research.

Keywords: longitudinal, methods, analysis, time, personality disorders
Contemporary Methodological Considerations for Key Issues in Research on Personality Disorder Development

Longitudinal research on the development of personality disorders (PDs) from early age onwards has only recently become part of scholars’ agenda (e.g., Shiner & Tackett, 2014). PDs have been traditionally defined as categorical entities, characterized by an enduring and stable course as of age 18 (American Psychiatric Association, 2000). This conceptualization resulted in numerous studies up until the 90’s restricted to adulthood and with almost no focus on natural development (Lenzenweger, 1999). The conventional perspective on PDs was also reflected in the predominant trait theories at that time, with seminal personality researchers arguing that personality was ‘set like plaster’ by the age of 25-30 (Costa & McCrae, 1994). Personality development was hence believed to follow genetically predetermined paths, with only small mean-level changes across adulthood due to biologically driven processes of maturation (McCrae et al., 2000).

With the entrance of the new millennium, more nuanced evidence on normal-range (e.g., Big Five) personality development emerged. This was primarily due to meta-analyses that separated mean-level stability from rank-order stability of personality traits across the lifespan (Roberts et al., 2006; Roberts & DelVecchio, 2000), the rise of a transactional perspective on personality development (e.g., Caspi & Shiner, 2006; Fruzzetti et al., 2005), advances in theoretical perspectives (e.g., on the social investment theory (Helson et al., 1984); Roberts et al., 2005), and key developmental mechanisms such as person-environment fit (Roberts & Robins, 2004). In addition, we gained more detailed knowledge on differential patterns of normative personality development for men versus women (Specht et al., 2011), and for higher- versus lower-order constructs of personality (Soto et al., 2011), while studies also showed age-graded changes in personality as a function of developmental transitions.
(Bleidorn, 2015). Consequently, the assumption of personality stability was revisited towards the consensus that personality development is characterized by both stability and change.

Almost at the same time, the PD field underwent a substantial paradigm shift, evolving from the compelling evidence that PDs can best be captured using dimensional rather than categorical taxonomies (Widiger, 2007). This taxonomic revolution from categories towards dimensions was of direct relevance for theory on PD development because the trait dimensions underlying PDs appeared to be conceptually and empirically related to general traits (Thomas et al., 2013; Widiger & McCabe, 2020). This common ground allowed for an expansion of knowledge and insights from studies on normal-range personality development to the research area of personality pathology. In addition, the increasing evidence on childhood roots of PDs (for a review see De Clercq & De Fruyt, 2007; De Clercq, 2018), the suitability of the five-factor model (FFM) of personality from childhood onwards (Caspi et al., 2005; De Fruyt et al., 2006; Shiner, 2009), as well as evidence on similar associations of FFM traits with PD categories in adolescence (De Clercq & De Fruyt, 2003, 2012; Tromp & Koot, 2009) stimulated the PD field to investigate developmental antecedents of PDs from early age onwards rather than adhering to the strict barrier of the age of 18.

Ever since, a flourishing field of research on the development of PDs in pre-adulthood has emerged (Klimstra et al., 2020; Sharp & De Clercq, 2020; Shiner & Tackett, 2014), primarily focusing at the between-person level and more recently also targeting process-based, within-person developmental issues (e.g., Giacomin & Jordan, 2016; Kaurin et al., in

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1 Throughout the literature, personality stability and change have been conceptualized in various ways. A first important distinction can be made between heterotypic and homotypic stability. Heterotypic stability pertains to stability of the underlying psychological construct across development, with the behavioral expressions of that construct being different at different ages. Homotypic stability, in turn, refers to stability of the same cognitions, behaviors and feelings over time. Researchers studying homotypic stability have typically focused on four types of stability and change: (a) absolute stability, or mean-level change, (b) differential stability, or rank-order consistency, (c) structural stability, or measurement and structural invariance over time, and (d) ipsative stability, or consistency of the patterning within an individual over time (Atherton et al., 2020a). In the present paper, we focus on methods that allow studying homotypic stability and more particularly absolute stability and change.
press). Also for adult age, significant advances in our understanding of developmental principles and processes of PD development have been made (Hartung et al., 2022; Hopwood et al., 2022; Wetzel et al., 2020), although such developmental issues in older adults are still largely understudied (Hill et al., 2021; van Alphen et al., 2015).

One of the main catalysts for this rapid growth in studies on PD development is the continuous stream of methodological and data-analytical innovations. Such innovations allow to increasingly improve our modeling and understanding of longitudinal data, and by doing so, they pave the way for enriching our knowledge on substantive topics pertaining to (1) the measurement of PD constructs, (2) the typicality of personality pathology, and (3) the processes underlying PD development. In the present paper, we aim to contribute to further progress in the field of PD development by highlighting a number of recent methodological innovations related to those three broad topics. As a set, those innovations allow addressing four key questions in PD developmental research: (1) How to deal with the richness of multi-informant ratings of personality pathology as a resource for new insights in PD development, (2) How to include information from both lower-and higher order constructs of personality pathology into longitudinal designs as to unravel broad versus specific growth processes from an integrative perspective, (3) How to model the typical features of comorbidity of personality pathology and a-specificity of developmental PD antecedents, and (4) How to comprehensively address processes of PD development, including the transactional nature of these processes as well as their continuous versus discontinuous growth features?

Before zooming in on each of these important questions, we first draw the attention to basic methodological issues that are critical in any kind of longitudinal research but fall beyond the scope of the present paper. A first issue has already received a lot of scholarly attention and pertains to the need to test measurement invariance of one’s constructs over time (Liu et al., 2017; Widaman et al., 2010). Second, when designing a study on PD development,
it is important to thoroughly reflect on the way in which one conceptualizes PDs (i.e.,
categorical or dimensional), particularly because stability versus change of personality
pathology across time appears to be influenced by the operationalization of the PD construct
itself (Clark, 2009). In general, categorical conceptualizations of PDs demonstrate higher
levels of instability across both short- and longer-term intervals (Skodol et al., 2013;
Zimmerman, 2012). The developmental course of underlying trait dimensions of personality
pathology, instead, is characterized by higher levels of stability, paralleling findings from
normal personality traits (Rodriguez-Seijas et al., 2020; Wright et al., 2015). One reason for
these contrasting findings may be the fact that categorical operationalizations of PD often rely
on very specific phenotypic symptoms that are more prone to fluctuations over time (Skodol
et al., 2011). In addition, categorical models may result in higher instability because certain
PD indicators are not yet present at a younger age (e.g., self-harm; Meza et al., 2021), are
expressed differently, or are overshadowed by age-related cognitive decline at an older age
(Van den Broeck et al., 2013). Finally, it has recently been highlighted that researchers
interested in longitudinal research should pay more close attention to connecting their
methods (e.g., timing, frequency, and number of assessment points) to theory. Hopwood et al.
(2021) provide several helpful guidelines in this regard, that may be consulted before
longitudinal designs are implemented.

In what follows, we review several recent methodological innovations that are directly
relevant to researchers interested in conducting longitudinal research on PDs. The innovations
pertain to (1) the measurement of PD constructs, (2) the typicality of personality pathology,
and (3) the processes underlying PD development. For each of those broad categories, we
review issues central to studying PD development (e.g., comorbidity) and discuss how recent
methodological innovations allow shedding light on those important issues. By doing so, we
hope to inspire researchers who are interested in PD development to explicitly look for ways
in which novel methodological strategies can be applied to provide better answers to fundamental issues (Marsh & Hau, 2007).

**Key considerations for contemporary longitudinal research within the PD field**

**(1) Measurement of Personality Pathology**

**Addressing the richness of multi-informant PD ratings in longitudinal data**

Personality pathology is traditionally known for its egosyntonic experience. This has led to the belief that personality vulnerabilities are more accurately rated by significant informants rather than by the individuals themselves (Lincoln et al., 2010; Randjbar et al., 2011), because people with personality pathology tend to attribute the difficulties they encounter externally while underestimating their trait vulnerability. Despite this widely held belief, however, recent meta-analytic research has shown that self-other agreement (SOA) of both categorical as well as dimensional operationalizations of PDs is similar to SOA observed for general traits (Oltmanns & Oltmanns, 2021). This is an important finding because it implies that self-ratings are at least as relevant for understanding PDs as they are for general traits, particularly regarding internalizing PDs (i.e., PDs defined by high Neuroticism) (Carlson et al., 2013). Moreover, although one of the most fundamental features of personality pathology is its relative consistency across different contexts (APA, 2000), active manifestations of the underlying vulnerability may depend upon situations or environmental factors (cf. trait activation theory; Tett et al., 2021). For example, Scott et al. (2017) demonstrated that amplifying levels of borderline personality symptoms are particularly observed after perceived rejection in interpersonal situations. Thus, it is reasonable that in the absence of perceived rejection (as a trait activator) those same individuals show different trait expressions (e.g., at work, home, or among friends). Hence, personality judgements from multiple contexts may result in situation-specific maladaptive personality ratings. Likewise, the evaluation of personality pathology may differ across situations because of different social
expectations or dynamics in the contexts themselves (Alaybek et al., 2018). By providing multiple perspectives, including a self-report perspective, on a target individual—with those different perspectives typically mapping upon different contexts—multi-informant data may thus provide a wealth of information.

Most importantly, these multi-informant data allow us to separate shared and unique informant perspectives on PD development. Shared perspectives on a target’s PDs capture core features of their personality on which everyone agrees (i.e., self-other and other-other agreement). Unique perspectives on a target’s PDs—and their behavioral manifestations—, in contrast, are asymmetric across informants due to role differences (e.g., being a parent or a teacher), informational differences (e.g., some behaviors or feelings are only known by the target), and motivational differences (e.g., impression formation might be present for some informant groups and not for others) (Vergauwe et al., in press). Important in this discussion is that multi-informant data are typically characterized by a mixture of shared and unique information on the target. Yet, the typical treatment of multi-informant data fails to do justice to this richness in the data. For example, focusing on longitudinal growth for each informant group separately is a practice that only informs us about the extent to which growth patterns across informant groups are similar or not. What such approach fails to address, however, is whether such similarity is driven by growth in the information that is shared across raters, by similar growth in the pieces of unique information, or by a combination of both.

A recently developed model that is of direct relevance to modeling multi-informant data on personality (pathology) is the Trait-Reputation-Identity (TRI) model. The TRI model has been specifically developed to capitalize on the richness of multi-informant data by teasing apart common and unique information in multisource personality ratings (McAbee & Connelly, 2016). Using bifactor modeling, the TRI model separates the information captured by multi-informant data into (i) information (or variation) that is shared by all informants (i.e.,
the Trait factor, represented by the general factor in the bifactor model indexed by ratings from all rater sources), (ii) unique self-perceptions (i.e., the Identity factor, represented by the specific factor indexed by the self-ratings), and (iii) impressions conveyed to others that are distinct from self-perceptions (i.e., the Reputation factor, represented by the specific factor(s) indexed by the other-ratings). In case of longitudinal data, the TRI bifactor model can be extended to examine change in the Trait, Identity and Reputation factors, which can be done by testing a latent change or latent growth curve model on the general and specific factors of the bifactor model (see Hatano et al., 2018).

Doing so can reveal potential differential growth for the shared perspectives on one’s personality pathology (i.e., changes in the underlying Trait factor), versus the unique self- and observer perceptions. For example, personality dysfunction in terms of Identity may for instance grow over time, while Reputation scores generated from observer reports may decrease for individuals who attempt to hide their maladaptive functioning to the exterior world. Or in case the different raters coincide with different contexts, such analysis may show whether changes are tied to a specific context (i.e., are observed for one or more of the specific factors) or whether they transcend the specific contexts (i.e., are observed for the general factor). Because of this reason, when deciding upon a multiple informant design, one should reflect upon age-sensitive relevant contexts for the target individual, with external informants preferably being connected to one specific context. For children and adolescents, these contexts have previously been defined as home, school, and peers (De Fruyt & De Clercq, 2014), while for adults, significant contexts for personality manifestations include the home- and work context, and being among friends (e.g., McAbee & Connelly, 2016).

Integrating broad versus narrow traits: Modeling PD Development at different bandwidths
Developmental trajectories of narrow traits, even when structured within the same domain, may differ substantially (Chopik & Grimm, 2019; De Clercq et al., 2017; Schwaba et al., 2022). Such differential growth at the narrow trait level happens because the development of maladaptive traits partly depends upon the etiological role of neurobiological and socialization processes that are involved in those traits (e.g., Depue & Lenzenweger, 2001; 2006). In this regard, especially adolescence has been identified as a crucial phase of actual onset of clinically significant personality pathology (Sharp et al., 2018), because of rapid neurological and hormonal changes at the biological level (Baird et al., 2005) that impact upon emotion regulation strategies, impulse, and cognitive control. At the same time, the fast growth towards autonomy and a reorientation from parents to peers is associated with an increased sense of self and consolidation of identity processes that are often related to instability in thoughts, behavior, and emotions (Koepke & Denissen, 2012). Similarly, at older age, the development of some maladaptive traits may interfere more with normative cognitive decline or physical health compared to other maladaptive traits. Moreover, the transition from work to retirement and the associated loss of certain functional roles (Hill et al., 2021; Schwaba & Bleidorn, 2019), or the death of the spouse (van Alphen et al., 2015) may also impact the development of specific maladaptive traits or aggravate specific personality pathology features while other features remain stable or even decline. These notions of differential development of specific trait facets underscore the importance of assessing personality pathology at the fine-grained level, as contrasting facet-level trajectories may average each other out at the broader trait level (Schwaba et al., 2022).

Rather than making the choice to model development in either broad traits or narrow facets, an elegant approach is to model the common (trait) and unique (facet) information simultaneously. This can be done by combining bifactor modeling and latent growth modeling (or any other model that allows modeling change/development over time). In the
bifactor model, each item simultaneously loads on a general factor and one or more specific factors (Reise, 2012). Because the general factor in the bifactor model is indexed by all items, it captures the variation that is shared by all items and can therefore be conceived of as the general trait. The specific factors, in turn, are indexed by specific subsets of items, and because in the bifactor model the variance captured by the general factor is independent from the variance captured by the specific factors, those specific factors represent unique, facet-level information exclusive to the general factor. In other words, the specific factors represent meaningful covariation that remains after extracting the general factor.

Although it is important to realize that interpreting specific factors (being facet-level information that is orthogonal to the general factor) is challenging, and although it is important to “avoid tenuous interpretations of the latent dimensions” (Bonifay et al., 2017, p. 185), we believe that there is promise in this approach because testing a (second-order) growth model on the bifactor factors offers a nuanced view on PD development, showing researchers how common and unique PD features (differentially) develop. In other words, such analysis might reveal whether development at the level of the features common to all facets is similar to developmental trajectories at the level of the unique facet-level features. If differential developmental patterns are found, this can shed light on how contrasting facet-level trajectories may average each other out at the broader trait level (Schwaba et al., 2022)^2.

(2) Modeling typical features of personality pathology

**Comorbidity among PDs**

The issue of comorbidity has received scant attention in scientific research (Clark, 2009). Overall, high rates of comorbidity have been found among different PDs, indicating that PDs overlap extensively. In psychiatric samples, more than half of the patients show two

^2 Note that bifactor models tend to overfit the data, implying that they not only capture systematic (meaningful) variance but also noise (Bonifay & Cai, 2017; Morgan et al., 2015). Hence, when comparing the bifactor model to competing models, evaluation of the models should always be done on both statistical and substantive grounds.
or more coexisting PDs (Widiger et al., 1991). Importantly, such patterns of comorbidity are not limited to adulthood and apply to younger age groups as well (Mann et al., 2020).

Two methodological perspectives on modeling comorbidity exist, with each perspective being linked to a different theoretical understanding of what drives comorbidity. The first perspective is known as the common cause model, which assumes that comorbidity results from a group of transdiagnostic liabilities affecting multiple disorders (Goh, 2021; Smith et al., 2020). The second perspective is the network perspective, according to which psychological disorders and comorbidity result from direct interactions between symptoms, with symptoms being associated to different disorders being called bridges (Goh & Martel, 2021; Groen et al., 2020; Jones et al., 2021).

In previous research, comorbidity has been mostly studied using cross-sectional designs. This is problematic, because concurrent associations may reflect artifactual overlap (e.g., due to shared criteria, such as impulsive substance use, or “state” common factors). Longitudinal associations, in turn, more likely reflect shared underlying pathological structures or processes (Clark, 2009). Moreover, from the perspective of the common cause model, the dominance of cross-sectional research implies that “little is known about the developmental dynamics of the hierarchical structure of psychopathology during critical periods such as childhood and adolescence” (Mann et al., 2020; p. 771). For the network perspective, the cross-sectional approach “has generally precluded a direct examination of (bi)directional relations among symptoms of psychological disorders” (Goh & Martel, 2021; p. 195). Because of these reasons, longitudinal studies are needed to elucidate the very nature of comorbidity (Klein & Schwartz, 2002).

From the perspective of the common cause model, comorbidity can be studied by looking at common growth across dark traits. Such common growth can be studied using the factor-of-curves (FOCUS) model, which is a combination of the latent growth model (LGM)
and the hierarchical factor model. In the FOCUS model, development in each trait dimension is modeled using LGM, while shared variance in the growth factors—or common growth—is captured using second-order factors (Wickrama et al., 2016). Using such an approach, Atherton et al. (2020b) demonstrated that attention-deficit/hyperactivity disorder [ADHD], oppositional defiant disorder [ODD], and conduct disorder [CD] share a common externalizing trajectory during adolescence. Similarly, De Clercq et al. (2017) revealed that childhood maladaptive traits as measured by the Dimensional Personality Symptom Itempool (DIPSI) show shared common growth across childhood, adolescence, and emerging adulthood, with this common growth factor capturing more than half of the variance of each trait.

The idea underlying the network perspective on comorbidity is that PDs and comorbidity among PDs result from direct interactions between symptoms. In other words, symptoms are assumed to be active components of PDs and demonstrate direct, dynamic, and potentially reciprocal relationships both with one another and with various risk markers (Borsboom & Cramer, 2013). Because of this reason, network models do not structure symptoms into PDs (like the common cause model does), but directly model the associations between the different symptoms. Network models hence provide a complementing perspective and focus on variance unique for pairs of variables, which gives insight in the interplay between psychological components (Epskamp et al., 2017). Specifically for modeling comorbidity, attention is paid to bridges or bridge symptoms, which are symptoms that connect different disorders. Those bridge symptoms have a central place in the network approach because they represent the common ground for those disorders.3 Using a dynamic

3 Network models are increasingly being applied in psychological science in general and research on PDs in particular. Despite their conceptual elegance, several aspects of psychometric networks have been subject to criticism. Neal and colleagues (2022) summarize four broad categories of critiques, pertaining to (1) model selection, (2) study design, (3) estimation reliability, and (4) interpretation of measures. Whereas several of these criticisms are less or even irrelevant for this particular application of psychometric networks (i.e.,
network approach, Köhne and Isvoranu (2021), for instance, studied comorbidity between PDs and mental disorders, showing direct associations between the symptoms of depression and borderline PD. Recently, the dynamic network approach has also been extended to person-specific networks (Epskamp, 2020). Those person-specific networks require intensive longitudinal data on a single individual (using designs such as daily diary or experience sampling studies) and may be particularly useful for defining targeted intervention efforts and evaluation of treatment effects (Goh & Martel, 2021).

**A-specificity but significant predictive validity of early personality vulnerabilities**

Increasing evidence shows that developmental precipitants of PDs are significant and thus valuable to include in studies on the etiology of personality pathology (Sharp & De Clercq, 2020). At the same time, however, the predictive validity of childhood PD traits appears to be a-specific (cf. principles of equi- and multifinality; Cicchetti & Rogosch, 1996), although preliminary evidence suggests increasing specificity from adolescence onwards (Sharp & De Clercq, 2020).

From this perspective, a viable way to study the predictive validity of childhood personality vulnerabilities for later PD outcome may be done using (longitudinal extensions of) the bifactor model. In the bifactor model, childhood personality indicators simultaneously load onto a general factor and specific factors, allowing for a straightforward test of how specific subdomains predict external variables, above and beyond the general factor (Chen et al., 2006). That is, in the context of the predictive validity of early maladaptive traits, the bifactor model can test the predictive validity of early general versus specific personality vulnerabilities for PD development. To the best of our knowledge, this has not been applied in the PD literature yet, although Olatunji et al. (2015) showed that the –cross-sectional rather than modeling of comorbidity in longitudinal data through bridge symptoms, researchers need to consider both the pros and cons before engaging with psychometric networks.
than longitudinal–relationship between disgust sensitivity and symptoms of obsessive-compulsive disorder (OCD) may be domain specific, with pathogen disgust having a consistent association with OCD above and beyond the general disgust factor. Moreover, longitudinal extensions of the bifactor model allow testing whether changes in the general liability factor and in the specific liability subdomains relate to changes in psychosocial problems. For example, combining bifactor modeling with latent change modeling, Hatano et al. (2018) showed that levels and changes in identity consolidation negatively related to levels and changes in psychosocial problems, while combining the bifactor model with a cross-lagged model revealed a bidirectional relationship between identity consolidation and psychosocial problems.

Although the bifactor model is “an excellent vehicle for studying the predictive validity of hierarchical constructs” (Zhang et al., 2021, p. 534), an important issue is that the model can be nonidentified in the context of prediction. A detailed treatment of the conditions under which nonidentification appears is beyond the scope of the current paper, but interested readers are referred to Zhang and colleagues (2021). More importantly, however, there are ways to deal with the nonidentification issue. A promising approach is resorting to augmented bifactor modes, which are restricted variants of the general bifactor model. The paper by Zhang et al. (2021) provides an excellent overview of these augmentation strategies.

(3) Processes of PD Development

Continuous versus discontinuous growth in personality pathology features

PDs typically develop in nonlinear and sometimes even discontinuous ways (Rutter et al., 2006; Sharp, 2020). As we mentioned earlier, growth rates of PDs tend to differ for different developmental phases due to neurological and hormonal changes, but also due to changes in people’s environment (e.g., going to school, retiring, …) (Bleidorn et al., 2018; Depue & Lenzenweger, 2001, 2006). Moreover, literature on therapeutic interventions
suggests that the patterns of change following psychotherapy are often discontinuous (Hayes et al., 2007). Such nonlinearities and discontinuities have important methodological implications for researchers, both in terms of measurement and modeling.

In terms of measurement, testing nonlinearity can only be done when one has sufficient assessment points (Hopwood et al., 2021). For example, whereas three assessment points are required to test linear growth, quadratic growth requires at least four and cubic growth requires five or more assessment points. Hence, it is important to properly align one’s expectations in terms of the growth dynamics with the frequency of one’s measurements. In case there is little theoretical or empirical ground for strong expectations about the form of growth, measuring more frequently is preferred because this allows for an empirical test of the more complex growth patterns (Hopwood et al., 2021).

In terms of modeling, nonlinearities can be tested by expanding the linear latent growth curve model (LGM; Collins, 2006) using higher-order (e.g., quadratic, cubic, …) terms, or by shifting to the latent basis model, in which the basis coefficients are freely estimated rather than predefined (Meredith & Tisak, 1990). However, whereas polynomials and particularly the latent basis model allow to flexibly capture nonlinear growth, they cannot model discontinuities in the growth trajectory.

To account for such discontinuities, one can turn to discontinuous growth modeling (DGM). Compared to the LGM, the DGM models trajectories before and after events (Bliese et al., 2020). Because of this feature, DGM can be used to test hypotheses about change associated with a single or multiple events. Of particular relevance is that those events can be planned, such as in case of psychotherapy, or unplanned, such as in case of the loss of a relative. In Abramov et al. (2020), for instance, DGM is used to test how borderline PD influences growth trajectories of trust in response to trust violation and repair events. Interestingly, the basic DGM can further be extended by for example modeling nonlinear
change associated with events. Finally, one can also predict all random components (i.e., intercept, trajectory before event, shift, and trajectory after the event) using level-2 predictors, which allows for the prediction of (discontinuous) change (Bliese et al., 2020). In terms of measurement, modeling discontinuities requires more frequent assessments than modeling a continuous process. The reason is that one models multiple trajectories (i.e., before and after the event) and one needs sufficient assessment points to model each of those trajectories.

**The transactional process of PD development over time**

Personality pathology develops in constant interaction with the environment (e.g., Franssens et al., 2021; Fruzzetti et al., 2005). In other words, PD traits are activated in a particular context, and those traits in turn evoke reactions from their environment. This basic developmental principle of mutual reciprocal effects between the individual and its environment applies across ages and reflects a complex transactional process of bidirectional influences. Of key importance is that this process occurs at the within-person level, while well-known models for examining longitudinal cause-effect associations, such as the Cross-Lagged Panel Model (CLPM), fail to disentangle these between-versus within-person effects (Hamaker et al., 2015). Consequently, the CLPM implicitly assumes that everyone varies over time around the same average, and that there are no trait-like differences that endure. This assumption is obviously highly problematic in the context of PDs.

The random-intercept CLPM (RI-CLPM) addresses this issue. In this model, random intercepts are used to disaggregate within- from between-person variability (i.e., by having a random intercept per individual, the assumption that everyone varies over time around the same average is no longer needed), after which the model can be tested at the appropriate within-person level. That is, in the RI-CLPM the autoregressive effects (of a construct on

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4 Note that the RI-CLPM assumes that there is a single source of between-person differences and that this source of between-person differences can be properly accounted for by the random intercepts (Grimm et al., 2021).
itself measured at a later time) and cross-lagged effects (of a construct on another measured at a later time) are tested on residuals (being the deviation of the observed score from the random intercept) (Grimm et al., 2021). Hence, compared to the CLPM, in which the autoregressive effects represent rank-order stability from one moment to the next, they represent a within-person carry-over effect in the RI-CLPM. Similarly, the cross-effects pertain to associations between deviations from the expected scores. In terms of the number of waves, the RI-CLPM requires three waves, whereas the CLPM can be tested with two waves only. Recently, the RI-CLPM has been successfully used in studies on PD development (Franssens et al., 2021) with the goal of unraveling more detailed insights in transactional processes both at the between- and within person level of borderline personality development in youth.

A second model that allows disaggregating between-person and reciprocal, prospective within-person components is the LGM-SR model (a latent growth curve model with structured residuals; Curran et al., 2014). Like the RI-CLPM, disaggregation happens by focusing on a part of the model that is often of little substantive interest to researchers: the residuals. Unlike the RI-CLPM, however, the LGM-SR builds on the latent growth model, implying that the residuals in the LGM-SR model represent deviations of the observed repeated measures from the underlying trajectory and therefore capture information about within-person processes of stability and change. Instead of allowing the time-specific residuals to covary in an unstructured way, the LGM-SR model specifies a particular structure in which later residuals are regressed on prior residuals. In the multivariate LGM-SR, this implies that the residual of variable Y at time t is predicted by the residual of variable Y at time t-1 (i.e., the autoregressive effect) and the residual of variable X at time t-1 (i.e., the

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5 With two waves of data the CLPM is just-identified (i.e., there are no degrees of freedom left), implying that the fit of the model to the data is perfect and can therefore not be tested. This is obviously sub-optimal.

6 Being an extension of the LGM, the LGM-SR is more flexible than the RI-CLPM because different LGMs can be specified to capture different types of between-person differences (Grimm et al., 2021).
cross-effect). The interpretation of those lagged effects is, however, the same as their interpretation in the RI-CLPM (see also Grimm et al., 2021). Recently, LGM-SR models have been used in Hopwood et al. (2022), in which developmental trajectories of borderline PD were investigated at the between- and within-person level.

Finally, cause-effect associations can also be tested using latent change score (LCS) modeling (McArdle, 2001). As its name suggests, LCS models changes from one occasion to the next. In the traditional LCS model these (latent) changes are modeled as a function of (a) a constant change parameter, capturing individual differences in one’s general increasing or decreasing trend across time, and (b) a proportional change parameter, capturing the extent to which change from t to t+1 is affected by the level of the variable at time t (see for instance Wright et al., 2015). Of interest to modeling cause-effect associations is the bi- or multivariate extension of the LCS model in which (latent) changes in variable Y between t and t+1 are modeled as a function of (a) a constant change parameter, (b) the previous state of Y (i.e., proportional change), and (c) the previous state of X. These latter paths are referred to as coupling parameters, with those coupling parameters capturing the extent to which one variable (X) triggers change in another variable (Y) (McArdle & Grimm, 2010). Yet another extension of the model, referred to as the LCS change-on-change model (LCS-CC), pertains to the inclusion of change-on-change relationships. Thus, in addition to (a) a constant change parameter, (b) a proportional change parameter, and (c) a coupling parameter, in this model (d) change from time t to time t+1 in one variable is also predicted from change from time t-1 to time t in the other variable. Hence, this extension allows testing whether change in one variable predicts change in another variable (Grimm et al., 2012). Both the traditional LCS model and the LCS-CC extension are tested in Orth et al. (2021), in which the relationship between low self-esteem and depression is investigated using different longitudinal models.

**Summary and conclusion**
Motivated by the belief that the emergence of novel elegant statistical models can substantially advance our understanding of PD change and development, the aim of the present paper was to draw the attention of scholars interested in studying PD development to a number of recent methodological innovations pertaining to (1) the measurement of PD constructs, (2) the typicality of personality pathology, and (3) the processes underlying PD development. Although our overview is by no means meant to be exhaustive, we hope that our paper inspires researchers interested in PD development to continuously look for novel methodological innovations to provide better answers to substantively important issues, thereby strengthening research and theories on PD development through the stimulation of both inductive and deductive research.

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