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A developmental approach to youth maladaptive personality traits: Variable- versus person-centered change in the transition from childhood to adolescence

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Abstract

Increasing evidence shows that personality pathology starts to develop from (late) childhood onwards. The current study extends previous research by examining maladaptive personality change using both a variable-centered approach (i.e., mean-level changes) and a person-centered approach (i.e., latent profile transitions). Data were used from a 3-wave longitudinal study on Dutch youth (at T1: N = 492, mean age = 10.1). Maladaptive personality traits (i.e., Emotional Instability, Disagreeableness, Introversion, and Compulsivity) were assessed yearly using the Dimensional Personality Symptom Item Pool (DIPSI). A Factor of Curves model indicated presence of a higher-order developmental factor, reflecting low initial levels and small decreases over time, which explained change in all DIPSI traits. Latent profile analyses revealed three quantitatively different maladaptive personality trait profiles. Latent Transition Analysis demonstrated substantial stability in profiles over time. Small groups showed a transition toward another (often more adaptive) profile. Although a person-centered approach may have some merit when aiming to detect high-risk subgroups, the current results suggest that a variable-centered approach—and a Factor of Curves model capturing shared underlying developmental processes in particular—is favorable over a person-centered approach.

Keywords

Dimensional Personality Symptom Item Pool, personality pathology, personality profiles, personality development, youth

Personality pathology does not appear out of nowhere in early adulthood (Cicchetti & Crick, 2009). Instead, there is growing consensus that a developmental perspective on personality pathology is critical for both understanding and targeting personality pathology in youth (Tackett et al., 2009; Widiger et al., 2009; De Clercq & De Fruyt, 2007). Specifically, to elucidate the pathways to personality pathology, it is important to examine maladaptive personality traits in youth, and in a longitudinal manner. Research that combines the two is scarce. The few studies conducted indicate that maladaptive personality trait features in childhood and adolescence may be important predictors for personality pathology outcomes in adulthood (Kotov et al., 2017; De Clercq & De Fruyt, 2007; De Fruyt & De Clercq, 2014).

To investigate the development of personality pathology, the traditional categorical approach in which normative personality is considered qualitatively distinct from personality disorders is inadequate (De Fruyt & De Clercq, 2014). Instead, the gradual development of personality pathology can be captured best using a dimensional conceptualization of personality pathology (Sharp et al., 2012, 2018). Such a conceptualization is well served by measures that have been developed to capture maladaptive personality traits, rather than clinical disorders. Moreover, dimensional measures have been suggested to be particularly well-suited to capture the higher (maladaptive) end of personality traits (Lynam, 2013; Nestadt et al., 2008), as well as the richness and complexity of maladaptive personality that may not be sufficiently characterized by measures originally designed for the description of adaptive personality traits (Tromp & Koot, 2010; Widiger & Trull, 1997; Wright et al., 2017). The Dimensional Personality

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Symptom Item Pool (DIPSI) has been specifically designed to assess personality pathology in children and adolescents (De Clercq et al., 2006). Using this questionnaire, Decuyper et al. (2011) showed that pathological personality traits captured additional variance in psychopathic characteristics that was not explained by a more general personality measure in youth. Similar results were found in a sample of clinical adolescents: Tromp and Koot (2010) demonstrated that pathological dimensions of personality afforded a supplementary contribution to the understanding of dysfunctional characteristics of and differentiation between adolescent personality disorders, above and beyond what was explained by traditional Big Five traits. The current study extends previous research on pathological personality traits in preadolescence by examining change in DIPSI traits using both a variable-centered approach (i.e., mean-level changes) and a person-centered approach (i.e., latent profile transitions).

Stability and change in youth (maladaptive) personality traits

So far, few studies examined stability and change in maladaptive personality traits. Although some support has been found that maladaptive personality traits consist of more than merely the maladaptive end of the adaptive traits (Decuyper et al., 2011; Tromp & Koot, 2010; Widiger & Trull, 1997; Wright et al., 2017), papers adopting an Item Response Theory approach indicated that normative personality and maladaptive personality align quite well, with pathological traits covering the extremes and normative personality covering the middle part of the same spectrum. Thus, maladaptive personality traits typically lay on a continuum with normative personality traits, in adults (Suzuki et al., 2015) as well as in youth aged 11–17 (van Dijk et al., 2021). This might imply that stability and change in maladaptive personality traits may look similar to stability and change in normative personality.

In normative personality science, there is much consensus that people's personalities change across the lifespan. In particular, when looking at mean-level changes in personality from adolescence until (late) adulthood, small changes have generally been found toward more "adaptive" personality trait levels (e.g., lower levels of neuroticism and higher levels of conscientiousness; e.g., Roberts & Wood, 2006). These changes toward more adaptive or desirable trait levels have been referred to as the "maturity principle" (Roberts & Wood, 2006; Damian et al., 2019). When looking at personality development from childhood to adolescence, a more diffuse picture appears. While some research found evidence for maturation in the transition from childhood to adolescence (Brandes et al., 2021), most studies have indicated that youth personality development does not fit the maturity principle very well (Denissen et al., 2013; Göllner et al., 2017; Soto & Tackett, 2015; van den Akker et al., 2014). Instead, findings from these studies support the "disruption hypothesis" (Soto & Tackett, 2015), proposing that the biological, social, and psychological transitions from childhood to adolescence are accompanied by temporary dips in some aspects of personality maturity. For example, Göllner et al. (2017) found that youth reported only increases in extraversion in the transition from childhood to adolescence (i.e., age 10–13). Neuroticism remained stable, while agreeableness, openness, and conscientiousness all decreased.

This lack of clear normative trends toward maturation in normative personality traits (e.g., Big Five) in the transition from childhood to adolescence raises questions about the development of maladaptive personality traits in youth. Based on the studies suggesting that youth maladaptive personality traits and normative personality traits lay on a continuum (e.g., van Dijk et al., 2021), change in maladaptive personality traits could be expected to reflect those found in normative traits. As of yet, only a few studies have provided empirical support for mean-level change in maladaptive personality traits in childhood and adolescence. Notably, these findings demonstrated that mean levels of most maladaptive traits (i.e., Emotional Instability, Disagreeableness, and Compulsivity) steadily declined over time (De Clercq et al., 2009; Johnson et al., 2000). Only levels of Introversion remained stable across (De Clercq et al., 2009). In addition, and also deviating from what has typically been found regarding normative personality development, smaller declines were found in youth with higher initial levels of maladaptive personality traits. This may indicate that these children prone to maladaptive personality continue to have elevated maladaptive personality trait levels later in life (De Clercq et al., 2009; Johnson et al., 2000).

These findings suggest that youth maladaptive personality trait changes do not align with the patterns found for normative youth personality development (i.e., supporting the disruption hypothesis). Moreover, De Clercq and colleagues argued that in the context of maladaptive personality traits, the maturity principle may apply for younger children than what has been suggested based on research concerning normative personality development (De Clercq et al., 2009). At the same time, this does not seem to generalize across all conceptualizations of maladaptive personality traits. While mean levels of aggression, dominance, and impulsivity decreased over time (i.e., suggesting maturation; De Clercq et al., 2017), mean levels of callous-unemotional traits have been found to be stable across childhood (Barry et al., 2008) and adolescence (Frick et al., 2014), as were mean levels of narcissism (Barry et al., 2008; De Clercq et al., 2017), impulsive conduct problems (Barry et al., 2008), resistance, and lack of empathy (De Clercq et al., 2017). In sum, research indicates that small mean-level changes in maladaptive personality traits are possible during childhood and adolescence. The nature of these changes, however, varied across traits and age, with some studies providing support for change toward maturation (i.e., a more desirable trait level), while others found stability or temporary dips (particularly in early and middle adolescence).

So far, studies examining mean-level changes in (maladaptive) personality traits have adopted a range of statistical models, ranging from repeated measure analyses (Roberts et al., 2001), multilevel modeling (e.g., De Clercq et al., 2009) to latent growth curve models (e.g., Brandes et al., 2021; Johnson et al., 2000; Klimstra et al., 2009). Typically, these models are run separately for each of the traits under study and therefore not accounting for potential correlations between (e.g., De Clercq et al., 2009) or shared development of (De Clercq et al., 2017) the different traits under study. A model that explicitly accounts for shared development is the Factor of Curves model (Isiordia et al., 2017; McArdle, 1988). The Factor of Curves model uses the first-order growth factors of the individual traits as indicators of a second-order growth factor, reflecting one shared developmental process (Wickrama et al., 2021). Additionally, in contrast to composite measures which generally assume that different subdomains make equal contributions, in a Factor of Curves model, first-order growth factors are allowed to differentially contribute to the second-order growth factor, providing maximal flexibility in terms of modeling both unique and shared growth (Wickrama et al., 2021). Notably, this approach was previously used by an earlier study by De Clercq et al. (2017) on maladaptive personality (i.e., dark traits) in children, demonstrating the potential of utilizing a Factor of Curves model for modeling longitudinal development of personality traits.

Change in maladaptive personality trait profiles

With the rising popularity of dimensional conceptualizations of pathological personality, research has increasingly used variable-centered approaches to study maladaptive personality traits (e.g., Aelterman et al., 2011; De Clercq et al., 2008; De Pauw et al., 2009). However, the dynamic organization of multiple personality traits within an individual has been argued to be fundamental to understand personality (Asendorpf et al., 2001; Meeus et al., 2011; Allport, 1937). A person-centered approach to personality, such as (latent) profile analysis, has been suggested to tap into this individual configuration of personality better than a variable-centered approach usually does (Meeus et al., 2011; Asendorpf et al., 2001).

Importantly, the robustness and meaningfulness of person-centered approaches have been questioned (e.g., Herzberg & Roth, 2006). The replicability of personality profiles is argued to depend on sample characteristics (age, gender, and culture), measures, and informants (De Fruyt et al., 2002; Donnellan & Robins, 2010; Rammstedt et al., 2004). Additionally, personality profiles are unlikely to be exhaustive; not every individual can be assigned to a specific personality profile (Freudenstein et al., 2019). While these issues should be acknowledged and taken into account in the interpretation of person-centered research findings, they do not necessarily limit the usefulness of personality profiles for applied purposes (De Fruyt et al., 2002): The main aim of person-centered research is to demonstrate that subgroups of individuals may have different personality profiles which have some external validity, not to demonstrate that the profiles are present in each sample and account for a considerable part of the individual profiles. This may be particularly the case in the context of maladaptive personality psychology and the clinical setting more broadly where a key aim is to understand the person—and his or her personality—as a whole. Also, a person-centered approach can identify relative homogeneous subgroups in a heterogeneous sample (Ferguson & Hull, 2018; Fisher & Robie, 2019), which may be useful when aiming to distinguish potentially small groups of individuals with maladaptive, potentially clinically problematic profiles from larger, normative groups characterized by more adaptive profiles. As such, the idea of understanding personality in terms of profiles rather than isolated traits has remained a compelling one that may have distinctive clinical relevance.

So far, empirical research has typically focused on normative personality trait profiles, such as conceptualized with Big Five and HEXACO. Empirical research has yielded some support for three to five qualitatively different personality profiles across childhood, adolescence, and adulthood (Asendorpf et al., 2001; Daljeet et al., 2017; Fruyt et al., 2002; Klimstra et al., 2009; Meeus et al., 2011; Herzberg & Roth, 2006). With regard to clinical personality disorder and maladaptive personality trait profiles, research is limited to studies focusing on (older) adolescent and adult samples. For example, in a sample of clinically referred middle to late adolescents, ten profiles were identified that resembled the categorical DSM-IV personality disorder taxonomy (Durrett & Westen, 2005). Most studies, however, examined typologies in the context of one specific personality disorder or domain. Findings from these studies are mixed. Ramos et al. (2014) identified an internalizing and an externalizing borderline personality disorder profile among clinically referred adolescents, whereas Bradley et al. (2005) found high-functioning internalizing and histrionic borderline personality disorder profiles, in addition to the depressive internalizing and angry externalizing types. Four profiles were also found in another study on clinically referred adolescents (aged 12–18; Slavin-Stewart et al., 2018), but in this study, the profiles were not qualitatively different but instead reflected the number of borderline symptoms. Also typological studies on psychopathy and schizotypy profiles have found indications of qualitatively different profiles (Erlenmeyer-Kimling et al., 1989; Veen et al., 2011) as well as quantitatively different profiles reflecting severity (Murrie et al., 2007; Tyrka et al., 1995). Only one study so far examined adolescent maladaptive personality trait profiles in a normative population sample, using a dimensional measure (i.e., the Personality Inventory for DSM-5 (PID-5): See et al., 2021). Findings revealed a hierarchical tree typology, suggesting three classes at the root of the tree representing high, medium, and low maladaptive personality trait levels (i.e., quantitative differences), and classes lower in the hierarchy suggesting subclinical variants of patterns that are often found in clinical samples (i.e., qualitative differences). For the transition from childhood to adolescence, research has only recently started to focus on maladaptive personality traits. Whether maladaptive personality traits profiles (qualitative or quantitative) can be found in the transition from childhood to adolescence is yet to be investigated.

If maladaptive personality traits profiles can be identified in the transition from childhood to adolescence, the next question concerns stability and change of such profiles. That is, do individuals remain in the same personality profile over time? To the best of our knowledge, no longitudinal studies on maladaptive trait profiles have been conducted, neither in child and early adolescent samples nor in older samples. However, knowledge on change in normative personality profiles in children and adolescents may assist in a first understanding of the development of maladaptive personality trait profiles. Studies investigating normative personality profiles longitudinally have yielded mixed results. In a timespan from six months to two years, stability of personality profiles ranged from 38% to 62.7% (Akse et al., 2007; Asendorpf et al., 2001; Van Aken & Dubas, 2004). A 5-year longitudinal study on change in early adolescent's normative personality profiles revealed somewhat higher stability: 73.5% of the adolescents remained stable, thus showed no transition to a different personality profile (Meeus et al., 2011). In case of transition from one profile to another, the change was generally characterized by a transition to a more favorable, adaptive personality type, aligning with findings from variable-centered research providing indications for maturation in maladaptive personality in late childhood (De Clercq et al., 2009) as well as in normative personality from middle adolescence onward (Roberts & Wood, 2006). These findings from normative personality profiles may imply that maladaptive personality profile transitions are possible, but empirical research is needed to test this hypothesis.

The current study

Building on the increasing acknowledgment of pathological personality development from childhood onward, the current study aims to replicate and extend existing empirical work on maladaptive personality development in the transition from childhood to adolescence. We distinguish a variable-centered approach, in which we investigate mean-level development in maladaptive personality traits (De Clercq et al., 2009), from a person-centered approach, in which we investigate whether subgroups can be identified that are characterized by different compositions of maladaptive personality traits, and whether membership of subgroups changes over time. Testing both a variable-centered model and a person-centered model in the context of a single study provides insight into the potential merit and contribution of each of the models. Specifically, the following research aims and hypotheses can be distinguished:

Variable-centered approach. (1) Using a Parallel Process model, mean-level changes in Disagreeableness, Emotional Instability, Introversion, and Compulsivity across two years are examined. Based on earlier research on maladaptive personality development in preadolescence (De Clercq et al., 2009), small decreases in youths' Disagreeableness, Emotional Instability, and Compulsivity but no significant change in Introversion are expected. (2) Using a Factor of Curves model (FCM), it is examined whether change in Disagreeableness, Emotional Instability, Introversion, and Compulsivity can be (partly) explained by one higher-order developmental factor (i.e., such a factor would thus be responsible for the relations among change in the lower-order DIPSI traits). It is hypothesized that one developmental factor can be identified which is responsible for maturation in Disagreeableness, Emotional Instability, and Compulsivity (i.e., a general decline in maladaptive personality over the three waves). Given the assumed stability of Introversion, it is expected that this trait does not contribute significantly to the general developmental factor.

Person-centered approach. (3) Latent Profile analysis is used to examine whether maladaptive personality profiles can be derived based on Disagreeableness, Emotional Instability, Introversion, and Compulsivity. Findings so far are mixed, with some studies identifying qualitatively different profiles (Ramos et al., 2014) and others providing mainly support for quantitatively different profiles (Murrie et al., 2007). However, we expect latent profiles reflecting the severity of maladaptive personality aligning the higher-order classes found by See et al. (2021), as this study appears to be the only study in adolescents focusing on maladaptive personality traits. (4) Finally, it is examined to what extent youth transition between personality profiles across the three waves, from childhood to adolescence. To the best of our knowledge, no empirical research has been published testing latent profile transitions in the context of maladaptive personality. Based on variable-centered research on maladaptive change and person-centered research on normative personality profiles, however, we expect that the maladaptive personality trait profiles are relatively stable (De Clercq et al., 2009). Thus, it is hypothesized that the majority of youth will not transition between profiles. When they transition, we expect this change to align with what has been found in research on normative personality traits. That is, the majority of transitions will be toward more adaptive personality profiles, reflecting maturation (Meeus et al., 2011).

Method

Sample and procedure

The data for the current study are part of a longitudinal study on vulnerability and resilience in the transition from childhood to adolescence. An initial number of N = 519 participants were recruited of which N = 492 provided data. Participants (N = 492) were on average 10.08 years old at baseline (SD = 0.48); 53% of the sample was male. Of the participants, 87.3% were born in the Netherlands; the most common other countries of birth were Turkey, Morocco, and China. At T2, 245 parents of participating children (87.3% mothers) reported on their and their partner's highest completed educational level. Most parents had completed higher vocational education (38.4% of responding parents, 31.1% of partners), secondary vocational education (31.0% of responding parents, 28.9% of partners), or university (15.9% of responding parents, 18.4% of partners).

Children were recruited from 24 primary schools and followed at three measurement points, each one year apart. The first measurement point started in the second half of the sixth year (equivalent to fourth grade); the final measurement point took place in the second half of the eighth year (equivalent to sixth grade). Written informed consent for participation was obtained from schools, teachers, parents, and children prior to participation. Data were collected in the classroom setting by trained research assistants, using computer or pen-and-paper questionnaires.

Data accessibility statement

The hypotheses of the current study were partly exploratory and not pre-registered. Sample size was planned for the larger research project based on a trade-off between feasibility and reaching appropriate power to address our general research aims (examining risk and protective factors in youth development; planned N = 500). As such, required sample size was not calculated in advance for the current study specifically.[1] Any data exclusions are disclosed in the method section and the demographic composition of our sample(s) is provided. Information on all procedures and measures used in this study is provided in the manuscript and at https://osf.io/x5vjq/. Data have not yet been used in other published papers (papers using other data from the sample have been submitted). Data have been scored in line with previous work using the DIPSI (e.g., de Clercq et al., 2009); small changes in item formulation have been explained in the Method section. No covariates were included in the models tested. We report basic descriptive statistics, effect sizes, exact p-values, and 95% confidence intervals were possible. Descriptive statistics of and correlations between all measures are reported. The analytical codes necessary to reproduce reported results can be retrieved from OSF: https://osf.io/x5vjq/. Data are not yet openly accessible as manuscripts on primary research questions are still in progress, but data are available from the authors upon request. Material and procedures were reviewed and approved by the faculty ethics review board of Tilburg University (EC-2016.63).

Instruments

Maladaptive personality trait symptoms. Maladaptive personality trait symptoms were measured using the Dimensional Personality Symptom Item Pool (DIPSI; De Clercq et al., 2006). The DIPSI is a 172-item questionnaire with answers reported on a five-point Likert scale ranging from "Does not apply to me at all" to "Applies to me very well." The DIPSI comprises 27 facets of maladaptive personality, which are organized into four higher-order factors. The facets of hyperexpressive traits, hyperactive traits, dominance-egocentrism, impulsivity, irritable-aggressive traits, disorderliness, distraction, risk behavior, narcissistic traits, inflexibility, affective lability, resistance, and lack of empathy load on the Disagreeableness factor; dependency, anxious traits, lack of self-confidence, insecure attachment, submissiveness, ineffective coping, separation anxiety, and depressive traits load on the Emotional Instability factor; shyness, paranoid traits, and withdrawn traits load on the Introversion factor; and perfectionism, extreme achievement striving, and extreme order load on the Compulsivity factor. The DIPSI is suitable for children and adolescents (6–18 years) and can be completed by self- or parent-report. In the current study, the DIPSI was completed by the youth themselves. Psychometric quality has been shown to be good; the factor structure of the DIPSI has high replicability across samples and convergent validity with other measures of maladaptive and adaptive personality (De Clercq et al., 2006). For the current study, the wording of 23 out of the 172 items was slightly revised compared to the original Flemish-Dutch version to make these items more suitable for Dutch youths.[2] Internal consistency in the current study was good to excellent across measurement points, with Cronbach's alpha values ranging from 0.96 to 0.97 for Disagreeableness, 0.95 to 0.96 for Emotional Instability, 0.90 to 0.91 for Introversion, and 0.85 to 0.86 for Compulsivity.

Analysis

Missing data analyses were carried out using SPSS version 26 (IBM Corp., 2019). Descriptive analyses, Confirmatory Factor Analysis, Factor of Curves (including Parallel Process), and Latent Transition Analyses (including Latent Profile Analysis) were carried out using Mplus, version 8 (Muthén & Muthén, 2017). A two-sided alpha level of .05 was used for significance testing. We did not apply traditional ways to correct for multiple testing (e.g., Bonferroni) as this does not suit the nature of the analyses; although multiple analyses were performed, these are all different types of analytical models which we are exploring, not variations of the same model.

Preliminary analyses

Missing data analysis. We tested whether missingness and dropout were dependent on background variables child sex and parental educational level (for missingness and dropout) and baseline scores on the four factors (for dropout) using independent samples t-tests for continuous variables and chi-square analysis for categorical variables. Missingness was not significantly related to child sex, χ^2 (1) = 1.39, p = .239, but related to lower parental educational level, t (224) = 2.99, p = .003. Dropout was not significantly related to child sex, χ^2 (1) = 1.26, p = .261, baseline Disagreeableness, t (409) = −1.31, p = .190, Emotional Instability, t (426) = −0.76, p = .450, Introversion, t (424) = −1.36, p = .173, or Compulsivity, t (425) = −0.44, p = .662. Dropout was significantly related to lower parental educational level, t (224) = 3.93, p < .001. However, missingness in parental education level and in DIPSI scores almost fully overlapped. Parental education level was measured in a questionnaire which had to be submitted separately by the parents of participants. When this parent questionnaire was missing, children were very likely to have missing data on the DIPSI (88.8% of children with missing DIPSI data did not have a parent questionnaire) and to drop out of the study (83.6% of children who dropped out did not have a parent questionnaire). Thus, because most children with missing data also had no data for parental education level, we did not consider it beneficial to use parental education level as an auxiliary variable for predicting missing DIPSI scores in our analyses.

Missing data were handled with Full Information Maximum Likelihood (FIML). For the Confirmatory Factor analyses, where the DIPSI factors were estimated as latent variables, the sample size was N = 492. However, when computing manifest DIPSI scores for subsequent analyses, a factor score for a case was set to missing when a certain percentage of its facets were missing (one fourth for Disagreeableness, one third for the other factors; De Clercq et al., 2006). Furthermore, cases for which all manifest scores for DIPSI factors were missing across measurement points were removed from the analyses, resulting in n = 477 for the main analyses. In selectivity analyses using t-tests for continuous variables and chi-square analysis for categorical variables, no significant differences were found between cases that were dropped in the main analyses versus those that were retained on child sex, χ^2 (1) = 0.35, p = .556, parental educational level, t (224) = −0.374, p = .708, baseline Emotional Instability, t (16.96) = 0.33, p = .372, baseline Introversion, t (424) = 1.78, p = .076, or Compulsivity, t (425) = 0.79, p = .216. We could not perform sensitivity analyses for baseline Disagreeableness due to too small cell sizes. Therefore, we compared the two groups on Disagreeableness at Wave 2. Again, there was no significant difference, t (282) = 0.65, p = .518.

Intraclass correlation and design effect. Because participants were recruited through schools, we tested the degree of similarity between participants within schools by calculating the intraclass correlations (ICC) and design effects (DE) for mean scores on each of the four DIPSI factors at baseline. ICCs ranged from 0.014 to 0.037; DEs ranged from 1.25 to 1.68. This indicates that there was no significant nonindependence caused by clustering within schools (Muthén & Satorra, 1995). We therefore did not account for clustering within schools in our analyses.

Confirmatory Factor Analysis and longitudinal measurement invariance. To confirm the factor structure of the DIPSI in the current sample and test whether this structure was similar across time, we carried out a Confirmatory Factor Analysis and then a test of longitudinal measurement invariance. Following De Clercq et al. (2006), we tested a confirmatory factor model with the Wave 1 data, with four higher-order factors which were each loaded on by the relevant facets (see Instruments section). We allowed the four latent factors to covary. The resulting model fitted the data close-to acceptably (Comparative Fit Index (CFI) = .852; Root Mean Square Error of Approximation (RMSEA) = .097) (Browne & Cudeck, 1993; Hu & Bentler, 1999; Niemand and Mai, 2018[3]). Next, we inspected the longitudinal invariance of the model by fitting a series of increasingly constrained models. We examined invariance on the level of the facets as indicators of the broad domains, and of the items as indicators of the facets. For each model, we tested whether a model of configural invariance (i.e., the model structure constrained across time), weak invariance (i.e., additional constrained factor loadings), strong invariance (i.e., additional constrained facet intercepts), and strict invariance (i.e., additional constrained residual variances of the facets) fit the data well and showed no significant decrease in fit. Model fit was compared based on the criteria by Chen (2007) in which changes in the CFI ≥ −0.01 and RMSEA ≥0.015 indicate significant change in model fit. As shown in Table 1, all models examining the facets as indicators of the broad domains had close to acceptable fit (Hu & Bentler, 1999). Moreover, there was no significant change in CFI or RMSEA between any of the models, indicating that our data met the assumptions of strict invariance and thus could be meaningfully examined across time. Correlations between latent factors in the strict invariance model are presented in Table 2.

For the items as indicators of the facets, we additionally found that most models fitted the data well (see Supplemental Material, Tables S1–S4). For the other 7 out of the 27 models, the model fit was only acceptable following the RMSEA statistic. For all facets of the Introversion and Compulsivity domains, the data met the assumptions for strict invariance. The facets of the Disagreeableness domain also showed strict invariance, except for one (i.e., the affective lability facet), for which partial strict invariance did hold. For Emotional Instability, strict invariance held for all facets except for the insecure attachment facet (i.e., partial strong invariance) and separation anxiety facet (i.e., strong invariance).

Variable-centered approach: Parallel Process and Factor of Curves model

To analyze change in maladaptive personality traits (i.e., Disagreeableness, Emotional Instability, Introversion, and Compulsivity) over time using a variable-centered approach, a two-step approach was followed consisting of (a) a Parallel Process model and (b) a Factor of Curves model. For these models, we used the mean scores on the four higher-order DIPSI factors Disagreeableness, Emotional Instability, Introversion, and Compulsivity at each time point. First, the Parallel Process model was fitted, which models intercorrelated growth curves of the four individual factors, but without a higher-order growth factor.

Subsequently, we continued with a Factor of Curves model by adding a higher-order growth factor. Because moderate to large negative correlations between intercepts and slopes within DIPSI factors were found in the Parallel Process model, we allowed these growth parameters to covary within factors. We used the marker variable approach, in which the factor loadings for the first indicator, Disagreeableness, were fixed to 1 and the means were fixed to 0 for scaling. Model fit for the Parallel Process model and Factor of Curves model was compared based on the criteria by Chen (2007) to decide which model best fit the data.

Table 1. Fit Statistics for Longitudinal Invariance Models.

	Chi^2 (df)	p	RMSEA	CFI	SRMR	RMSEA Power
Configural invariance	7549.71 (3045)	<.001	.055	.802	.190	1.00 (CF)
Weak invariance	7655.51 (3094)	<.001	.055	.799	.192	1.00 (CF)
Strong invariance	7838.87 (3148)	<.001	.055	.793	.192	1.00 (CF)
Strict invariance	7974.04 (3202)	<.001	.055	.790	.193	1.00 (CF)

Note. N = 492. CF = close-fit hypothesis.

Table 2. Correlations for Latent Variables in the Strict Invariance Model (Facets as Indicators of Factors).

		1	2	3	4	5	6	7	8	9	10	11
1	Disagreeableness T1	-										
2	Emotional Instability T1	0.82***	-									
3	Introversion T1	0.86***	0.95***	-								
4	Compulsivity T1	0.82***	0.75***	0.83***	-							
5	Disagreeableness T2	0.17***	-	-	-	-						
6	Emotional Instability T2	-	0.08***	-	-	0.80***	-					
7	Introversion T2	-	-	0.05	-	0.78***	0.89***	-				
8	Compulsivity T2	-	-	-	0.12**	0.72***	0.76***	0.68***	-			
9	Disagreeableness T3	0.16***	-	-	-	0.27***	-	-	-	-		
10	Emotional Instability T3	-	0.06**	-	-	-	0.04	-	-	0.77***	-	
11	Introversion T3	-	-	0.03	-	-	-	0.11*	-	0.74***	0.93***	-
12	Compulsivity T3	-	-	-	0.18***	-	-	-	0.26***	0.64***	0.75***	0.72***

Note. $N = 477$. * = $p < .05$, ** = $p < .01$, *** = $p < .001$.

Person-centered approach: Latent Profile and Latent Transition Analysis

To analyze change in maladaptive personality traits over time using a person-centered approach, we fitted Latent Profile and Latent Transition Analysis models. Both are data-driven approaches in which profiles (i.e., configurations of score patterns on a number of indicators, shared by subsamples of participants) are detected within the full sample. Whereas Latent Profile Analysis models these profiles at isolated measurement points, Latent Transition Analysis is a longitudinal analysis in which individuals' probabilities of moving from one profile to another over time are estimated. Again, mean scores on the four DIPSI factors Disagreeableness, Emotional Instability, Introversion, and Compulsivity were used as indicators in the Latent Profile and Latent Transition Analysis.

Latent Profile Analysis. First, the optimal number of profiles was determined for each measurement point separately using Latent Profile models. Latent Profile models with one to five profiles were fitted for each measurement point separately. The optimal number of profiles was determined using several model fit statistics: The Akaike information criterion (AIC), Bayesian information criterion (BIC), and sample-size adjusted Bayesian information criterion (SSA-BIC) indicate whether model fit of a k+1 model is improved relative to a k model, with smaller numbers indicating model fit. Because these criteria tend to decrease regardless when adding more profiles, we also investigated the magnitude of decrease, favoring larger decreases over smaller ones. Second, significant values of the Vuong–Lo–Mendell–Rubin likelihood ratio test (VLMR-LRT) indicate improvement in model fit from a k to k+1 model. Third, entropy and average classification probabilities for the most likely class (ACPMLC) are criteria for the clarity and accuracy of classification of individuals into profiles. Values upward of 0.80 for entropy and 0.70 for ACPMLC reflect good classification quality (Clark & Muthén, 2009; Nylund-Gibson & Choi, 2018). Fourth, profiles should be clearly distinguishable, conceptually meaningful (i.e., noteworthily different from each other, not simply the result of dividing an existing profile into several slightly different profiles) and sufficiently large (we considered 5% of the sample the minimum).

Latent Transition Analysis. After deciding on the optimum number of profiles at each measurement point, a Latent Transition model was fitted for all three measurement points together. To test whether the number of profiles k found in the Latent Profile models was indeed the best solution longitudinally, Latent Transition models with k, k-1, and k+1 profiles were additionally fitted. To further explore the best fitting model, we also compared models with and without a second-order transition (i.e., from the first to the third measurement point); and with full longitudinal measurement invariance (i.e., means of the factors within profiles were constrained to remain equal over time), full noninvariance (i.e., means of the factors within profiles are freely estimated at all time points), and partial measurement invariance (i.e., a solution in which some means are freely estimated and some are constrained over time, based on findings from the full noninvariance model). Full longitudinal measurement invariance is typically assumed and preferred in Latent Transition Analysis because it indicates the structure and meaning of the latent profiles is stable over time (Nylund et al., 2006). For each step, change in model fit was assessed using AIC, BIC, SSA-BIC, and chi-square difference tests for robust maximum likelihood estimation methods (i.e., using the loglikelihood and scaling correction factors; Muthén & Muthén, n.d)

Comparison of variable-centered and person-centered models

Finally, we compared the model fit of the final variable-centered model with the model fit of the final person-centered model. Because these models are not nested, we could not compare them directly based on absolute model fit criteria. Therefore, we used the information criteria AIC, BIC, and SSA-BIC to determine model quality based on a trade-off between model fit and complexity (Burnham & Anderson, 2004; Vrieze, 2012).

Results

Descriptive analyses

Descriptive statistics and correlations of the full sample on the main constructs (measured as manifest variables) across three measurement points are presented in Table 3.

Variable-centered approach

Parallel Process model. The Parallel Process model had good overall fit (CFI = 0.995, TLI = 0.981, RMSEA = 0.043, probability that RMSEA ≤0.05 p = .654, SRMR = 0.025; see Table 4). All growth parameters were significant indicating change over the three waves in each of the DIPSI factors (Intercepts: $B = 1.751$ to 1.962, all $p < .001$; Slopes: $B = -0.055, p = .016$ to $B = -0.087, p < .001$), and pairs of growth parameters were all significantly correlated. Furthermore, correlations between intercepts ($r = 0.720$–0.898) and slopes (r = 0.574–0.887) among the four factors were generally larger than those between intercept and slope within each factor ($r = -0.541$–0.670). This indicates that it is likely that a shared higher-order growth factor exists, explaining development of the four factors over time (Wickrama et al., 2021). We thus continued to fit a Factor of Curves model and tested its model fit against the Parallel Process model.

Parallel Process and Factor of Curves model fit

Both the Parallel Process and Factor of Curves model had good overall fit, and the criteria did not clearly favor one model over the other; ΔRMSEA remained under the cutoff of 0.015, but ΔCFI was exactly on the cutoff of −0.01. Because the results of the Parallel Process model consistently suggested a shared higher-order growth factor and all model fit statistics were highly similar, we followed the suggestion of Duncan and Duncan (1996) to use the more parsimonious Factor of Curves model for interpretation of our variable-centered analysis. See Table 4 for an overview of fit statistics.

Factor of Curves model

The Factor of Curves model had good overall fit (CFI = 0.985, TLI = 0.970, RMSEA = 0.054, probability that RMSEA ≤0.05 p = .309, SRMR = 0.038; see Table 4). Interpretation of the results of the Factor of Curves model showed that all individual growth parameters (intercepts and slopes) of the four DIPSI factors loaded significantly on the higher-order intercept and slope ($\lambda = 1.039$ to 1.199, all $p < .001$). This indicates that all individual DIPSI growth parameters contributed significantly to the higher-order growth factor. The higher-order growth factor showed a developmental pattern of relatively low initial levels (B = 1.923, $p < .001$) and a negative slope ($B = -0.066$, $p < .001$), indicating a decrease in overall maladaptive personality over time. The latent slope was standardized by dividing it by the standard deviation of the latent intercept. This outcome approximates Cohen's d. Following the guidelines of Cohen's d, the magnitude of the effect did not reach the threshold for a small effect (B/SD I = −0.121; Cohen's d ≥ 0.2 constitutes a small effect; Cohen, 1988). Significant variance of the higher-order intercept (σ^2 = 0.185, p < .001) and slope ($\sigma^2 = 0.039$, $p = .006$) indicated that there may be significant interpersonal differences in initial levels and overall development of maladaptive personality over time. There was a significant negative covariance between the higher-order intercept and slope, ($\sigma f_0, f_s = -0.057$, $p = .001$), which translates to a correlation of moderate magnitude ($r = -0.673$, $p < .001$). This

Table 3. Descriptive Statistics and Correlations for Manifest Variables.

		Range	M	SD	1	2	3	4	5	6	7	8	9	10	11
1	Disagreeableness T1	1–5	1.93	0.54	-										
2	Emotional Instability T1	1–5	1.92	0.62	.75***	-									
3	Introversion T1	1–5	1.76	0.55	.76***	.84***	-								
4	Compulsivity T1	1–5	1.97	0.65	.76***	.67***	.70***								
5	Disagreeableness T2	1–5	1.86	0.55	.64***	.49***	.44***	.43***	-						
6	Emotional Instability T2	1–5	1.78	0.55	.45***	.62***	.50***	.40***	.73***	-					
7	Introversion T2	1–5	1.63	0.53	.47***	.54***	.57***	.35***	.69***	.80***	-				
8	Compulsivity T2	1–5	1.89	0.63	.45***	.45***	.36***	.53***	.68***	.66***	.52***	-			
9	Disagreeableness T3	1–5	1.77	0.51	.45***	.27***	.28***	.31***	.60***	.34***	.44***	.35***	-		
10	Emotional Instability T3	1–5	1.75	0.58	.24**	.35***	.27***	.22***	.34***	.48***	.48***	.29***	.71***	-	
11	Introversion T3	1–5	1.63	0.53	.27***	.28***	.32***	.18*	.31***	.36***	.53***	.19*	.68***	.82***	-
12	Compulsivity T3	1–5	1.86	0.61	.22**	.26***	.19*	.36***	.30***	.34***	.27***	.51***	.60***	.66***	.54***

Note. N = 477. * = $p < .05$, ** = $p < .01$, *** = $p < .001$.

Table 4. Fit Statistics for Parallel Process and Factor of Curves Models.

	Chi^2 (df)	P	RMSEA (Δ)	CFI (Δ)	SRMR	RMSEA Power	AIC	BIC	SSA-BIC
Parallel Process	30.24 (16)	.017	.043	.995	.025	0.76 (CF) 0.94 (PF)	3170.01	3478.41	3243.54
Factor of Curves	81.42 (34)	<.001	.054 (0.011)	.985 (−0.010)	.038	0.96 (CF)	3185.19	3418.57	3240.83

Note. N = 477. CF = close-fit hypothesis, PF = poor-fit hypothesis.

indicates that higher initial levels of overall maladaptive personality were related to a stronger decline over the three waves.

Regarding the individual growth parameters of the four DIPSI factors, only the intercept of Emotional Instability remained significant after controlling for the higher-order growth factor (B = 0.403, p = .012). None of the slopes remained significant after controlling for the higher-order factor (B = −0.002 to 0.018, p = .306 to .918). Thus, the development in the DIPSI factors over time was well-captured by the higher-order growth process. Large amounts of variance in individual growth parameters were explained by the higher-order growth parameters (R^2 = 0.686 to 0.976, all p < .001). However, significant residual variance remained for all individual intercepts (σ^2 = 0.028, p = .019 to σ^2 = 0.059, p < .001) and for the individual slopes of Disagreeableness (σ^2 = 0.018, p = .001) and Introversion (σ^2 = 0.014, p = .037). This indicates that after controlling for a higher-order growth factor, there may still be interpersonal variance in initial levels of all four DIPSI factors and in the development of Disagreeableness and Introversion over time.[4] See Table 5 for all parameter estimates from the Factor of Curves model. Figure 1 shows a visual representation of the estimated growth curves of the DIPSI factors and the higher-order growth factor.

Person-centered approach

Latent Profile Analysis. Latent Profile models with one to five profiles were estimated for each of the three measurement points. For the third measurement point, the best loglikelihood value could not be replicated upon estimation of the model with five profiles, indicating that solutions were based on local maxima. Therefore, only solutions with one to four profiles are reported for the third measurement point.

For each measurement point, the magnitude of decrease in AIC, BIC, and SSA-BIC and significance of VLMR-LRT indicated that a model with three profiles had the best fit to the data. Furthermore, the entropy and classification probabilities indicated that the models with three profiles provided good and highly accurate classification of individuals. Lastly, the models with three profiles yielded distinct, sufficiently large, and conceptually meaningful profiles at each time point. Therefore, a model with three profiles at each time point was considered the best fitting solution. See Table 6 for an overview of fit statistics for these models.

Latent Transition Analysis

We first compared model fit for Latent Transition models with two, three, and four profiles. In line with the Latent Profile results, the model with three profiles had a significantly better fit than the model with two profiles as indicated by AIC, BIC, SSA-BIC, and $\Delta\chi 2$ (see Table 7). Although $\Delta\chi 2$ was also significant for the comparison between the models with three and four profiles, the model with four profiles showed a decidedly smaller decrease in AIC, BIC, and SSA-BIC. The solution with four profiles resulted in a profile that was not sufficiently distinct or conceptually meaningful; it simply split the most common profile into two profiles with slightly different indicator means. Furthermore, model identification problems arose when estimating the model with four profiles, indicating the model was too complex. We therefore chose to retain the model with three profiles.

We then tested this model against a model with an additional second-order transition. The second-order transition did not significantly improve model fit, as demonstrated by BIC, SSA-BIC, and $\Delta\chi^2$. We therefore chose to retain the model with only first-order transitions.

To test whether the assumption of full longitudinal measurement invariance held, the model with full longitudinal measurement invariance was first compared to a full noninvariance model. Model fit results were mixed (see Table 7). On the one hand, significance of $\Delta\chi^2$ indicated a significant improvement in model fit over the full invariance model, and AIC was slightly lower for the full noninvariance model. On the other hand, BIC and SSA-BIC were higher. Inspection of the profile means in the full noninvariance model indicated that the size and content of the profiles was close to identical across measurement points. However, there was a slight dip in the means of some indicators at the second measurement point, particularly in the moderate and maladaptive profile. We therefore tested a partial invariance model, in which means were constrained to be equal within profiles at the first and third measurement points but freely estimated at the second measurement point, against the full invariance model. Again, results were inconsistent: significance of $\Delta\chi^2$ indicated significant improvement in model fit by allowing partial invariance. AIC was slightly lower for the partial invariance model. However, BIC and SSA-BIC indicated worse model fit for the partial invariance model. All in all, information criteria and $\Delta\chi^2$ did not unanimously favor one model over the other. It is common for partial invariance and full noninvariance Latent Transition models to have an advantage over full invariance models based on $\Delta\chi^2$, but not on BIC and SSA-BIC, because more parameters are constrained to be equal in a full invariance model (e.g., McElroy et al., 2017; Moore et al., 2019). In these cases, it is preferable to interpret the full invariance model when the number and structure of classes across time is consistent (Lanza et al., 2003). In the full invariance model, the profiles and transition probabilities can be more meaningfully interpreted over time (Nylund, 2007). Given these considerations, supported by the highly stable ordering and content of the profiles over time and the lack of theoretical justification for a partial invariance model, we chose to select the full measurement invariance model with three profiles as the final model for further interpretation.

Latent profiles

The most common latent profile (49% of the sample at T1) in the final model was characterized by a homogenous profile of low scores on all four DIPSI indicators. We therefore named this profile “low.” The second most common profile (38.6% of the sample at T1) had a similarly homogenous profile with scores that were somewhat higher, which we named “moderate.” The least common profile (12.5% of the sample at T1) had elevated scores on all

Table 5. Model Results for the Factor of Curves Model.

Higher-Order Growth Factor Loadings

			Estimate	95% CI	SE	Est/SE	p
Higher-order growth factor: I/S	By	Disagreeableness: I/S	1.000[a]	-	0.000	-	-
		Emotional Instability: I/S	1.199[b]	1.036; 1.362	0.083	14.412	<.001
		Introversion: I/S	1.039[b]	0.897; 1.182	0.073	14.310	<.001
		Compulsivity: I/S	1.052[b]	0.909; 1.194	0.073	14.448	<.001

Higher-order growth factor means and variances

		Estimate	95% CI	SE	Est/SE	Stand. Est.	p
Higher-order growth factor: I	Mean	1.923	1.873; 1.973	0.025	75.558		<.001
	Variance	0.185	0.124; 0.246	0.031	5.967		<.001
Higher-order growth factor: S	Mean	−0.066	−0.102; −0.029	0.018	−3.561	−0.121[c]	<.001
	Variance	0.039	0.011; 0.062	0.014	2.767		.006

Higher-order growth factor covariances

			Estimate	95% CI	SE	Est/SE	p
Higher-order growth factor: I	With	Higher-order growth factor: S	−0.057	−0.092; −0.023	0.018	−3.247	.001

Intercepts

	Estimate	95% CI	SE	Est/SE	Stand. Est.	p
Disagreeableness: I	0.000[a]	-	0.000[a]	-		-
Disagreeableness: S	0.000[a]	-	0.000[a]	-		-
Emotional Instability: I	−0.403	−0.717; −0.088	0.160	−2.510		.012
Instability: S	−0.007	−0.039; 0.025	0.016	−0.430	−0.002[c]	.667
Introversion: I	−0.249	−0.524; 0.026	0.140	−1.777		.076
Introversion: S	−0.002	−0.017; 0.053	0.016	−0.103	−0.001[c]	.918
Compulsivity: I	−0.060	−0.336; 0.217	0.141	−0.423		.672
Compulsivity: S	0.018	−0.017; 0.018	0.018	1.023	0.006[c]	.306

Residual variances

	Estimate	95% CI	SE	Est/SE	p
Disagreeableness: I	0.059	0.039; 0.078	0.010	5.832	<.001
Disagreeableness: S	0.018	0.007; 0.029	0.005	3.288	.001
Emotional Instability: I	0.028	0.005; 0.052	0.012	2.340	.019
Emotional Instability: S	0.001	−0.011; 0.014	0.006	0.224	.823
Introversion: I	0.034	0.011; 0.056	0.012	2.937	.003
Introversion: S	0.014	0.001; 0.028	0.007	2.080	.037
Compulsivity: I	0.059	0.018; 0.100	0.021	2.844	.004
Compulsivity: S	0.012	−0.011; 0.035	0.012	1.032	.302

Covariances

			Estimate	95% CI	SE	Est/SE	p
Disagreeableness: I	With	Disagreeableness: S	−0.005	−0.016; 0.007	0.006	−0.760	.447
Emotional Instability: I	With	Emotional Instability: S	−0.003	−0.017; 0.011	0.007	−0.408	.683
Introversion: I	With	Introversion: S	−0.007	−0.022; 0.007	0.007	−1.024	.306
Compulsivity: I	With	Compulsivity: S	0.007	−0.018; 0.031	0.013	0.534	.594

R^2

	Estimate	SE	Est/SE	P
Disagreeableness: I	.759	0.046	16.489	<.001
Disagreeableness: S	.686	0.103	6.652	<.001
Emotional Instability: I	.904	0.041	21.789	<.001
Emotional Instability: S	.976	0.107	9.161	<.001
Introversion: I	.855	0.049	17.507	<.001
Introversion: S	.748	0.117	6.389	<.001
Compulsivity: I	.776	0.072	10.751	<.001
Compulsivity: S	.783	0.178	4.403	<.001

Note. I = intercept, S = slope. [a] Disagreeableness is the marker variable; its growth parameters were fixed to zero and its loadings on the higher-order growth factor to one for scaling. [b] Loadings of growth parameters on the higher-order intercept were constrained to be equal to loadings on the higher-order slope within each DIPSI factor. [c] Slope standardization: $\frac{Mean\,S}{(SE\,I * \sqrt{N})}$.

indicators compared to the low and moderate profile. We therefore named this profile "high." Proportions and mean scores on each factor per profile are presented in Table 8. Figure 2 shows a visual representation of the profiles.

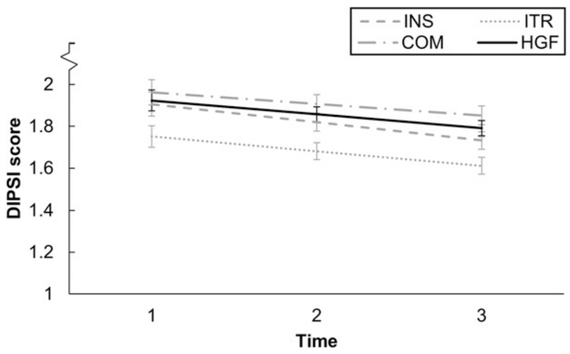

Figure 1. Plot of Estimated Growth Curves of the DIPSI Factors and Higher-Order Growth Factor. *Note. Y*-axis edited for legibility; actual range is 1–5. INS = Emotional Instability, ITR = Introversion, COM = Compulsivity, HGF = higher-order growth factor. Disagreeableness was used as the marker variable and thus no growth curve is estimated. Error bars reflect 95% confidence intervals.

Latent profile transitions. Initially, 23 different transition patterns were found out of the 27 possible patterns (3 classes and 3 measurement points, thus 3^3). However, many transition patterns were very rare, containing only one or a few cases. We therefore only interpreted transition patterns for which the confidence interval did not contain zero. This threshold was reached when the pattern was found in five or more cases, resulting in nine meaningful, different transition patterns observed across n = 451 youths.

Constant profile membership across time was the norm; 60.5% of youths remained in the same profile across all time points. The most common pattern was constant and low (46.3% of the sample). 10.4% of youths remained constantly in the moderate class, and 3.8% remained constantly in the high class. Youths who transitioned typically did so once (96.6% of transitioners; 38.1% of the sample), with transitions being more likely from T2 to T3 (68.6% of once-transitioners; 26.2% of the sample). Among youth who transitioned at least once, the low profile was the most common endpoint (68.0%; 26.8% of the sample), with the moderate profile being the second most common endpoint (32.0%; 12.6% of the sample). Transitions for which the high profile was the endpoint were rare; none of their confidence intervals reached the threshold for

Table 6. Model Fit Indices for Latent Profile Models across Measurement Points.

								Proportions				
Time	Profiles	AIC	BIC	SSA-BIC	VLMR-LRT *p*	Entropy	ACPMLC	1	2	3	4	5
1	1	3035.79	3068.26	3042.87	-	-	-	1				
	2	2217.04	2269.81	2228.55	<.001	0.90	0.97	0.68	0.32			
	3	1921.78	1994.84	1937.72	.012	0.88	0.95	0.53	0.36	0.11		
	4	1806.04	1899.40	1826.42	.147	0.89	0.94	0.49	0.01	0.36	0.13	
	5	1689.23	1802.89	1714.03	.694	0.86	0.91	0.35	0.24	0.31	0.10	0.01
2	1	1930.24	1959.43	1934.06	-	-	-	1				
	2	1421.39	1468.83	1427.60	<.001	0.92	0.95	0.80	0.20			
	3	1259.18	1324.86	1267.78	.011	0.85	0.93	0.57	0.32	0.12		
	4	1213.46	1297.39	1224.45	.122	0.79	0.90	0.32	0.40	0.17	0.11	
	5	1180.58	1282.76	1193.97	.797	0.83	0.89	0.33	0.16	0.03	0.08	0.41
3	1	1231.56	1257.24	1231.90	-	-	-	1				
	2	941.72	983.44	942.27	.017	0.92	0.97	0.75	0.25			
	3	824.35	882.12	825.11	.017	0.92	0.96	0.26	0.69	0.05		
	4	758.15	831.97	759.12	.188	0.88	0.95	0.40	0.35	0.05	0.20	

Note. N = 428 at T1, *N* = 284 at T2, *N* = 183 at T3. Sample sizes are smaller than the full sample size because each time point is estimated separately in Latent Profile Analysis and thus dropout cases are not taken into account.

Table 7. Model Fit Indices for Latent Transition Models.

Model	Profiles	2nd Order Transition	Invariance	AIC	BIC	SSA-BIC	*LL*	*SCF*	*Δχ2 (DF)*	*p Δχ2*
1	2	-	Full	4497.76	4601.95	4522.61	−2223.88	1.63		
2	**3**	**-**	**Full**	**3901.44**	**4059.80**	**3939.20**	**−1912.72**	**1.65**	**370.93 (13)$_1$**	**< .001**
3	4	-	Full	3695.08	3990.98	3765.63	−1776.54	1.22	380.16 (33)$_2$	<.001
4	3	Yes	Full	3906.76	4081.80	3948.49	−1911.38	1.66	1.51 (4)$_2$	0.825
5	3	-	Partial	3890.72	4099.10	3940.40	−1895.36	1.5149	31.84 (12)$_2$	0.002
6	3	-	Noninvariance	3897.49	4155.88	3959.10	−1886.74	1.48	42.85 (24)$_2$	0.010
									12.92 (12)$_5$	0.375

Note. N = 477. AIC = Akaike information criterion, BIC = Bayesian information criterion, SSA-BIC = Sample-size adjusted Bayesian information criterion, LL = loglikelihood, SCF = scaling correction factor, DF = degrees of freedom. Numbers in subscript refer to the comparison model.

Table 8. Profile Means and Proportions for the Latent Transition Model.

Profile	Proportion			Disagreeableness				Emotional Instability				Introversion				Compulsivity			
	T1, %	T2, %	T3, %	M	95% CI M	Z	95% CI Z	M	95% CI M	Z	95% CI Z	M	95% CI M	Z	95% CI Z	M	95% CI M	Z	95% CI Z
Low	49.0	61.4	61.3	1.55	1.49; 1.61	−0.63	−0.78; −0.49	1.44	1.40; 1.49	−0.68	−0.78; −0.59	1.35	1.31; 1.40	−0.64	- 0.73; −0.55	1.56	1.51; 1.62	−0.58	- 0.69; −0.48
Moderate	38.6	28.0	31.0	2.11	2.04; 2.18	0.40	0.26; 0.54	2.13	2.02; 2.25	0.43	0.22; 0.64	1.91	1.82; 2.01	0.37	0.18; 0.56	2.21	2.10; 2.33	0.41	0.21; 0.60
High	12.5	10.6	7.7	2.81	2.64; 2.99	1.73	1.45; 2.02	3.00	2.86; 3.13	1.94	1.73; 2.15	2.76	2.60; 2.93	1.95	1.66; 2.24	2.91	2.72; 3.09	1.52	1.27; 1.77

Note. N = 477. M = unstandardized indicator scores; Z = standardized indicator scores.

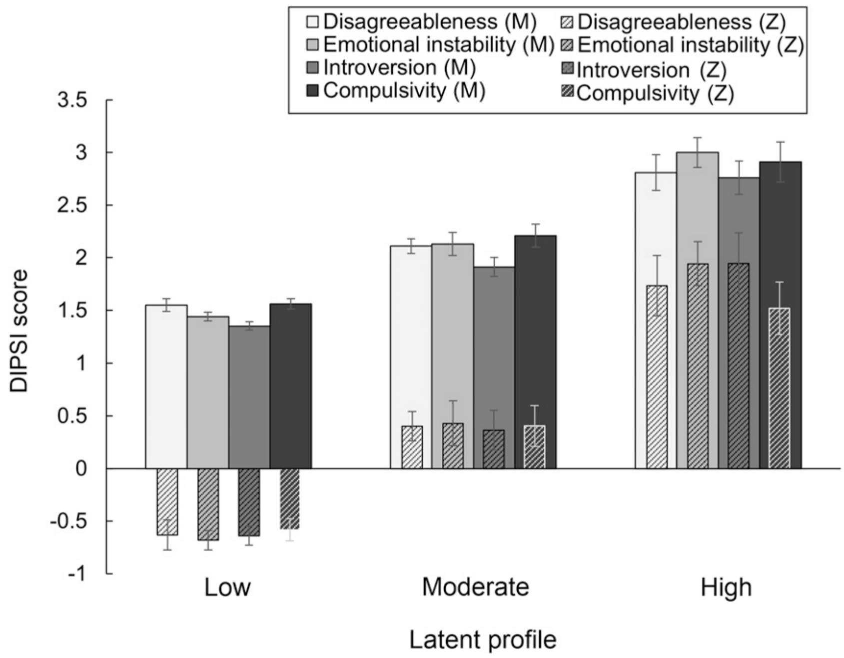

Figure 2. Profiles of Indicator Scores for the Low, Moderate, and High Profile. *Note.* *N* = 477. M = unstandardized indicator scores; Z = standardized indicator scores. Error bars reflect 95% confidence intervals.

interpretation. When looking at overall patterns among youth who transitioned at least once, ending up in a more adaptive profile than where they started was most common (84.3%; 33.3% of the sample), followed by ending up in a more maladaptive profile (12.4%; 4.9% of the sample). Lastly, 3.4% of youth who transitioned (1.3% of the sample) did so toward a more adaptive profile but then transitioned back into their original profile. No transition patterns toward a more maladaptive profile and then back to the original profile reached the confidence interval threshold for interpretation. An overview of transition patterns and their frequencies is presented in Table 9.

Comparison of variable-centered and person-centered models

Using the information criteria, we compared the variable-centered Factor of Curves model (see Table 4) and the person-centered Latent Transition model (see Table 7). AIC, BIC, and SSA-BIC were all lower for the Factor of Curves model, indicating this model had a better trade-off between model fit and complexity.

Discussion

Building on the increased acknowledgment of childhood as an important period in the onset of personality pathology, the current study aimed to replicate and extend existing empirical work on maladaptive personality development in the transition from childhood to adolescence. We distinguished a variable-centered approach, focusing on mean-level change in maladaptive traits, from a person-centered approach, in which we investigated profiles characterized by combinations of maladaptive personality traits as well as transitions between these profiles over time.

Variable-centered approach: Modest mean-level declines in maladaptive personality

With regard to the variable-centered approach, a Parallel Process model showed highly similar development in all DIPSI factors, reflecting relatively low initial levels and small decreases over time. These findings confirmed our first hypothesis concerning decreases in Disagreeableness, Emotional Instability, and Compulsivity, but not Introversion. For Introversion, a similar pattern was found as for the other four factors, although based on previous research, no change was expected (De Clercq et al., 2009). Subsequently, using a Factor of Curves model, it was demonstrated that the individual growth parameters of all DIPSI factors loaded significantly on one higher-order developmental factor. This higher-order factor had the same growth parameters as the individual growth curves: relatively low initial levels, a very small but significant decrease over time, and a negative intercept-slope covariance, indicating that youth with higher initial levels of maladaptive personality showed stronger declines over time. The higher-order developmental factor explained a substantial amount of variance in all individual growth parameters, and none of the individual slopes were significant after controlling for the higher-order factor. Thus, confirming our second hypothesis, one shared developmental process, which seems to reflect a developmental trend toward maturation, explained development of the four DIPSI factors over time.

The declines in maladaptive personality traits levels, as well as the higher-order factor explaining shared

Table 9. Latent Profile Transition Patterns, Frequencies, and Proportions.

T1	T2	T3	Frequency	95% CI Frequency	Percentage	95% CI Percentage
Low	Low	Low	209	188; 230	43.82	39.36; 48.27
Moderate	Moderate	Low	74	59; 89	15.51	12.26; 18.76
Moderate	Low	Low	47	34; 60	9.85	7.18; 12.53
Moderate	Moderate	Moderate	47	34; 60	9.85	7.18; 12.53
High	High	Moderate	29	19; 39	6.08	3.94; 8.22
High	High	High	17	9; 25	3.56	1.90; 5.23
Low	Low	Moderate	15	8; 22	3.15	1.58; 4.71
Low	Moderate	Moderate	7	2; 12	1.47	0.39; 2.54
Moderate	Low	Moderate	6	1; 11	1.26	0.26; 2.26

Note. N = 451.

development, seem to contradict earlier evidence for temporal "dips" in normative personality traits (e.g., Emotional Stability and conscientiousness) found in research on early adolescent personality development (Soto & Tackett, 2015). Instead our results align with findings on personality development from adolescence into adulthood, indicating that change is typically in the direction of adaptation and maturation (e.g., Johnson et al., 2000; Klimstra et al., 2009; Roberts et al., 2006). Possibly, temporal dips are highly age-specific and related to unique early adolescent developmental tasks (e.g., gaining autonomy from parents, changing peer relationships). So far, dips are mainly found in youth aged 13–15, reflecting an interruption of general trends toward maturation starting already in (late) childhood and—after the dip—continuing from middle adolescence onward (Soto & Tackett, 2015). This might explain why we did not find support for temporal dips in the transition from childhood into adolescence (age 10–12). An alternative explanation may lie in our focus on maladaptive personality traits, rather than normative personality traits such as the Big Five. While normative and maladaptive personality traits have been demonstrated to lay on a continuum (van Dijk et al., 2021), the difference between our findings and those on normative personality traits may suggest that developmental processes may differ. Indeed, in the study by De Clercq et al. (2009) using the same instrument, a similar age group, and a similar study duration, mean-level declines were shown in Disagreeableness, Emotional Instability, and Compulsivity (although in this study, mean-level declines were only found between T1 and T2, not between T2 and T3). Thus, the current findings seem to provide a robust replication of mean-level pathological personality trait change in the transition from childhood to adolescence. Only for Introversion, do the results differ: De Clercq et al. (2009) found mean levels of Introversion to be stable over time, whereas in our study, Introversion contributed as well to the general developmental factor of decreasing scores. An explanation for this difference may be reporter discrepancies: De Clercq et al. (2009) used maternal reports, whereas the current study used youth self-reports. Previous research has indicated low to moderate interrater agreement for parent–adolescent ratings of the adolescents' personality (Laidra et al., 2006). Moreover, Tackett et al. (2013) demonstrated informant discrepancies across DIPSI trait domains, with lowest agreement being revealed for Compulsivity, followed by Introversion.

Person-centered approach: Quantitatively different profiles and stability or adaptive change over time

Using a person-centered approach and confirming our third hypothesis, we found three profiles: low, moderate, and high. These profiles did not show qualitative differences in their composition but merely reflected quantitative differences in overall levels of maladaptive personality. This aligns with the broad quantitatively different classes found by See et al. (2021) in their work on maladaptive personality trait profiles in middle adolescents, while contradicting earlier research identifying qualitatively different normative personality profiles (i.e., undercontrollers, overcontrollers, resilients; Asendorpf et al., 2001; De Fruyt et al., 2002; Klimstra et al., 2009; Meeus et al., 2011). The conclusion that maladaptive personality is a dimensional construct on which individuals vary across a spectrum with some showing low levels, some moderate, and few high levels of the traits seems to mirror critiques to person-centered approaches in general emphasizing problems with regard to the robustness of qualitatively different profiles (De Fruyt et al., 2002; Donnellan & Robins, 2010; Herzberg & Roth, 2006; Rammstedt et al., 2004). Specifically, it confirms concerns with regard to the merit and meaningfulness of a person-centered approach, as creating quantitatively different profiles may come at the cost of subtle dimensional differences covered with a variable-centered approach, without providing any fundamentally new insights above and beyond what a variable-centered approach offers.

Subsequently, using Latent Transition Analysis, it was examined whether individuals changed profile across the three waves. As hypothesized, remaining in the same personality profile was the most common pattern. Specifically, 60.5% of youth had the same personality profile across two years. This finding is largely in line with previous studies on normative personality profiles (e.g., Meeus et al., 2011). The nature of the transitions we found was also in agreement with findings from studies on normative personality; transitions toward a more adaptive profile were most common (e.g., Meeus et al., 2011). Notably, both profile stability (in contrast to switching back and forth between profiles: Klimstra et al., 2012; Roberts et al., 2001) and transitions toward more adaptive profiles (Klimstra et al., 2009) have been described as indications of maturation. As such, both the stability and the change toward more adaptive profiles that was present in our sample can be interpreted as personality maturation.

Integrating the various research findings from the current study, it is remarkable how consistent the patterns are across the various analytical approaches. The Parallel Process model, the Factor of Curves model, and the Latent Transition model all demonstrated that maladaptive personality change in the transition from childhood to adolescence is characterized by small but robust changes toward maturation. This, however, does not imply that all models are identical in terms of fit to our data. The variable-centered Factor of Curves model was superior to the person-centered Latent Transition model in terms of trade-off between model fit and complexity. In hindsight, the Factor of Curves model has proven to be an especially good fit for our data, given the high intercorrelations between the four different DIPSI factors (Wickrama et al., 2021). This, in combination with the lack of support for qualitatively different profiles, seems to indicate that a variable-entered approach—and the Factor of Curves model specifically—should be generally favored over a person-centered approach.

At the same time, even after controlling for the shared developmental trend toward maturation, our variable-centered approach indicated significant residual variance in the development in both Disagreeableness and Emotional Instability. This indicates that there are individuals for whom the process of maturation may not apply. One advantage of the person-centered Latent Transition Analysis is that it enables detection of developmental patterns that deviate from the norm. In our study, a subsample of youth (4.9%) was identified showing transitions toward more maladaptive profiles, as well as a subsample of youth that consistently remained in the high maladaptivity profile (3.8%). Keeping in mind the non-clinical nature of the overall sample, membership of these subsamples may indicate current or future problems and thus have clinical relevance. While previous studies (e.g., See at al., 2021) suggested that understanding personality pathology in terms of profiles might have distinctive clinical relevance compared to focusing on isolated traits, the current study is the first to actually test stability and change in maladaptive personality traits and trait profiles within the context of a single study.

Limitations and future recommendations

Some limitations should be noted. To start, while this study extends previous research on youth personality development by focusing on maladaptive personality traits, our findings reflect stability and change present in the general Dutch population of youth in the transition from childhood to adolescence. However, although youth were recruited at schools across the Netherlands, given the longitudinal dropout, our sample is still a convenience sample and not fully representative for the Dutch population. Moreover, our findings cannot be generalized to a clinical sample of youth. Our finding that there may be (groups of) individuals who do not show maladaptive personality development toward maturation highlights the need for longitudinal research examining maladaptive personality traits and trait profiles in clinical and at-risk youth. Relatedly, a crucial next step would be the identification of risk and protective factors related to maladaptive personality development. Future research using larger samples and preferably also more waves is needed to identify factors that may drive less favorable transitions and map long-term development of these youth (i.e., do they catch-up or are they at risk for the development of personality pathology later in life?). Another clear limitation of the current study is the use of self-reports only. Although the psychometrics of adolescents' self-reports on personality have been found to be accurate (Soto et al., 2008), multi-informant data are necessary to establish construct validity of and a more complete perspective on emerging personality pathology (Tackett et al., 2013; Tackett, 2010). Therefore, it is advised that future studies take both self-reports and parent reports into account to additionally address potential reporter discrepancies (Laidra et al., 2006). Additionally, one of the big merits of the DIPSI is the validated lower-order factor structure enabling it to study facets of Disagreeableness, Emotional Instability, Compulsivity, and Introversion (Brandes et al., 2020). Unfortunately, the current sample size did not allow fitting lower-order DIPSI facets in a Factor of Curves and/or Curve of Factors modeling approach (Wickrama et al., 2021). Future research using a substantially larger sample could help gain more detailed insight in the development of the different facets of maladaptive personality. On a similar note, larger samples would also enable fitting more advanced person-centered models such as Hierarchical tree typology. Using this method, earlier research revealed subclasses of qualitatively different pathological personality trait profiles within the broader quantitatively different classes (See et al., 2021). Clearly, a larger sample size is recommended for future research. Also, it should be noted that the magnitude of the correlations differed substantially between the manifest and latent correlations. Latent correlations are typically larger as they are stripped from measurement error (Cole & Preacher, 2014), but the substantial difference in the current study indicates that measurement error might have been particularly large. This might also explain the relatively low rank-order stability. Furthermore, we did not apply traditional correction for multiple testing because we exploratively compared a number of distinct models. However, findings could be assessed more conservatively by applying an alpha level of .01 instead of .05. In the Factor of Curves model, all higher-order growth parameters and their covariances would remain significant, as well as the proportion of variance in lower-order growth factors explained by the higher-order growth factors. The few lower-order growth parameters that are significant at the current alpha level of .05 would become nonsignificant, further confirming the explanatory power of the higher-order growth factor. For the Latent Profile Analysis, the decision between a two- and three-class model may now appear somewhat ambiguous, as VLMR-LRT would become nonsignificant at three classes. However, taking the other fit statistics into account, a three-class model would still be preferable. Thus, our conclusions would remain the same when applying a more conservative alpha level, which suggests our findings are likely to be robust. Related to this is the issue of power to detect a target effect. Although our study mostly evidenced a lack of change (i.e., stability), we cannot exclude the possibility that we lacked the power to detect a potential small slope effect. Analyses to estimate power to detect effects are specific for the estimated model and population values. As such population values are unknown (i.e., previous research often only reported parameter estimates relevant for their research question), a meaningful analysis was not possible.

Also, in a more recent version of the DIPSI, "oddity" is added as a fifth maladaptive personality factor, which was not considered in the current study. Including "oddity" has been suggested to enable an even more comprehensive description of personality pathology compared to the 172-item version used in the current study (Verbeke & De Clercq, 2014). A final limitation of the current study that should be mentioned is that the various hypotheses were rather general and (more specific) hypotheses were not pre-registered.

Conclusion

In the current study, maladaptive personality development was examined in the transition from childhood to adolescence using both a variable-centered and a person-centered approach. The variable-centered approach indicated an overall mean-level decline in maladaptive personality that largely aligns with research on normative personality development (Klimstra et al., 2009) and the findings by De Clercq et al. (2009) on youth maladaptive personality traits. The person-centered approach further confirmed these findings by identifying quantitatively different profiles and demonstrating that youth showed generally either stability or change toward a more adaptive profile over time. Although a person-centered approach may have some merit when aiming to detect high-risk subgroups, integrating the current results suggests that a variable-centered approach—and a Factor of Curves model capturing shared underlying developmental processes in particular—is favorable over a person-centered approach.

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The analysis scripts used for this article can be accessed at https://osf.io/x5vjq/. Data are not yet openly accessible as manuscripts on primary research questions are still in progress but are available from the authors upon request.

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Supplemental Material

Supplemental material for this article is available online.

Notes

1. While power analyses were not conducted in advance, following a suggestion by the Reviewers, we determined power for the variable-centered models (i.e., Confirmatory Factor Analysis with configural, weak strong, and strict longitudinal invariance, Parallel Process, and Factor of Curves) using the RMSEA power analysis method. This method indicates whether there is enough power to detect various levels of model misspecification based on the number of degrees of freedom in the model and the sample size (MacCallum et al., 1996; Van Dijk et al., 2020). Following Van Dijk et al. (2020), we first tested the close-fit hypothesis (i.e., whether there is sufficient power to detect that the model does not fit closely to reality), using a null RMSEA value of ≤0.05 and alternative RMSEA value of 0.08. When the close-fit hypothesis did not reach power of 0.80, we tested the poor-fit hypothesis (i.e., whether there was sufficient power to detect that a model has poor fit), using a null RMSEA value of ≤0.05 and alternative RMSEA value of 0.09 (MacCallum et al., 1996; Van Dijk et al., 2020). We used RMSEA power analysis software by Preacher and Coffman (2006). All Confirmatory Factor Analysis models had sufficient power to detect if the model was not close to reality. The Parallel Process model did not have adequate power to detect if the model was close to reality, but this model did have sufficient power to detect poor fit. The Factor of Curves model had sufficient power to detect if the model was not close to reality.
2. At Wave 2, a subsample of youth (n=150) filled in both the original and the reworded questions of the DIPSI. For this subsample, the internal consistency of both versions was calculated to enable comparison between the original version and the version with the reworded items. For the version with the reworded items, Cronbach's alpha values at Wave 2 were .96 for Disagreeableness, .95 for Emotional Instability, .91 for Introversion, and .83 for Compulsivity. The internal consistency of the DIPSI factors in the original Flemish-Dutch version was similar: .96 for Disagreeableness, .95 for Emotional Stability, .90 for Introversion, and .84 for Compulsivity.
3. While our CFI does not reach the traditional thresholds of >.90 (Hu & Bentler, 1999; Browne & Cudeck, 1993), recent literature on fit indices for Structural Equation Modeling advises caution in adhering to any hard cut-offs. Specifically, Niemand and Mai (2018) argue for more flexible cut-offs, in particular when using more complex models and/or smaller sample sizes (as is the case in the current study).
4. To illustrate the variance in development over time, we created a Figure showing the estimated trajectories on each of the four DIPSI factors of a random subsample of n = 100 (we did not include the full sample so that the lines can be more easily distinguished). This Figure is uploaded as supplemental material S6.

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