General Growth Mixture Analysis of Adolescents' Developmental Trajectories of Anxiety: The Impact of Untested Invariance Assumptions on Substantive Interpretations

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Abstract

Substantively, this study investigates potential heterogeneity in the developmental trajectories of anxiety in adolescence. Methodologically, this study demonstrates the usefulness of General Growth Mixture Analysis (GGMA) in addressing these issues and illustrates the impact of untested invariance assumptions on substantive interpretations. This study relied on data from the Montreal Adolescent Depression Development Project (MADDP), a four-year follow-up of over 1000 adolescents who completed the Beck Anxiety Inventory each year. GGMA models relying on different invariance assumptions were empirically compared. Each of these models converged on a five-class solution, but yielded different substantive results. The model with class-varying variance-covariance matrices was retained as providing a better fit to the data. These results showed that although elevated levels of anxiety may fluctuate over time, they clearly do not represent a transient phenomenon. This model was then validated in relation to multiple predictors (mostly related to school violence) and outcomes (GPA, school dropout, depression, loneliness and drug-related problems).

KEYWORDS: anxiety, adolescence, growth mixture analysis, latent class growth analysis, invariance.

General Growth Mixture Analysis of Adolescents' Developmental Trajectories of Anxiety:

The Impact of Untested Invariance Assumptions on Substantive Interpretations

Complex substantive issues often require sophisticated methodologies—this is the essence of substantive-methodological synergies (Marsh & Hau, 2007). Substantively, this study investigates heterogeneity in the developmental trajectories of anxiety in adolescence and evaluates the construct validity of the extracted latent trajectory classes in relation to predictors and outcomes. Methodologically, this study shows the usefulness of General Growth Mixture Analysis (GGMA) (Muthén, 2002; Muthén & Asparouhov, 2009; Muthén & Shedden, 1999) in addressing these issues and illustrates the effects of untested invariance assumptions on substantive interpretations.

Substantive Issues: The Development of Anxiety in Adolescence

Secondary school[1] years are a critical developmental period for adolescents. During this period, they evolve in a changing social context while simultaneously coping with puberty. This results in major transformations in how they perceive themselves and interact with others (Eccles et al., 1993; Steinberg & Morris, 2001). Today, there is ample evidence that secondary school years are marked by transformations that can be stressful and anxiety-generating for adolescents (Roeser, Eccles, & Sameroff, 2000). Indeed, anxiety disorders appear to be one of the most prevalent forms of psychopathology in adolescence (Costello, Egger, & Angold, 2005; van Oort, Greaves-Lord, Verhulst, Ormel & Huizink, 2009). Furthermore, the diagnostic system underpinning most epidemiological studies provide little information regarding symptoms that do not meet diagnostic criteria, but are still associated with functional impairments (Hale, Raaijmakers, Muris, van Hoof, & Meeus, 2008; van Oort et al., 2009). Ultimately, anxiety, especially when it first appears in childhood or adolescence, tends to be associated with increased risks for future problems such as depression, drug abuse, loneliness, low educational achievement, and dropout (Costello et al., 2005; Duchesne, Vitaro, Larose, & Tremblay, 2008; Essau, Conradt, & Peterman, 2002; Woodward & Fergusson 2001).

Understanding the development of anxiety in community samples of youths is thus central to the comprehension of adolescent development and to the design of prevention or mental health promotion programs intended to facilitate the transition to adulthood (e.g. Feng, Shaw, & Silk, 2008; van Oort et al., 2009). However, before investing in programs targeting adolescents at risk for anxiety, it must first be determined whether anxiety is a stable state that hinders normative development or a transient "normative" phenomenon that disappears on its own following the successful negotiation of developmental tasks, as suggested by Hall's (1904) Storm and Stress theory of adolescence. In other words, should we directly target anxiety or should we simply help youths successfully negotiate developmental tasks, while tolerating "normative" anxiety? Research results are unclear and vary across studies. Indeed, while they show that previous levels of anxiety predict later levels of anxiety, the observed relationships and rates of recurrence or chronicity remain low (e.g. Bosquet & Egeland, 2006; Essau et al., 2002; Hankin, 2008; Keller et al., 1992; Last, Hansen, & Franco, 1997). The possibility that the stability of anxiety could vary in specific subgroups may reconcile these results.

A promising way of addressing these questions is to search for heterogeneity in the trajectories of anxiety in adolescence. This search generally requires more than two repeated assessments of the same individuals and allows the investigation of the shape and intra-individual stability of these trajectories, as well as of the inter-individual variability around the estimated average trajectories. A recent literature review conducted within several databases (Current Contents, Medline, Psychology and Behavioral Science Collection, PsychINFO) revealed only four studies, based on two community samples, that investigated the trajectories of anxiety in adolescence (Crocetti, Klimstra, Keijsers, Hale, & Meeus, 2009; Hale et al., 2008, 2009; van Oort et al., 2009). Three of these did so relying on latent curve modeling (LCM; Bollen & Curran, 2006). LCMs allow only the estimation of the average trajectory of all individuals, as well as for inter-individual variability around this trajectory.

In a longitudinal study of two cohorts of 913 early (10–15 years old) and 379 middle (16–18 years old) adolescents measured five times over five-years, Hale et al. (2008, 2009) found that levels of generalized anxiety tended to decrease (i.e. negative slope) in early and middle adolescent boys, but to increase (i.e. positive slope) in early adolescent girls. For the other types of anxiety disorders (panic disorder, school anxiety, social phobia), gender differences were still present but not as marked, with girls' and boys' symptoms showing decreasing tendencies over time. Moreover, their results show that girls presented generally higher levels of anxiety than boys. These findings confirm those from previous studies showing that gender is an important factor to consider in studies of anxiety in adolescence (e.g. Costello et al., 2005). In a similar study, van Oort et al. (2009) measured anxiety symptoms three times (biennially) over a five-year period in a sample of 1653 early adolescents (10–12 years old). Their results show that anxiety tends to follow a curvilinear trend across adolescence, presenting an initial decrease followed by a slight increase. They also showed that girls presented higher levels of anxiety than boys, but that this difference remained constant throughout adolescence.

These studies revealed significant variations between gender groups, as well as significant inter-individual heterogeneity/variability around the estimated trajectories. Although some predictors were included in attempts to explain part of this variability, the possibility remains that unobserved subpopulations (e.g. subgroups of students with increasing, unstable or persistently low levels of anxiety) were present and responsible for the observed heterogeneity. General Growth Mixture Analysis (GGMA: Muthén, 2002; Muthén & Asparouhov, 2009; Muthén & Shedden, 1999)—a combination of LCMs and latent class/latent profile analyses—was designed to explain developmental heterogeneity by separating a general population into latent classes of individuals presenting qualitatively and quantitatively distinct profiles of change over time (Li, Duncan, Duncan, & Acock, 2001; Muthén, 2002). Although GMMA would be particularly helpful in studying the stability and shape of anxiety trajectories in adolescence, only one study did so using Hale et al.'s (2008, 2009) data set described earlier. In this study, Crocetti et al. (2009) reported the presence of two latent trajectory classes. One was characterized by initially low levels of anxiety that decreased over time (91.3% of the sample, half of which were boys) and another small one was characterized by initially high levels of anxiety that increased over time (8.7% of the sample, less than a third of which were boys). Given the methodological challenges of GGMA, which will be addressed later, and the few studies that investigated anxiety trajectories in community samples of adolescents, generalization of these results is limited. Moreover, three studies were located in which restricted GGMA-like analyses were conducted in samples of children, and these studies converged on three (Côté, Tremblay, Nagin, Zoccolillo, & Vitaro, 2002; Côté et al., 2009) or four (Feng, Shaw, & Silk, 2008) class solutions, reinforcing the need for replication.

In addition, as mentioned by van Oort et al. (2009), none of these studies investigated the role of psychosocial risk factors other than socio-demographic characteristics on anxiety trajectories. This is surprising since the only way to support a substantive interpretation of latent trajectory classes as reflecting significant subgroups of students is to embark on a process of construct validation (Bauer & Curran, 2004; Marsh, Lüdtke, Trautwein, & Morin, 2009; Morin, Morizot, Boudrias, & Madore, in press; Muthén, 2003). In GGMA, investigating the construct validity of latent trajectory classes involves showing that they present meaningful and distinct patterns of associations with theoretically significant covariates (antecedents and outcomes) not directly used in the classification algorithm. In the present study, the construct validity of the latent trajectory classes will be investigated in relation to outcomes known to be associated with anxiety (see earlier presentation: depression, loneliness, drug-related problems, educational achievement, school dropout) and to exposure to school violence.

School Violence as a Predictor of Anxiety in Adolescence

Among the various facets of school experiences, exposure to violence may play, through its stressfulness and potential to interrupt unfinished developmental tasks, an important role in the development of anxiety (Card, Stucky, Sawalani, & Little, 2008; Grills & Ollendick, 2002; Hawker, & Boulton, 2000; Janosz et al., 2008). Violence is a growing and significant problem in schools around the world with serious implications for students' mental health and well-being (Due, Holstein, et al., 2005; Nansel et al., 2004; Smith, Morita, Junger-Tas, Olweus, Catalano, & Slee, 1999). School violence is a complex phenomenon that encompasses generic feelings of school safety, as well as direct or indirect exposure to "any verbal, physical, psychological or visual manifestation intended to directly or indirectly threaten, harm or control the physical or psychological integrity, rights or property of others within the school setting" (Janosz et al., 2008, p. 602). Exposure to school violence is an unsettling and stressful experience for youths who may as a result become psychologically distressed, anxious and hyper-vigilant (Gladstone, Parker, & Malhi, 2006; Grills & Ollendick, 2002).

Unfortunately, few studies investigated the relationships between school violence and anxiety (e.g. Card et al., 2008; Gladstone, Parker, & Malhi, 2006; Grills & Ollendick, 2002; Hawker & Boulton, 2000), and even fewer did so longitudinally (e.g. Janosz et al., 2008; Kennedy, Bybee, Sullivan, & Greeson, 2009; Mrug & Windle, 2010). Thus, although the associations observed between direct (aggression, victimization) and indirect (witnessing) exposure to school violence were moderate, most results are cross-sectional and fail to consider the full complexity of school violence as well as the developmental trajectories of exposed youths. Results from the few longitudinal studies

(Janosz et al., 2008; Kennedy et al., 2009; Mrug & Windle, 2010) showed that, although being a victim of school violence was the strongest predictor of internalizing problems, witnessing school violence as well as generic feelings of insecurity in school significantly added to the prediction. Although some results suggest that students from different backgrounds present different levels of sensitivity to the effects of school violence (Kennedy et al., 2009; Mrug & Windle, 2010), it remains unknown how exposure to school violence may modify the shape of adolescents' anxiety trajectories.

Methodological Issues: The Impact of Untested Invariance Assumptions in GGMA

GGMA is part of the generalized latent variable modeling framework proposed by Muthén (2002; also see Muthén & Asparouhov, 2009; Skrondal & Rabe-Hesketh, 2004). More specifically, GGMA extends LCMs using a categorical latent variable "to represent a mixture of subpopulations where population membership is not known but must be inferred from the data" (Li et al., 2001, p. 494). Assume a quadratic growth model for the outcome y_{it} where *i* is the index for individual and *t* is the index for time. To this model, add *c*, a categorical latent variable with *k* levels (k = 1, 2, …, K) that is estimated from the data, with each individual *i* having a probability of membership in each of the *k* levels.

$$y_{it} = \sum_{k=1}^{K} p(c=k)[\alpha_{iyk} + \beta_{1iyk}\lambda_t + \beta_{2iyk}\lambda^2{}_t + \varepsilon_{yitk}] \quad (1)$$

$$\alpha_{iyk} = \mu_{\alpha yk} + \zeta_{\alpha yik} \quad (2)$$

$$\beta_{1iyk} = \mu_{\beta 1yk} + \zeta_{\beta 1yik} \quad (3)$$

$$\beta_{2iyk} = \mu_{\beta 2yk} + \zeta_{\beta 2yik} \quad (4)$$

The *k* subscript indicates that most parameters are allowed to vary between the estimated latent trajectory classes and that each latent trajectory class could thus be defined by its own latent curve model based on independent covariance matrices and mean vectors. More precisely, α_{iyk}, β_{1iyk} and β_{2iyk} respectively represent the random intercept, random linear slope and random quadratic slope of the trajectory for individual *i* in latent trajectory class *k*; ε_{yitk} represents the time- individual- and class-specific errors; $\mu_{\alpha yk}$, $\mu_{\beta 1yk}$ and $\mu_{\beta 2yk}$ represent the average intercept, linear slope and quadratic slope in latent trajectory class *k*; and $\zeta_{\alpha yik}$, $\zeta_{\beta 1yik}$ and $\zeta_{\beta 2yik}$ are disturbances reflecting the variability of the estimated intercepts and slopes across cases within latent trajectory classes. These disturbances have a mean of zero and a variance-covariance matrix represented by Φ_{yk} :

$$\Phi_{yk} = \begin{bmatrix} \psi_{\alpha\alpha yk} & & \\ \psi_{\alpha\beta 1 yk} & \psi_{\beta 1\beta 1 yk} & \\ \psi_{\alpha\beta 2 yk} & \psi_{\beta 1\beta 2 yk} & \psi_{\beta 2\beta 2 yk} \end{bmatrix} \tag{5}$$

Errors (ε_{yitk}) are generally assumed to have a mean of 0 and to be uncorrelated over time, across cases or with the other model parameters. Most models assume that all cases have the same error variance for each time period but allow these errors to vary across periods. Time is indicated by λ_t, which represents the loadings of the time-specific measurement points on the slope factor and is coded to reflect the intervals between measurement points. For instance, in a model including five measurement points equally spaced, it might be appropriate to estimate the intercepts of linear trajectories at Time 1 [$E(\alpha_{iyk}) = \mu_{y1k}$], such that λ_t is coded $\lambda_1 = 0$, $\lambda_2 = 1$, $\lambda_3 = 2$, $\lambda_4 = 3$ and $\lambda_5 = 4$ (see Biesanz, Deeb-Sossa, Papadakis, Bollen, & Curran, 2004). As the latent classes are unknown but estimated from the data, GGMA estimates a probability of membership in each latent trajectory class for all individuals, which is reflected in the first part of the equation $\sum_{k=1}^{K} p(c = k)$. These probabilities add up to one for each individual across all classes and unconditionally over all classes. Finally, these models allow the inclusion of predictors of class membership. The predictors may also predict the intercept, slopes, time-specific indicators and distal outcomes, and these relationships may be freely estimated in each latent trajectory class. As these additional equations are not directly relevant to the methodological issue pursued here, they will not be presented (but see Muthén, 2002, 2004).

In this generic specification of GGMA, the *k* subscript indicates that most parameters may be allowed to vary across latent trajectory classes (time codes are usually fixed and constrained to equality over groups, although only two of them need to be fixed to 0 and 1 respectively, while the remaining ones can be freely estimated; see Ram & Grim, 2007, 2009). However, in practice, fully variant GGMAs are seldom estimated, due in part to frequent estimation and convergence problems, as well as to the popularity of simpler, restricted parameterizations. Perhaps the most widely known restricted parameterization of such models comes from Nagin’s (1999, 2010) group-based latent class growth analysis (LCGA) in which the variances of the latent growth factors (intercept and slopes) are constrained to zero, thus eliminating the latent variance-covariance matrix out of the model (Φ_{yk} = 0). In this sense, LCGA is essentially a restricted form of GGMA in which all members of a latent trajectory class are assumed to follow the same trajectory. Nagin (2010, p.61) describes LCGA as an approximation of the distribution "by a finite number of trajectory groups" representing the "point of support" of the distribution. Nagin (2010, p. 64) compares LCGA with LCMs by saying that LCGA "focuses on the identification of different trajectory shapes and on examining how the prevalence of the shape and shape itself relates to predictors. By contrast, standard growth curve modeling focuses on the population mean trajectory and how individual variation about that mean relates to predictors." GGMA allows the examination of both types of questions since it allows for the estimation of latent trajectory classes marked by different average shapes, while including within-class variability.

LCGAs are arguably the most widely used form of GGMA and were used in the three preceding studies of children's anxiety trajectories (Côté et al., 2002, 2009; Feng et al., 2008). The reliance on LCGAs, even more than the age difference, could explain the different results obtained in these studies compared with Crocetti et al.'s (2009) study of adolescents. LCGAs have been previously shown to potentially result in the over-extraction of latent trajectory classes (e.g. Bauer & Curran, 2004; Muthén & Muthén, 2000). With one exception (Muthén et al., 2002) in which it was noted that relying on class-varying covariance matrices could make a substantive difference, the few illustrations of this effect to date show that LCGAs yield more classes, some of which differ only quantitatively and are combined when GGMAs are applied to the same data (e.g. Muthén & Muthén, 2000). However, Crocetti et al. (2009) also relied on a restricted form of GGMA based on the defaults of the Mplus software (Muthén & Muthén, 2008). These defaults specify the $\mu_{\alpha yk}$, $\mu_{\beta 1 yk}$ and $\mu_{\beta 2 yk}$ parameters as freely estimated in all classes but constrain the latent variance-covariance parameters as well as the time-specific residuals to equality across classes ($\Phi_{yk} = \Phi_{y}$ and $\varepsilon_{yitk} = \varepsilon_{yit}$). Although these restrictions are common, simulation studies have shown that similar restrictions could result in the over-extraction of latent classes and biased parameter estimates in the context of GGMA and mixture models more generally (Bauer & Curran, 2004; Enders & Tofighi, 2008; Lubke & Muthén, 2007; Lubke & Neale, 2006, 2008; Magidson & Vermunt, 2004).

Unfortunately, the adequacy of these restricted parameterizations is seldom verified. At least in the research reviewed here, none of the authors justified the restricted parameterization they relied on, nor did they empirically test these restrictions in relation to the fit of the model. This is important, as these restrictions may substantively change the results. It is also worrisome, since these comparisons are simple to execute on the basis of the various information criteria routinely used to compare the fit of alternative models with varying numbers of latent classes. In addition, although classical likelihood ratio tests cannot be used to compare models with different numbers of classes, they can be used to compare models with the same number of classes but different specifications to complement the information criteria comparisons (Bauer & Curran, 2004; Eid, Langeheine, & Diener, 2003; Li et al., 2001; Petras & Masyn, 2010). We argue that these restrictions are testable invariance assumptions (Eid et al., 2003; Meredith, 1993) rather than distinct models designed to answer different questions.

Methodologically, this study is designed to illustrate the effects of relying on such untested invariance assumptions on substantive interpretations. Apparently, many applied researchers fail to verify the adequacy of these assumptions based on the dubious belief that the resulting “statistical” biases will remain small, or that the unnecessary additional classes will in fact represent only quantitative variations of the “real” classes. When the objective of the research is to come up with a reasonable approximation of reality rather than a picture that is exact to three decimal spaces, as is usually the case in applied psychological or social science, these apparently slight biases may appear tolerable. We will illustrate that failing to verify the adequacy of these invariance assumptions can be far more problematic. It should be noted that although additional misspecifications, such as assuming linear trajectories (Bauer & Curran, 2004; Voelkle, 2008) or class-invariant covariate effects (Petras & Masyn, 2010), were also reported to result in biased estimates, the effects of these misspecifications will not be illustrated here. Indeed, in the first case, preceding results (van Oort et al., 2009) provide ample justification for including curvilinear trends in the models. In the second case, the strategy pursued in this study is specifically designed to illustrate how the invariance of covariate effects can be systematically investigated. However, only the best-fitting model will be interpreted.

The Present Study

This study relies on GGMA to investigate heterogeneity in the developmental trajectories of anxiety in adolescence and illustrates the effects of untested invariance assumptions on substantive interpretations. In addition, the construct validity of the extracted latent trajectory classes will be investigated by verifying their associations with predictors and outcomes.

Method

Participants

The Montreal Adolescent Depression Development Project (MADDP; Morin, Janosz, & Larivée, 2009) is a four-year prospective longitudinal study of over 1000 adolescents evaluated six times over this period. This project was initially designed as a one-year follow-up study, with three measurement points. All seventh-grade students from five Montreal-area secondary schools were asked to participate in the project in September 2000, right after the secondary school transition. Parents of the 1553 eligible participants were informed of the project through a letter accompanied by a consent form describing the first three measurement points: September/October 2000 (Time 1), February 2001 (Time 2; anxiety was not measured at Time 2) and May/June 2001 (Time 3). Only 10 parents refused to let their child participate. The remaining 1543 students were asked to sign a consent form. A total of 1370 agreed to participate (66 refused) and completed Time 1 measures (104 were sick or absent, could not be reached and thus could not consent) and at least one of the remaining two measurement points. Only 3 more were lost due to chronic absenteeism during the first year.

These 1370 participants were then contacted during their second year of secondary school (eighth grade: 2001–2002) to participate in a longer-term follow-up comprising three additional years, with one measurement period per year (Time 4, 5 and 6, with Time 4 being close to one year after Time 3). From those participants, 1034 were included in the longer-term follow-up study: (i) 58 refused to sign the consent form in year 2; (ii) 142 were absent or had changed schools and were impossible to locate during year 2; and (iii) 136 were excluded due to parental refusal. Of those, 1011 were included in the present study. The remaining 23 failed to complete at least three (out of five) valid measurements of anxiety. This sample was predominantly of a French-Canadian Caucasian background (79.07%) and almost equally split across genders (53.71% males). At Time 1, the mean age of the participants was 12.66 years (SD = 0.69). Of these students, 48.86% attended public schools, 30.37% attended private schools, and 20.77% attended a public school for gifted students.

Attrition analyses were conducted to compare the present sample to the 1370 subjects who were part of the year 1 initial follow-up. These analyses revealed that compared with the participants, the lost students were a little older ($t = 2.49$, $df = 1060$, $p \leq .05$) and slightly more likely to come from public schools ($\chi^2 = 21.77$, $df = 2$, $p \leq .01$) and more unstable families ($t = 2.930$, $df = 1365$, $p \leq .01$). They also presented higher levels of behavioral disorders in the year preceding the study ($t = 2.847$, $df = 1274$, $p \leq .01$) and in the first year of the study ($t = 3.508$, $df = 1282$, $p \leq .01$). However, they did not differ in terms of: gender ($\chi^2 = 0.01$, $df = 1$, $p \geq .01$), nationality ($\chi^2 = 11.29$; $df = 9$; $p \geq .01$), anxiety at the beginning ($t = 1.172$, $df = 1367$, $p \geq .01$) or at the end of the first year of the study ($t = 2.124$, $df = 1284$, $p \geq .01$), victimization ($t = 1.477$, $df = 1261$, $p \geq .01$), witnessing school violence ($t = 0.569$, $df = 1273$, $p \geq .01$) or feelings of security ($t = -2.395$, $df = 1268$, $p \geq .01$).

Measures

Demographic variables. We obtained participants' genders (0=Male, 1=Female) and ages from school records. Parents' education levels and an index of family instability were added to the list of predictors to estimate the impact of school violence over students' background characteristics. Parental education levels were assessed through a parental questionnaire, and the mother's and father's education levels were averaged to provide a global indicator. Missing data were imputed with answers from adolescents' reports of their parents' education. Family instability was measured at Time 1 with a five-item index of the instability level of the participants' family life in the year preceding the study (parental separation, remarriage, death, moving) inspired by similar measures by Le Blanc (1996).

Anxiety. Anxiety was assessed with the French adaptation (Freeston, Ladouceur, Thibodeau, Gagnon, & Rhéaume, 1994) of the Beck Anxiety Inventory (Beck & Steer, 1993a) at Times 1, 3, 4, 5 and 6 ($\alpha = .88$ to $.91$). This 21-item questionnaire measures the presence and intensity of anxiety symptoms (e.g. "nervous", "difficulty breathing"), which are rated on a four-point scale (from not at all to severely) according to how much participants were bothered by them during the past week.

School violence. School violence was assessed with multiple indicators. students' *victimization* at school was assessed at Time 2 with a 14-item index ($\alpha = .83$) from the School Socioeducational Environment Questionnaire (SEQ), validated in a sample of more than 70 000 adolescents from 159 secondary schools (Janosz & Bouthillier, 2007). These items are rated on a five-point (from never to four times or more) frequency scale (e.g. "Since the beginning of the school year": "Students physically attacked you," "students insulted or humiliated you"). Students' *witnessing* of school violence was assessed at Time 2 with a 10-item index (α = .83) also taken from the SEQ. Students were asked to indicate on a five-point scale (from never to almost every day), while ignoring rumors: "Since the beginning of the school year, how often have you observed or have you been informed of the following problems at your school?": "threats among students (blackmail, harassment, etc.)," "fights among students (not rough playing)," etc. Students' *feelings of (in)security* at school were evaluated at Time 2 with a five-item scale (α = .80) from the SEQ. Students' agreement with statements such as "there is a risk of being assaulted in this school" and "there are areas in this school where students are afraid to go" was rated on a four-point scale ranging from totally disagree to totally agree. Students' levels of *externalizing behaviors* were assessed with 19 items from Le Blanc's (1996) Measures of Quebec Adolescent' Social and Personal Adjustment, an instrument that was validated on a representative sample of the Quebec adolescent population. Items assessing the frequency of behavioral deviance (e.g. "Used hashish or marijuana," "skipped school") and criminal delinquency, as represented by theft (e.g. "Stole something worth between $10 and $100") and aggressions (e.g. "Carry a weapon"), were retained. These items are retrospective and students were asked how often (on a four-point frequency scale ranging from never to very often) they committed the listed acts during the previous year (Time 1; α = .88) or since the beginning of the school year (Time 3; α = .88).

Developmental outcomes. Adolescents' *GPAs* one year after the end of the study and *school dropout* within one year of the expected graduation date (i.e. generally two years after the end of the study) were obtained from the Quebec Ministry of Education records. Participants' levels of *depression* and *loneliness* were assessed during the last year of the study using, respectively, the 21-item (α = .92) French version (Gauthier, Morin, Thériault, & Lawson, 1982) of the Beck Depression Inventory (Beck & Steer, 1993b) and five items (α = .80) from the French adaptation (Vitaro, Pelletier, Gagnon, Baron, 1995) of the Asher, Hymel and Renshaw (1984) questionnaire. The Beck Depression Inventory includes 21 items rated on a behaviorally anchored rating scale ranging from 0 (absence of symptoms) to 3 to assess symptom severity during the past week including today. The items retained to assess loneliness (e.g. "I feel lonely at school," "I don't have any friends at school") were those with the highest loadings in Asher et al.'s (1984) study and were rated on a four-point scale ranging from not true to very true. The presence of social and personal problems emerging from *drug abuse* was evaluated with nine items (α = .93) developed specifically for the MADDP on the basis of: (i) Zoccolillo, Vitaro and Tremblay's (1999) adaptation of Ewing's (1984) CAGE questionnaire for drug-related problems and (ii) the items used in the Epidemiological Catchment Area Study to assess the social consequences of drug abuse (Robins & Regier, 1991). These items are rated on a combination of yes-no answer scales (e.g. "were you ever drugged at school," "did you ever feel bad or guilty about your drug use") and of behaviorally anchored answer scales (e.g. "In which circumstances do you most often use drugs: never, alone, with friends at school, with friends out of school").

Analyses

In this study, quadratic models with one to seven latent trajectory classes of anxiety were estimated according to three distinct parameterizations[2]: (i) LCGA (Φ_{yk} = 0); (ii) Mplus defaults (GGMA-MD; Φ_{yk} = Φ_{y}); and (iii) a GGMA model with freely estimated latent variance-covariance matrices in all classes (GGMA-LV; Φ_{yk}). In all models, the latent variable means were freely estimated in all classes ($\mu_{\alpha yk}$, $\mu_{\beta 1yk}$, and $\mu_{\beta 2yk}$) and the time-specific errors were constrained to invariance across classes ($\varepsilon_{yitk} = \varepsilon_{yit}$). Models in which all parameters ($\mu_{\alpha yk}$, $\mu_{\beta 1yk}$, $\mu_{\beta 2yk}$, Φ_{yk} , and ε_{yitk}) were freely estimated in all classes were also specified (Enders, & Tofighi, 2008). Unfortunately, these models either did not converge or converged on improper or unacceptable solutions (negative variance estimates, non-positive definite Fisher Information matrix, empty or very small classes, etc.) and on non-replicated log likelihood (even after multiple attempts involving multiple starts, user-defined starts, etc.). This suggests that those models, which may have been overparameterized, are inadequate and that more parsimonious models may be more appropriate (e.g. Henson, Reise, & Kim, 2007; Nylund, Asparouhov, & Muthén, 2007; Tolvanen, 2007). It should be noted that for the GGMA-MD and GGMA-LV models to converge on proper solutions, the variability of the quadratic slope parameter had to be fixed to 0 ($\zeta_{\beta 2yik}$ = 0, thus $\psi_{\beta 2\beta 2yk}$ = 0, $\psi_{\beta 1\beta 2yk}$ = 0, and $\psi_{\alpha\beta 2yk}$ = 0). The growth parameters' variance-covariance also had to be fixed to zero in the lowest class of the GGMA-LV models ($\Phi_{yk=low}$ = 0), which is consistent with the presence of a stable non-anxious latent class. Since anxiety symptoms were assessed five times at one-year intervals, the time codes used in the current study are -1, 0, 1, 2, 3[3]. The decision to estimate the intercept of the latent trajectories at the second measurement point is consistent with the fact that Time 1 was conceptualized as the MADDP baseline control measurement point and most predictors were assessed at Time 2 (thus allowing for temporal ordering of the predictors with the intercept of the predicted trajectories).

The analyses reported in this study were performed using Mplus 5.1 (unconditional models) and Mplus 6 (models with predictors and outcomes) (Muthén & Muthén, 2010). Mplus relies on the robust maximum likelihood estimator (MLR) to estimate GGMA model parameters (Muthén & Shedden, 1999). Full-information MLR was used to account for the remaining missingness on the anxiety indicators (Little & Rubin, 2002). An important challenge in GGMA consists in avoiding converging on a local solution (i.e. false maximum likelihood), a problem that may stem from inadequate start values. It is thus recommended to use multiple random sets of start values (Hipp & Bauer, 2006; McLachlan & Peel, 2000), an issue that was apparently disregarded in the previous LCGA and GGMA studies of anxiety trajectories. In this study, 1000 random sets of start values were requested for each model, with the 100 best retained for final optimization. All models converged on a replicated solution and can confidently be assumed to reflect a “real” maximum likelihood.

Another challenge in GGMA is determining the number of latent classes in the data. One important set of criteria used to guide this decision is related to the substantive meaning and theoretical conformity of the extracted classes (Bauer & Curran, 2003; Marsh, Lüdtke et al., 2009; Muthén, 2003), as well as to the statistical adequacy of the solution (Bauer & Curran, 2003). A number of statistical tests and indices are available to help in this decision process. Recent simulation studies indicate that four of these various tests and indicators are particularly effective in choosing the model which best recovers the sample’s true parameters in GGMA (Nylund et al., 2007; Tofighi & Enders, 2007; Tolvanen, 2007) and other forms of mixture models (Henson et al., 2007; McLachlan & Peel, 2000; Yang, 2006). They are: (i) the Consistent Akaïke Information Criterion (CAIC: Bozdogan, 1987), (ii) the Bayesian Information Criterion (BIC: Schwartz, 1978), (iii) the sample-size Adjusted

BIC (ABIC: Sclove, 1987), and (iv) the Bootstrap Likelihood Ratio Test (BLRT; McLachlan & Peel, 2000. Additional studies indicate that the ABIC and the Akaïke Information Criterion (AIC: Akaïke, 1987) are also effective in comparing models relying on different within-class specification or invariance assumptions (Lubke & Neale, 2006, 2008). In line with these results, these indicators (AIC, CAIC, BIC, ABIC, BLRT) will be reported. A lower value on the AIC, CAIC, BIC and ABIC suggests a better-fitting model. The BLRT is a parametric likelihood ratio test obtained through resampling methods (100 bootstrap samples were drawn for each model) that compares a *k*-class model with a *k-1*-class model. A significant *p* value indicates that the *k-1* class model should be rejected in favor of a *k* class model. As a complement, Petras and Masyn (2010) suggest graphically presenting information criteria through "elbow plots" illustrating the gains associated with the addition of latent classes. In these plots, the point of formation of a first angle indicates the optimal number of classes in the data. Finally, the entropy indicates the precision with which the cases are classified into the various extracted latent classes. Although entropy should not be used to determine the model with the optimal number of classes (Lubke & Muthén, 2007), it provides a summary of classification accuracy. Entropy varies from 0 to 1, with values closer to 1 indicating less classification errors.

Once the final unconditional model was chosen, predictors were incorporated into this model (Clark & Muthén, 2010; Petras & Masyn, 2010). As Mplus does not allow for missing data on exogenous predictors, they were imputed with the EM algorithm from SPSS 15.0 "missing values" (Little & Rubin, 2002). Imputed estimates were conditional on all predictors used in the study. Given the low levels of missing data (0% to 7.22%, M = 3.61%, SD = 3.03%), multiple imputation was not deemed necessary (Graham, 2009). A baseline conditional model was first estimated in which predictors were allowed to predict class membership through a multinomial logistic regression. Then, additional models were tested in which predictors were allowed to influence the trajectory factors one at a time, and in which these effects were progressively allowed to vary across classes. These models were compared on the basis of the information criteria and of Likelihood Ratio Tests (LRT)[4].

Direct inclusion of the predictors in the model is known to result in a more precise estimation of their effects (Bolck et al., 2004; Clark & Muthén, 2010) and in more accurate classifications (Lubke & Muthén, 2007). However, the substantive interpretation of the latent classes should remain qualitatively similar by omission of the predictors and should not change following their inclusion into the model (Marsh, Lüdtke et al., 2009; Morin et al., in press). Observing such changes would indicate that the nature of the latent classes does in fact depend on the choice of the predictors, which is not supposed to happen (Marsh, Lüdtke et al., 2009; also see Anderson & Gerbing, 1988). More precisely, the inclusion of predictors directly in a GGMA model is based on the assumption that the causal ordering is from the predictors to the latent classes, and Marsh, Lüdtke et al. (2009) argue that qualitative changes in the latent classes following the inclusion of predictors may indicate a violation of this assumption. No such changes occurred in the present study after the predictors were included.

Conversely, outcomes were not incorporated directly into the model, since doing so would involve including them as mixture indicators, thus allowing them to influence the nature of the latent classes (Petras & Masyn, 2010). Since as many outcomes as time-specific trajectory indicators were considered and these outcomes were used to validate the profiles rather than define them, we relied on the Mplus *AUXILIARY (e)* function to compare probability-based latent classes on the outcomes. This method allows us to consider the probability that each individual has of being a member of all classes rather than assigning individuals to their most likely class membership, as is commonly done in biased multiple-step procedures (Bolck et al., 2004). The *AUXILIARY (e)* function relies on a Wald chi-square test based on random pseudo-class draws and tests the equality of outcome means across latent classes (see Asparouhov & Muthén, 2007; Wang, Brown, & Bandeen-Roche, 2005).

Results

Unconditional Models

The fit indices for the LCGA, GGMA-MD and GGMA-LV models are reported in Table 1. When the recommended AIC and ABIC from models with similar numbers of classes are compared, the results clearly show that the GGMA-LV parameterization is superior to the more restricted alternatives (the results from unreported LRTs, as well as the CAIC and BIC, also confirm this interpretation). However, the results show that information criteria continue improving when latent classes are added for each of the parameterizations considered separately. This is not surprising given the large sample size and sample size dependency of these indicators. Indeed, for real data based on a large-enough sample size, the information criteria will always choose the most complex and, ultimately, the saturated model, as in the present investigation (Marsh, Hau, & Grayson, 2005; Marsh, Hau & Wen, 2004; Marsh, Lüdtke et al., 2009). Therefore, it has been recommended not to use goodness-of-fit indices according to absolute “golden rules,” but to rely on a theoretically grounded subjective evaluation of models based on parameter estimates, as well as to inspect these parameters for statistical conformity (Bauer & Curran, 2003; Marsh, Lüdtke et al., 2009; Muthén, 2003). Examining the statistical conformity of the models proved helpful and revealed that all models including six or more latent trajectory classes resulted in the extraction of at least one very small class including less than 1% of the students ($n \leq 10$) and parameter estimates that were hard to interpret. This clearly argues against these models and confirms that their apparently better fit may simply be related to the sample size dependency of information criteria (Marsh, Lüdtke et al., 2009). However, all of the remaining models proved substantively interpretable. Thus, without clear a priori assumptions, we followed Petras and Masyn’s (2010) suggestion to rely on elbow plots. As an example, the elbow plot for the GGMA-LV model, which clearly suggests a five-class solution, is reported in Figure 1. The elbow plots for the LCGA and GGMA-MD also converged on a five-class solution. This result is interesting and goes against the common belief that when the fit of restricted models (LCGA or GGMA-MD) is less than the fit of less restricted models (GGMA-LV), they will tend to result in the over-extraction of latent trajectory classes as a way to compensate for unmodeled within-class heterogeneity. The results show that this is not necessarily the case. Rather, retaining a model based on erroneous untested invariance assumptions may result in radically different solutions.

The five-class LCGA, GGMA-MD and GGMA-LV solutions are graphically presented in figures 2a, 2b, and 2c and present important substantive differences. The LCGA results suggest that the majority of students (73.5%) present a trajectory characterized by a persistently very low level of anxiety over the secondary school years. Two additional latent trajectory classes are characterized by consistently moderately elevated (16.7%) and highly elevated (2.3%) levels of anxiety, leading to the conclusion that anxiety (or the absence thereof) is a highly stable phenomenon, at least in 92.5% of the students. The remaining two latent trajectory classes present a time-dependant profile characterized by increasing (2.9%) or decreasing (4.7%) levels of anxiety over the study period.

In contrast, results from the GGMA-MD solution suggest that anxiety symptoms may represent a transient phenomenon among adolescents, including classes of students presenting: (i) initially high and rapidly decreasing levels of anxiety (2.5%); (ii) initially moderate and decreasing anxiety symptoms (14.0%); (iii) initially low anxiety symptoms that rapidly increase near the end of the study (2.7%); and (iv) initially low levels of anxiety that rapidly increase to peak at the midpoint of the study period and decrease back to normal levels at the end (3.9%). The remaining class, once again, comprises a majority of students (76.8%) who present a trajectory characterized by consistently very low levels of anxiety over the secondary school years.

Finally, results from the GGMA-LV solution revealed that anxiety symptoms tend to present a profile that remains mostly steady over time, although high levels of anxiety may also present an elevated level of variability over time. The parameter estimates from this model are reported in Table 2, where variance estimates were converted to standard-deviation equivalents by taking their square roots to ease their interpretation. These results revealed three latent trajectory classes presenting constant levels of anxiety over time and respectively characterized by a complete absence of anxiety (19.9%), a persistently low level of anxiety (39.7%) and a continually high level of anxiety (30.0%). Although these trajectory classes present significant linear and quadratic slopes, these estimates remain low and mostly serve to characterize within-class variability. Finally, the remaining two latent trajectory classes present anxiety levels that remain very high over the course of the study, while also presenting important curvilinear trends. In one of these classes, the anxiety level appears to peak during secondary school years and to reach a lower, yet still elevated, levels of anxiety near the periods of transition located at the beginning and end of the study (4.9%). Conversely, students from the remaining class present anxiety levels that peak near the school transitions and reach lower, yet still elevated, levels of anxiety during the secondary school years (5.4%).

These results provide a very different picture of anxiety in adolescence. It is true that the three solutions graphically present some similarities. For instance, the LCGA and GGMA-LV models show that anxiety is generally not a transient phenomenon, although in the LCGA, two small classes present only temporarily elevated levels of anxiety. Similarly, the GGMA-MD model also presents similarities with both the LCGA (classes 2 and 4) and the GGMA-LV (class 3) models. However, the GGMA-LV model also presents some specificity that goes beyond the previous descriptions. For instance, the

GGMA-LV model reveals that what both the LCGA and GGMA-MD models described as a single latent trajectory class presenting persistently low levels of anxiety and including over 75% of the students could be better represented as two distinct latent trajectory classes: one including students who never showed any sign of anxiety and another including students who constantly present very low levels of anxiety. These two classes include close to 60% of the sample, which is less than the 75% estimate from the LCGA and GGMA-MD models. Similarly, the GGMA-LV model reveals that almost a third of the study participants present persistently moderate levels of anxiety over the study period, showing that anxiety symptoms are indeed highly prevalent and do not represent a transient phenomenon. The two remaining classes form mirror images of each other, and each include about 5% of the students. In both of these classes, anxiety levels remain high over the course of the study and apparently show a great deal of reactivity to unmeasured external events: secondary school years in one case and school transitions in the other case. These two classes will hereafter be referred to as showing school-related and transition-related anxiety. Overall, in the GGMA-LV model, 40% of the students present elevated levels of anxiety over the secondary school years, contrasting with the 25% estimate from the LCGA and GGMA-MD models. Similarly, perhaps the most significant difference between the LCGA/GGMA-MD and the GGMA-LV is related to the more-even distribution of students in the latent classes. If meaningfully associated with covariates, this more-even distribution would allow the design of interventions targeting more substantial segments of the population. This is interesting given the high cost of programs aimed at highly specific segments of the population.

As previously indicated, all of the available information supports the superiority of the GGMA-LV model, which was retained as the final unconditional model in the present study. Detailed results from the other models were presented only to illustrate the impact of relying on untested invariance assumptions and should not be interpreted as showing the instability of GGMA solutions. Indeed, all of the models tested here proved statistically stable and converged on properly replicated solutions. It should be noted that if the three- or four-class models had been retained instead of the five-class model, the substantive differences between the three parameterizations would have been similar.

Predictors of the Latent Trajectory Classes

The preceding results showed that the GGMA-LV presented a better fit to the data and an apparently more elegant solution than the more restricted LCGA and GGMA-MD. However, the only way to ensure that the extracted latent classes reflect significant subgroups of students is to evaluate their construct validity in relation to theoretically meaningful covariates (Bauer & Curran, 2004; Marsh, Lüdtke et al., 2009; Morin et al., in press; Muthén, 2003). To this end, the school-violence indicators measured during the first year of the study and demographic background controls were added as predictors to the final five-class GGMA-LV model. The results from these analyses are reported at the bottom of Table 1. The appropriateness of these variables as predictors is confirmed by the fact that their inclusion did not result in any form of qualitative modification to the GGMA-LV trajectories (Marsh, Lüdtke et al., 2009; Morin et al., in press). First, the predictors were allowed to predict latent class membership. The next step was to investigate whether the predictors had effects on the latent trajectories remaining unexplained by their effects on class membership. This was done by estimating additional models in which the predictors were allowed to influence the latent trajectory factors and in which these effects were progressively allowed to vary across classes. The results show that allowing the predictors to influence the trajectories' intercepts significantly improved the fit of the model (LRT = -34.530, $df = 8$, $p \leq .01$), whereas allowing them to also influence the trajectories' linear (LRT = -1.321, $df = 8$, $p \geq .05$) and linear + quadratic (LRT = -14.288, $df = 16$, $p \geq .05$) slopes did not. Finally, the results show that allowing the effects of the predictors on the trajectories' intercepts to vary across latent classes did not improve the fit of the model (LRT = -20.163, $df = 32$, $p \geq .05$)[5].

The results from these predictions are reported in Table 3, and the mean levels of the various continuous predictors within each latent trajectory class are illustrated in Figure 3. The results show that most of the predictors present meaningfully differentiated patterns of associations with the latent trajectory classes, except for family demographic characteristics. It should be noted that, although this effect is non-significant, Figure 3 shows that the transition-related-anxiety class presents a slightly higher level of family instability before the start of the study. Conversely, gender appears to represent an important predictor of class membership (and of the trajectories' intercepts). Therefore, gender allows a clear differentiation between all classes: girls make up 27.0% of class 1 (non-anxious), 77.2% of class 2 (school-related), 56.3% of class 3 (high), 54.0% of class 4 (transition-related) and 45.6% of class 5 (low). Indeed, gender allows for a clear distinction between both low classes, with the non-anxious class presenting a significantly lower proportion of girls, which suggests that most girls will present at least some level of anxiety during adolescence. Furthermore, the latent trajectory class including the highest proportion of females is the school-related-anxiety class, which suggests that girls may be particularly sensitive to the anxiety-generating factors that might be present in secondary schools. Although gender is the sole predictor allowing a direct differentiation between both low classes (low versus non-anxious) and between both of the high and varying classes (school-related and transition-related), this differentiation was highly significant. In addition, both low classes and both high and varying classes can also be differentiated from each other by the fact that they do not differ in the same manner from the remaining classes, which confirms their meaningfulness.

The facets of school violence that were measured in the present study also present a meaningful pattern of associations with the latent trajectory classes. Interestingly, students' levels of externalizing behaviors in the year prior to the start of the study (measured at Time 1) predict only the intercepts of the latent trajectories as well as membership in the transition-related-anxiety class in comparison with the low class. Conversely, students' levels of externalizing behaviors during the first year of the study (measured at Time 3) predict membership in the school-related-anxiety class versus the low, high and non-anxious classes. Students' feelings of security at school show a similar pattern of associations with class membership. These results regarding the school-related-anxiety class suggest that aggressive and insecure youths are particularly likely to experience elevated levels of anxiety during the secondary school years. In addition, the results show that their insecurity may be related to victimization, which reliably distinguish the anxious classes (high, school-related, transition-related) from the low-anxiety classes (low and non-anxious). Finally, students' feelings of security at school, as well as potentially associated experiences of witnessing school violence (which also predicts the intercepts), differentiate the transition-related-anxiety class from the low class. These results suggest that the transition-related-anxiety class may be characterized by initially aggressive youths who, upon entering secondary school, were exposed to high levels of school violence (as witnesses and victims) while becoming less aggressive, possibly as a way to avoid anxiety-generating violent situations.

Outcomes of the Latent Trajectory Classes

The relationships between the outcomes and the five latent trajectory classes are reported at the top of Table 4. These results confirm the meaningfulness of the extracted solution. The results show that students' GPAs at the end of the study are significantly lower in the non-anxious class than in the high and low classes. Likewise, the results show that the lowest rates of loneliness are observed in students from the non-anxious class, who present significantly lower levels than those from both the high and transition-related-anxiety classes. Interestingly, these results can be partly explained by the greater proportion of boys in the non-anxious class, since girls are known to generally present higher levels of academic achievement (e.g. Freudenthaler, Spinath, & Neubauer, 2008) and sensitivity to social isolation and interpersonal problems (e.g. Cross & Madson, 1997; Feingold, 1994). However, gender cannot be taken as the sole explanation for these results, since the GPA and loneliness levels observed in the school-related-anxiety class, which mostly includes girls, do not significantly differ from the levels observed in the other classes. This suggests that high levels of anxiety may partly offset the benefits of being female regarding GPA and dampen girls' needs for social integration.

Students from the transition-related-anxiety class present the lowest GPAs of all at the end of the study and this level is significantly lower than in both the high and low classes. Similarly, students from the school- and transition-related anxiety classes present the highest school dropout rates, which are significantly higher than those observed in both the high and low classes. Students from the school-related-anxiety class also present the highest levels of drug-related problems, although they differ significantly only from the low-anxiety class on this outcome. Finally, depression levels differed in most of the latent trajectory classes in a manner that parallels their anxiety levels, confirming the known comorbidity between depression and anxiety (Angold, Costello, & Erkanli, 1999). More precisely, both the school- and transition-related anxiety classes present the highest levels of depression, followed by the high class, then the low class, and finally the non-anxious class.

These results show that for both the school-related and transition-related anxiety classes, something is not going well during the secondary school years. For the transition-related-anxiety class, the life transitions appear particularly stressful, and the results suggest that this may be due to the fact that, for members of this class, the end of the secondary school is marked by academic problems, depression and loneliness. For many of these students (36.5%), we know that the next transition will be marked by dropping out of school, which may represent a highly stressful experience. For the school-related-anxiety class, the results are similar but reveal higher levels of drug-related problems near the end of the study, corresponding to the point where their anxiety levels are decreasing. This observation suggests that members of this class may be abusing drugs as a way to treat their anxiety (e.g. Comeau, Stewart, & Loba, 2001). The dulling effects of drugs may also explain why members of this class present lower GPA and felt lonelier than may be expected on the basis of their gender.

Associations between Latent Trajectory Classes and Covariate Trajectories

Since at least two of the latent trajectory classes present anxiety levels that are marked by important changes over time, a final post-hoc verification of the construct validity of the solution was conducted by testing the associations between the extracted latent classes and the developmental trajectories of the covariates (i.e. predictors and outcomes) used in the present study. Once again, the covariates were not directly integrated in the GGMA-LV model due to their large number. To do so would have meant either incorporating the covariates' trajectories as mixture indicators or treating the covariates as time-varying covariates with class-specific effects. Both options would likely have resulted in entirely different latent trajectory classes. Instead, we estimated traditional LCMs on each covariate (with full-information MLR estimation) and saved the intercept, linear slope and quadratic slope factors from these models. The latent trajectory classes of anxiety from the final GGMA-LV model were then contrasted on these factor scores with the Mplus *AUXILIARY (e)* function. For most covariates measures were available at least once a year, allowing the estimation of quadratic trajectories. However, measures of depression and drug-related problems were available only between the second and last years of the study, resulting in the estimation of linear trajectories with intercepts fixed at the fourth time point (year 2). Trajectories were not estimated for background controls, which were either time-invariant (gender) or measured only at the beginning of the study (parents' education, family instability), or for the school dropout measure, which was taken only at the end of the study.

The results from these additional analyses show that the latent trajectory classes of anxiety present meaningful patterns of associations with the covariates' trajectories, as reported at the bottom of Table 4. For four of the covariates (i.e. witnessing school violence, GPA, loneliness, and drug-related problems), the differences were significant only on the intercepts of the covariates' trajectories. This suggests that the latent anxiety classes already differed on these covariates at the start of the study and that these differences remained mostly stable over the course of the study. The current results nicely complement those from the predictors' analyses by showing that, although witnessing school violence predicted membership only in the transition-related versus the low-anxiety classes, most latent classes present levels of exposure to this variable that differ in a manner directly related to their level of anxiety. This is consistent with the previously identified direct effect of school-violence witnessing on the intercepts of the anxiety trajectories. The results also suggest that the differences between the latent classes in GPA, loneliness and drug-related problems may have been more pronounced at the start of the study than they were at the end. However, the differences remain consistent with the previously reported results and show that students from the school-related and transition-related anxiety classes already presented lower levels of GPA and higher levels of loneliness and drug-related problems at the start of the study. The remaining three latent classes (non-anxious, low and high) differ from one another in a manner consistent with previous results, although they all present a more adapted profile than the school-related-anxiety and transition-related-anxiety classes.

Finally, at least some differences between the latent trajectory classes of anxiety were found on the linear and/or quadratic slope factors of the trajectories of the remaining four covariates, in addition to multiple intercept differences mostly confirming previous results. To facilitate the interpretation of these differences, the trajectories of these covariates within each of the five latent trajectory classes of anxiety are graphically presented in Figure 4. The differences observed on the intercept factor of the covariates' trajectories show that the non-anxious and low-anxiety classes present the most adaptive level on these covariates, that the school-related and transition-related anxiety classes present the least adaptive level, and that the high-anxiety class presents an intermediate profile on these covariates. These differences in these intercepts closely replicate the results from the preceding analyses and will not be discussed further. Regarding students' feelings of security, the results show that members of the school-related-anxiety class show more pronounced increases over time than those from the transition-related-anxiety class, who themselves present a more pronounced U-shape trend over time than members of the low-anxiety class. The results for externalizing behaviors are even more interesting in that they show that students from the school-related-anxiety class present the steepest increases over the course of the study, with significantly higher linear slopes than students from the non-anxious, high and transition-related-anxiety classes. In addition, the quadratic slope factor of the externalizing behaviors' trajectories significantly differs between the school-related and transition-related anxiety classes in a manner that parallels their trajectories of anxiety, with an inverted U-shape trend in the school-related-anxiety class and a U-shape trend in the transition-related-anxiety class.

Finally, the results show that the slope factors of the depression and victimization trajectories also differ significantly among many of the latent trajectory classes, becoming more pronounced as initial levels of victimization and depression increase. More precisely, the higher the initial level of depression and victimization, the more pronounced its decrease over time. In addition, victimization trajectories showed a more pronounced quadratic trend in the transition-related-anxiety class (the decrease over time in victimization flattens out at the end of the study) than in the non-anxious class.

Discussion

This study is a substantive-methodological synergy aimed at verifying the developmental heterogeneity in the trajectories of anxiety in adolescence, while illustrating the usefulness of GGMA in addressing these issues and providing a practical illustration of the effects of untested invariance assumptions on substantive interpretations. In addition, the construct validity of the extracted latent trajectory classes was investigated by testing their associations with predictors and outcomes.

Methodological Implications: The Substantive Impact of Untested Invariance Assumptions

Methodologically, this study provides an illustration of the impact on substantive interpretations of relying on untested invariance assumptions in GGMA. The results from the GGMA-LV models were compared to the results from LCGA and GGMA-MD models, which are currently the most widely used GGMA parameterizations. Perhaps not surprisingly, the GGMA-LV models provided a better fit to the data than the more restricted models, suggesting that the implicit invariance assumptions of those restricted models were not adequate, or at least not empirically optimal, in the present study. However, the observation that the three types of models converged on five-class solutions is surprising and goes against the common belief that when more restricted models fit less than less restricted models, they will tend to result in the over-extraction of latent trajectory classes as a way to compensate for unmodeled within-class heterogeneity. The results show that this is not necessarily the case and that retaining a model based on erroneous untested invariance assumptions may rather result in radically different substantive solutions.

Results for the LCGA model suggested that the majority of students (73.5%) presented a persistently low level of anxiety and that two additional latent trajectory classes also presented anxiety levels (low and high) that remained constant over time. This suggests that anxiety (or the absence thereof) is a highly stable phenomenon for 92.5% of the students. In contrast, the GGMA-MD solution suggested that when anxiety symptoms are present, they represent a transient phenomenon, as illustrated by four small classes of students presenting changing levels of anxiety. Yet, this solution also showed the presence of a latent trajectory class comprising a majority of students (76.8%) presenting very low and constant levels of anxiety. The retained GGMA-LV solution provides a different picture on many levels. First, the observed variability in students' developmental trajectories seem to be more evenly partitioned into the latent trajectories classes: whereas the LCGA and GGMA-MD solutions resulted in the extraction of one very large latent class and four very small latent classes, the GGMA-LV resulted in a more even distribution of participants across latent classes. Second, the results revealed that what was previously aggregated into a single latent trajectory class of students presenting persistently low levels of anxiety could in fact be separated into two latent trajectory classes that could be meaningfully distinguished on the basis of some of the covariates (gender, depression, loneliness and GPA) used in this study. One includes students (19.9%) who never showed any sign of anxiety while the other (39.7%) included students presenting some anxiety symptoms, albeit at very low levels, over the course of the study. These two classes include close to 60% of the sample, which is lower than the 75% suggested by the restricted models. Finally, the GGMA-LV solution revealed that three latent trajectory classes of students present anxiety levels that remain persistently high over the course of the study, in stark contrast with at least the GGMA-MD results, which mostly depicted anxiety as transient. Although two classes presented highly changing levels of anxiety, they remain in the high range over all measurement periods.

These results cast serious doubts on the results from previous studies of anxiety trajectories conducted in child and adolescent populations, which relied on restricted GGMA parameterizations without verifying the validity of these restrictions and implicit invariance assumptions (Côté et al., 2002, 2009; Crocetti et al., 2009; Feng et al., 2008). The fact that these studies did not address, at least not explicitly, the issue of random starts and the risk of converging on a local maximum (Hipp & Bauer, 2006) exacerbates these problems. This may explain the divergence of results obtained between these studies and the present one. But as LCGA and GGMA-MD are the most widely used parameterizations of GGMA models, the present results also have wider generalizability. Indeed, the adequacy of these restrictions is unfortunately seldom tested in applied research. This lack of verification often stems from the impression that the resulting “statistical” biases will remain substantively meaningless, or that the additional classes will represent only quantitative variations of the “real” classes and still provide a reasonable approximation of reality. Our results rather show that these restricted parameterizations can result in radically different substantive solutions. Thus, we argue that these restrictions should be considered as testable invariance assumptions (e.g. Eid et al., 2003; Meredith, 1993) rather than as distinct models designed to answer different questions. We thus invite researchers—as well as reviewers—to seriously question the use of these restricted parameterizations when the adequacy of their underlying invariance assumptions is not explicitly addressed in the paper.

Substantive Implications: The Developmental Trajectories of Anxiety in Adolescence

Hall’s (1904) classical Storm and Stress conception characterized adolescence as a period of inevitable, but transient, turmoil. The present study is clearly not the first to disconfirm this vision of adolescence (Arnett, 1999; Steinberg & Morris, 2001), and shows that a majority of youths possess the necessary resources to face the developmental challenges of adolescence without developing alarming levels of anxiety. Furthermore, the results show that, when elevated levels of anxiety are present, as is apparently the case for close to 40% of adolescents, they clearly do not represent a transient phenomenon. This finding is supported by the fact that the observed elevated trajectories remained persistently high over the course of the study and were associated with significantly worse developmental outcomes (lower GPA, school dropout, depression, loneliness and drug-related problems). Conversely, few students (approximately 20%) go through adolescence without ever presenting any signs of anxiety. The remaining youths (close to 40%) present at least some signs of anxiety over the course of the secondary school years, albeit at very low levels. Could these youths, marked by few developmental problems but still continuously slightly anxious, correspond to what the Storm and Stress theory characterized as the normative turmoil of adolescence? Interestingly, the present results parallel those from previous typological descriptions of behavioral problems in childhood and adolescence (Kamphaus, Huberty, DeStefano, & Petowskey, 1997; Kamphaus, Petowskey, Cody, Rowe, & Huberty, 1999; Morizot & Tremblay, 2002), which depicted: (i) a normatively low group, comprising a majority of youths and matching the low class identified here; (ii) a small very well-adjusted group, analogous to the non-anxious class identified here; (iii) a larger slightly elevated group, comprising up to 30% of the youths, similar to the high class identified here.

These results suggest the presence of five different developmental pathways that present meaningful associations with predictors related to students' exposure to school violence at the beginning of the study, with important developmental outcomes measured at the end of the study, as well as with the trajectories followed by these covariates over time. Although the construct validation process followed in the present study is quite extensive, it was designed to show how comprehensive this process can be, as well as how time-varying covariate associations with GGMA trajectories could be investigated without having to incorporate these variables directly into the model. As emphasized earlier, two of the observed latent trajectories comprise students who never show signs of anxiety over the course of the study and students who continuously present very low levels of anxiety. The main difference observed between these trajectories is that boys make up an overwhelming 73.0% of the non-anxious one. This suggests that most girls present at least some signs of anxiety over the secondary school years, which is consistent with the results from preceding studies showing higher levels of anxiety in girls compared with boys (Hale et al., 2008, 2009; van Oort et al., 2009). Confirming the meaningfulness of distinguishing these two latent classes, they also differ on some of the outcomes measured in this study, with members of the non-anxious class presenting lower levels of GPA, depression and loneliness than members of the low class. These results are likely related to the greater proportion of boys in the non-anxious class, since girls are known to present higher levels of depression (Angold & Worthman, 1993; Bebbington, 1996) and GPA (Freudenthaler et al., 2008).

Three of the observed latent trajectory classes present persistently elevated levels of anxiety and in two of them, the levels fluctuate widely over the secondary school years. One of these classes includes students whose initially high levels of anxiety rise to a peak during the secondary school years and fall back to their initial levels by the end of the study. This trajectory includes a majority of girls, which is interesting since girls: (i) often start puberty earlier than boys, and thus more often experience puberty and the secondary school transition simultaneously (Angold & Worthman, 1993); and (ii) are known to be more sensitive than boys to the effects of some social experiences (Cross & Madson, 1997; Feingold, 1994) that are common in secondary schools, such as academic and social competition and social network disruptions (Eccles, Lord, & Midgley, 1991; Eccles et al., 1993). In addition, the results show that members of this latent class can also be distinguished by their higher levels of externalizing behavior problems over the course of the study, as well as by their elevated levels of victimization and feelings of insecurity. These results are consistent with previous research showing that bullying and victimization may be mutually reinforcing whereby prior bullying behavior may lead to later victimization, and prior victimization may lead to later bullying behavior as victims attempt to defend themselves (e.g. Marsh, Parada, Craven & Finger, 2004).

Another latent trajectory class comprises students whose anxiety levels apparently peak near the school transitions, while remaining elevated in between. Interestingly, this latent trajectory class shows a slightly higher level of family instability and the highest level of externalizing behavior problems before the start of the study. The results suggest that the students from this latent class may be initially aggressive children who, upon entering secondary school, were exposed to elevated levels of school violence (as witnesses and victims) while becoming slightly less aggressive, possibly as a way to avoid anxiety-generating violent situations. Interestingly, the trajectories of externalizing behaviors observed in these two latent classes closely mirror their anxiety trajectories.

In both of these elevated and unstable classes, the levels of school dropout, loneliness, drug-related problems and depression over the course of the study are the highest and GPAs are the lowest. Clearly, something is not going well during the secondary school years for these students. The fact that over a third of the students from these classes will eventually drop out of school confirms previous results showing that internalizing disorders may represent a potentially important predictor of school dropout (Fortin, Royer, Potvin, Marcotte, & Yergeau, 2004; Janosz, Le Blanc, Boulerice, & Tremblay, 2000). Although members of these two latent trajectory classes present few significant differences from one another (the clearest one being on the trajectories of externalizing behavior problems), they do present differentiated patterns of distinctions from the remaining classes. This shows that the students from the transition-related-anxiety class have the lowest levels of GPA while those from the school-related-anxiety class have the highest levels of drug-related problems. These results should be put into perspective. Indeed, since girls tend to present higher levels of academic achievement (e.g. Freudenthaler et al., 2008) and lower levels of drug-related problems (e.g. Degenhardt et al., 2008; Robbins, 1989) than boys, the low levels of GPA and elevated levels of drug-related problems observed in the school-related-anxiety class are particularly alarming, as girls form 75% of this class. In addition, the normative decrease in depression observed in all students is also significantly reduced in the transition-related-anxiety class versus the school-related-anxiety class. Thus, although the next transition for a substantial number of students from these two latent trajectory classes will be marked by dropping out of school, which can be a highly stressful experience in itself, this next transition may have a completely different meaning in both latent classes. Indeed, the results hint at the possibility that members of the school-related-anxiety class may see school dropout as an opportunity for a new beginning outside of an unpleasant academic experience. Conversely, members of the transition-related-anxiety class may see it as a personal failure, which would explain their rising levels of anxiety and more stable levels of depression at the end of the study. Alternatively, students from the school-related-anxiety class may be abusing drugs as a way to self-medicate for anxiety (e.g. Comeau et al., 2001), or may be doing so more effectively than students from the transition-related-anxiety class, hence being somewhat dulled to the stressfulness of school dropout. Finally, students from the transition-related-anxiety class may be simply more sensitive to transitions, possibly as a result of previous negative experiences. Unfortunately, the data did not allow us to test these hypotheses.

A third latent trajectory class includes students presenting moderately elevated levels of anxiety that remain stable over the course of the study. Interestingly, these students present a profile on the covariates that generally falls in between the profiles of students from the non-anxious and low-anxiety classes on the one hand and from the school-related and transition-related anxiety classes on the other hand. In this latent trajectory class, anxiety levels do not fluctuate, thus appearing generally unrelated to the social experiences of secondary schools, and may be due to exposure to more stable risk factors not measured in the present study, such as hereditary predispositions or stable family difficulties (e.g. Bögels & Brechman-Toussaint, 2006; Murray, Creswell, & Cooper, 2009). This hypothesis should be more thoroughly investigated in future studies. However, these students present worse developmental outcomes than students from both the persistently low and non-anxious classes and present elevated levels of anxiety. As such, they should clearly be more thoroughly studied and targeted in the context of school-based preventive or curative interventions. The present results even suggest that the cut-off scores proposed for the Beck Anxiety Inventory (Beck & Steer, 1993a) may be helpful in identifying these latent classes of students. Indeed, Beck and Steer (1993a) suggest scores of 8 to 15 to identify mild levels of anxiety, which correspond to most students from the constantly high-anxiety class once within-class variability is considered. They also suggest scores of 16+ to indicate moderate to severe anxiety, which corresponds to the anxiety levels observed in the school-related and transition-related anxiety classes when their levels start to peak. Without advocating the blind use of cut-off scores as the sole “golden rule” for identifying these subgroups, we note their potential usefulness as part of a wider assessment package given their consistency with the present results.

Limitations and Directions for Future Research

Although great precautions were taken to avoid the problems most commonly associated with GGMA, a number of limitations remain. In our view, the two most serious are related to the sample and the need to expand on the range of models considered in future studies. First, this study relied on a short-term (i.e. 4-year) follow-up of a convenience sample of students following secondary school transition. Although the results from the last measurement point were interpreted as preceding the next transition, one full year remained before the real, “normative,” transition. However, this limitation is somewhat offset by the use of governmental data collected after the end of the study to assess GPA and school dropout. In addition, the attrition rate, albeit consistent with the rates generally reported in similar studies, remain high, and its impact on the generalizability of the results remains unknown. This limitation underscores the need to replicate the present findings, and to do so on more diversified and representative samples. Pending their replication, the extracted latent classes remain preliminary, and care should be taken to avoid their reification. Second, although we also attempted to extract models in which the time-specific disturbances were freely estimated in all classes (Enders & Tofighi, 2008), these models failed to converge on proper solutions. Although the extensive verifications that were done allow us to confidently conclude that these models did not provide an adequate representation of the data, this conclusion should be limited to the present results, and applied research should systematically test the adequacy and usefulness of this additional invariance assumption.

In addition, we believe that at least two potentially important issues should be addressed in the context of future studies. First, the various information criteria commonly used in mixture modeling to help in choosing the "right" number of classes in the data present a known sample-size dependency. This means that given a large enough sample, they will always converge on the most complex model. Marsh et al. (2005) argued that sample-size dependency is not an appropriate criticism of these indices in that more information is available when samples are larger. From a statistical perspective, it is thus justified to consider more complex models with larger samples. Nevertheless, this calls into question the assumption that there is a "right" number of groups (also see Marsh, Lüdtke et al., 2009). Rather, the extracted groups may simply reflect a useful heuristic to describe what happens in a particular sample, underlying the need for replication on more representative samples. Clearly, the selection of the "right" number of groups cannot be based solely on a mechanical application of recommendations about fit indices. As argued by Marsh, Lüdtke et al. (2009) and others (Bauer & Curran, 2004; Morin Muthén, 2003), there will always be a degree of subjectivity and a need for informed, professional judgment. Clearly, this is an area in need of further research and more guidance for applied research.

Second, although anxiety is known to possess state-trait properties (Endler & Kocovski, 2001)—that is stable (trait) and reactive (state) components—this distinction was not taken into account in this study. More precisely, in generic LCMs and GGMA models, only the overall intra-individual trajectories (i.e. the trait component) are estimated without taking into account the sometimes-strong autocorrelations influencing adjacent, state-like, time points. More precisely, LCMs and GGMA consider that time-specific deviations from the overall trajectories represent random "errors" to be controlled rather than substantively meaningful deviations from the generic trajectory. Such deviations may represent state-like "shocks" to the overall trajectories (due to meaningful situation-specific perturbations), which may exert a lasting influence on these trajectories. Such time-specific, state-like relations may even be quite strong and/or vary across time and thus potentially bias the estimation of the trajectories by causing them to be "absorbed" by the remaining parameters of the model (Sivo, Fan, & Witta, 2005). In the present study, the longitudinal design comprises widely spaced time points not ideally suited to the study of state-trait models. New developments allowing the incorporation of state and trait components in the context of mixture models have been recently proposed (Courvoisier, Eid, & Nussbeck, 2007) and should clearly be investigated in future studies.

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Endnotes

[1] This study relies on data collected in Quebec (Canada), where children start school around the age of 6 and usually remain in the same elementary school until grade 6, after which they experience the secondary school transition (close to the age of 12), where they remain for five years (grades 7 to 11).

[2] Models were estimated with manifest time-specific indicators, as is common in GGMA. Still, longitudinal models based on manifest indicators may present problems, as they rely on the (often-untested) assumption of strict longitudinal measurement invariance and may confound unstable reliability with stability/instability of the construct (Meredith, 1993; Marsh, Muthén, et al., 2009). Preliminary analyses confirmed that this assumption was reasonably met in the present study.

[3] When participants differ in age, relying on uniform time codes, versus individual-specific codes, may result in estimation bias (Metha & West, 2000). In the present study, this limitation is partly offset since all participants are quite close in age and of the same grade level. Moreover, uniform time coding could still be appropriate when (Metha & West, 2000): (i) the regression of the intercept of the LCM on participants' age at Time 1 is equal to the slope factor, and (ii) the regression of the slope on age at Time 1 is equal to zero. Both conditions were reasonably met in the present study.

[4] Classical LRTs may not be used to compare GGMA models with differing numbers of classes. However, they may be used to compare models based on the same variables and number of latent classes, differing on the pattern of free versus constrained parameters (e.g. Petras & Masyn, 2010). LRTs are computed as minus two times the difference in the log likelihood of the nested models and are interpreted as chi-square with degrees of freedom equal to the difference in free parameters between both models. As this study relied on MLR, the LRT needs to be divided by its scaling correction composite, *cd*, where: (i) $cd = (p0 * co - p1 * c1) / (p0 - p1)$; (ii) $p0$ and $p1$ are the number of free parameters in the nested and comparison models; and (iii) $c0$ and $c1$ are the scaling correction factors for the nested and comparison models (Muthén & Muthén, 2008; Satorra, & Bentler, 1999).

[5] To verify that the clustering of students within schools did not influence the results, conditional models were also estimated with four dummy variables representing the five schools added to the predictors. These predictors were non-significant and their presence did not modify the results.

Table 1

Fit Indices from Alternative LCGA, GGMA-MD, and GGMA-LV Models

Model	LL	#fp	SF	AIC	CAIC	BIC	ABIC	Entropy	BLRT
LCGA									
1 Class	-16544	8	2.844	33105	33152	33144	33119	Na	Na
2 Class	-15987	12	3.039	31999	32070	32058	32020	0.881	< 0.001
3 Class	-15859	16	3.600	31750	31844	31828	31778	0.883	< 0.001
4 Class	-15761	20	3.638	31563	31681	31661	31598	0.887	< 0.001
5 Class	-15682	24	3.054	31413	31555	31531	31454	0.900	< 0.001
6 Class	-15632	28	2.836	31320	31486	31458	31369	0.911	< 0.001
7 Class	-15569	32	2.356	31202	31391	31359	31258	0.909	< 0.001
GGMA-MD									
1 Class	-16000	11	3.225	32021	32086	32075	32040	Na	Na
2 Class	-15864	15	3.267	31758	31847	31832	31784	0.897	< 0.001
3 Class	-15763	19	2.510	31563	31676	31657	31597	0.925	< 0.001
4 Class	-15678	23	3.638	31402	31538	31515	31442	0.913	< 0.001
5 Class	-15607	27	2.775	31268	31428	31401	31315	0.919	< 0.001
6 Class	-15549	31	2.207	31160	31343	31312	31214	0.921	< 0.001
7 Class	-15512	35	2.066	31094	31301	31266	31155	0.923	< 0.001
GGMA-LV									
1 Class	-16000	11	3.225	32021	32086	32075	32040	Na	Na
2 Class	-15659	15	2.284	31347	31436	31421	31373	0.722	< 0.001
3 Class	-15502	22	2.198	31048	31179	31157	31087	0.740	< 0.001
4 Class	-15366	29	1.919	30790	30962	30933	30840	0.757	< 0.001
5 Class	-15261	36	1.756	30594	30807	30771	30657	0.786	< 0.001
6 Class	-15212	43	1.531	30510	30764	30721	30585	0.801	< 0.001
7 Class	-15172	47	1.343	30438	30717	30670	30520	0.802	< 0.001
5-Class GGMA-LV model with predictors									
1. P -> C	-15159	68	1.487	30855.	30453	30788	30572	0.794	Na
2. P -> C and I (INV.)	-15145	76	1.416	30891	30441	30815	30574	0.791	Na
3. P -> C, I-S (INV.)	-15135	84	1.376	30935	30438	30851	30585	0.797	Na
4. P -> C, I-S-Q (INV.)	-15092	92	1.289	30912	30367	30820	30528	0.808	Na
5- P -> C and I (VAR.)	-15098	108	1.362	31052	30413	30944	30601	0.792	Na

Note. LL = Model loglikelihood; #fp = number of free parameters; SF: scaling factor of the robust Maximum Likelihood estimator; AIC = Akaïke Information Criterion; CAIC = Consistent AIC; BIC = Bayesian Information Criterion; ABIC = sample-size Adjusted BIC; LMR = Lo-Mendel and Rubin's Likelihood Ratio Test; BLRT = Bootstrap Likelihood Ratio Test; P -> = the predictors were allowed to influence…; C: membership into the latent classes; I = intercept of the latent trajectories; S = linear slope of the latent trajectories; Q = quadratic slope of the latent trajectories; INV. = prediction invariant across latent classes; VAR. = prediction allowed to vary across latent classes; ** : $p \leq .01$

Table 2

Results from the final unconditional 5-class GGMA-LV model

Parameter	C1 (no anxiety) Estimate (t)	C2 (high, school-related) Estimate (t)	C3 (high, stable) Estimate (t)	C4 (high, transition-related) Estimate (t)	C5 (low, stable) Estimate (t)
$\mu_{\alpha yk}$	2.31 (11.16)**	21.18 (9.87)**	10.29 (17.63) **	15.27 (10.58)**	5.56 (15.01)**
$\mu_{\alpha yk}$	0.93 (6.84)**	8.24 (5.91)**	-1.62 (-3.67)**	-8.76 (-8.55)**	0.51 (2.35)*
$\mu_{\beta 2yk}$	-0.49 (-6.27)**	-3.82 (-5.36)**	0.56 (3.85) **	3.86 (8.61)**	-0.32 (-4.14)**
$\sqrt{\psi_{\alpha\alpha yk}}$	0.00 (NA)	6.53 (5.41)**	5.30 (9.51)**	8.90 (6.42)**	2.21 (8.02)**
$\sqrt{\psi_{\beta 1\beta 1yk}}$	0.00 (NA)	3.28 (1.96)*	3.01 (8.45)**	6.34 (4.86)**	1.27 (6.58)**
$\sqrt{\psi_{\beta 2\beta 2yk}}$	0.00 (NA)	0.00 (NA)	0.00 (NA)	0.00 (NA)	0.00 (NA)
$r(\psi_{\alpha\beta 1yk})$	0.00 (NA)	-0.31 (-1.42)	-0.60 (-12.69)**	-0.59 (-6.40)**	-0.67 (-10.96)**
ε_{yi1}	1.05 (3.73)**	--	--	--	--
ε_{yi2}	7.43 (10.22)**	--	--	--	--
ε_{yi3}	5.30 (8.09)**	--	--	--	--
ε_{yi4}	5.84 (8.82)**	--	--	--	--
ε_{yi5}	0.92 (1.25)	--	--	--	--

Note.C1-C5: latent trajectory classes 1 to 5; t = estimate / standard error of the estimate (t value are computed from original variance estimate and not from their square roots); NA = not applicable; --: parameter specified as invariant; r = correlation; other terms defined as in formulas 1-5; ** : p ≤ .01; * : p ≤ .05.

Table 3

Results from the multinomial logistic and multiple regressions predicting class membership and the intercepts of the trajectories.

	Vs. C1 (non-anxious)								Vs. C5 (low)					
	C2 (school related)		C3 (high)		C4 (transition)		C5 (low)		C2 (school related)		C3 (high)		C4 (transition)	
Predictor	Coeff. (s.e)	OR	Coeff. (s.e)	OR	Coeff. (s.e)	OR	Coeff. (s.e)	OR	Coeff. (s.e)	OR	Coeff. (s.e)	OR	Coeff. (s.e)	OR
Gender	**2.93 (0.50)****	**18.67**	**1.51 (0.35)****	**4.54**	**1.77 (0.47)****	**5.88**	**0.77 (0.34)***	**2.16**	**2.16 (0.44)****	**8.65**	**0.74 (0.26)****	**2.10**	**1.00 (0.39)****	**2.73**
Fam. Instability	-0.09 (0.13)	0.91	-0.05 (0.08)	0.95	0.09 (0.11)	1.10	0.01 (0.08)	1.01	-0.10 (-0.12)	0.90	-0.06 (0.07)	0.94	0.09 (0.10)	1.09
Parental Educ.	0.09 (0.11)	1.10	0.04 (0.08)	1.04	0.14 (0.10)	1.15	0.07 (0.06)	1.07	0.03 (0.10)	1.03	-0.03 (0.06)	0.97	0.08 (0.09)	1.08
Ext. behav. (T1)	0.05 (0.04)	1.05	0.04 (0.03)	1.04	0.06 (0.04)	1.06	0.00 (0.04)	1.00	0.05 (0.03)	1.05	0.04 (0.02)	1.04	**0.06 (0.03)***	**1.06**
Ext. behav. (T3)	**0.07 (0.03)***	**1.07**	0.01 (0.03)	1.01	0.02 (0.03)	1.02	0.01 (0.03)	1.01	**0.06 (0.02)****	**1.06**	0.01 (0.02)	1.01	0.02 (0.03)	1.02
Feelings of security	**-0.76 (0.26)****	**0.47**	-0.01 (0.19)	0.99	-0.40 (0.25)	0.67	0.07 (0.21)	1.08	**-0.83 (0.23)****	**0.44**	-0.09 (0.18)	0.92	**-0.47 (0.23)***	**0.62**
Victimization	**0.10 (0.04)****	**1.10**	**0.08 (0.03) ***	**1.09**	**0.10 (0.04)****	**1.11**	0.01 (0.04)	1.01	**0.09 (0.04)***	**1.09**	0.07 (0.04)	1.07	**0.09 (0.04)***	**1.09**
Witnessing	0.00 (0.03)	1.00	0.02 (0.02)	1.02	0.04 (0.02)	1.05	0.00 (0.02)	1.00	0.01 (0.03)	1.01	0.02 (0.02)	1.02	**0.05 (0.02)***	**1.05**

	Vs. C3 (high)				Vs. C4 (transition)		
	C2 (school related)		C4 (transition)		C2 (school related)		Intercept
Predictor	Coeff. (s.e)	OR	Coeff. (s.e)	OR	Coeff. (s.e)	OR	Coeff. (s.e)
Gender	**1.42 (0.49)****	**4.12**	0.26 (0.43)	1.30	**1.16 (0.51)***	**3.17**	**0.58 (0.24)***
Fam. Instability	-0.04 (0.12)	0.96	0.15 (0.10)	1.16	-0.19 (0.14)	0.83	0.07 (0.05)
Parental Educ.	0.05 (0.10)	1.06	0.10 (0.10)	1.11	-0.05 (0.12)	0.95	0.02 (0.05)
Ext. behav. (T1)	0.01 (0.02)	1.01	0.02 (0.02)	1.02	-0.01 (0.29)	0.99	**0.02 (0.01)***
Ext. behav. (T3)	**0.06 (0.02)***	**1.06**	0.01 (0.03)	1.01	-0.04 (0.03)	1.04	-0.01 (0.01)
Feelings of security	**-0.75 (0.23)****	**0.47**	-0.39 (0.24)	0.68	-0.36 (0.03)	0.70	-0.02 (0.11)
Victimization	0.02 (0.02)	1.02	0.02 (0.03)	1.02	-0.01 (0.03)	1.00	-0.01 (0.01)
Witnessing	-0.02 (0.03	0.98	0.03 (0.02)	1.03	-0.04 (0.03)	0.96	**0.02 (0.01)***

Note: C1-C5: latent trajectory classes 1 to 5; s.e. = standard error of the coefficient (the coefficient divided by its standard error is equivalent to a t score and indicate the significance of the effect); OR = Odds Ratio; * $p \leq .05$; ** $p \leq .01$

Table 4

Results from the Wald Chi-Square (χ^2) Tests of Mean Equality of the Auxiliary (e) Analyses of Developmental Outcomes and Covariates Trajectories

	Class specific means/proportions					Wald Wald Chi-Square (χ^2) Tests of Mean Equality									
	1: N-A	2: S-R	3: H	4: T-R	5: L	1 vs 2	1 vs 3	1 vs 4	1 vs 5	2 vs 3	2 vs 4	2 vs 5	3 vs 4	3 vs 5	4 vs 5
Developmental Outcomes															
GPA	72.415	73.647	74.697	70.396	74.978	0.31	3.88*	1.09	5.57*	0.23	1.48	0.39	4.89*	0.07	6.37*
Dropout	22.0%	33.4%	20.5%	36.5%	17.4%	2.21	0.15	3.48	1.42	2.93	0.10	4.62*	4.25*	0.72	6.53*
Depression	1.669	12.024	8.447	14.192	4.616	46.48**	128.01**	33.56**	68.68**	4.90*	0.67	23.20**	6.62**	34.47**	19.41**
Loneliness	1.053	1.168	1.137	1.224	1.095	2.88	9.09**	3.96*	2.94	0.20	0.28	1.22	0.99	2.45	2.25
Drugs	4.203	6.658	5.216	5.428	4.632	5.22*	3.21	1.27	0.65	1.84	0.77	3.85*	0.04	1.20	0.57
Post hoc probing of class difference on the covariates (predictors and outcomes) LCM trajectory factors															
I. Ext. beha.	4.745	9.129	6.041	8.291	4.643	20.14**	7.89**	16.23**	0.06	10.00**	0.47	22.50**	6.27*	10.69**	17.91*
S. Ext. beha.	0.410	1.181	0.495	0.228	0.550	4.91*	0.26	0.28	0.99	3.86*	4.39*	3.55	0.59	0.16	0.96
Q. Ext. beha.	0.048	-0.113	0.068	0.152	0.064	2.58	0.14	0.10	0.11	3.36	4.01*	3.42	0.650	0.01	0.80
I. Feel. Sec.	3.001	2.748	2.957	2.660	3.076	14.37**	1.06	22.68**	3.20	10.59**	1.09	28.34**	17.79**	10.23**	37.54**
S. Feel. Sec.	0.060	0.093	0.063	0.026	0.065	1.71	0.04	1.92	0.12	1.44	4.44*	1.35	2.31	0.02	2.80
Q. Feel. Sec.	0.020	0.016	0.020	0.029	0.019	0.63	0.03	2.56	0.21	0.50	3.46	0.32	2.90	0.09	3.84*
I. Victim.	17.284	19.438	18.402	19.341	17.401	35.76 **	29.66**	21.11**	0.49	7.57**	0.03	33.92**	4.13*	26.51**	19.50**
S. Victim.	-0.809	-1.083	-0.961	-1.204	-0.819	6.65**	5.26*	10.15**	0.03	1.34	0.66	6.96**	3.88*	5.97*	10.51**
Q. Victim.	0.044	0.092	0.087	0.141	0.064	0.825	1.61	3.90*	0.37	0.01	0.66	0.32	1.38	0.66	2.99
I. Witness.	19.720	23.336	21.412	24.845	19.429	16.56**	9.02**	34.47**	0.34	4.79*	1.80	22.21**	15.38**	17.22**	42.79**
S Witness.	1.401	2.420	1.607	1.129	1.627	1.94	0.34	0.15	0.52	1.20	1.85	1.28	0.44	0.00	0.53
Q. Witness.	-0.598	-0.889	-0.664	-0.611	-0.646	3.02	0.69	0.01	0.46	1.75	1.68	2.28	0.11	0.06	0.05
I. GPA	74.121	71.301	74.983	70.717	75.428	3.84*	0.82	4.55*	2.14	6.69**	0.09	9.56**	7.04**	0.29	9.65**
S. GPA	-0.871	-0.337	-0.823	-0.084	-0.751	1.60	0.03	2.29	0.21	1.36	0.18	1.10	2.00	0.09	1.86
Q. GPA	-0.048	-0.096	-0.046	-0.162	-0.057	0.53	0.00	2.00	0.06	0.58	0.51	0.38	2.02	0.09	1.87
I. Loneli.	1.192	1.320	1.232	1.329	1.218	13.86**	8.68**	6.49*	4.00*	6.38*	0.02	8.85**	3.20	0.97	4.29*
S. Loneli.	-0.118	-0.115	-0.121	-0.122	-0.117	0.18	1.82	0.55	0.03	1.02	0.76	0.12	0.01	2.06	0.66
Q. Loneli.s	0.026	0.022	0.029	0.028	0.026	0.61	2.23	0.242	0.03	2.08	0.97	0.75	0.09	1.66	0.16
I. Dep.	3.639	14.953	8.544	12.047	5.742	104.19**	139.72**	43.26**	55.88**	30.20**	2.97	69.37**	6.90**	42.26**	24.33**
S. Dep.	-0.345	-1.115	-0.584	-0.762	-0.452	103.52**	77.40**	28.50**	27.34**	45.76**	10.72**	77.35**	4.82*	22.24**	15.78**
I. Drugs	3.139	6.365	4.199	4.647	3.100	16.1***	5.68*	3.85*	0.01	7.27**	2.76	17.90**	0.32	6.89**	4.31*
S. Drugs	0.742	0.585	0.760	0.793	0.897	0.47	0.02	0.04	1.54	0.45	0.48	2.02	0.02	1.34	0.20

Note. 1:N-A = the non-anxious class (class 1); 2: S-R: the school-related anxiety class (Class 2); 3: H: the high anxiety class (Class 3); 4: T-R: the transition-related anxiety class (Class 4); 5: L: the low anxiety class (Class 5); I: the intercept factor of the covariate trajectory; S: the linear slope factor of the covariate trajectory; Q: the quadratic slope factor of the covariate trajectory; The pairwise Wald Chi-Square (χ^2) tests of mean equality are based on a single degree of freedom. * $p \leq .05$; ** $p \leq .01$

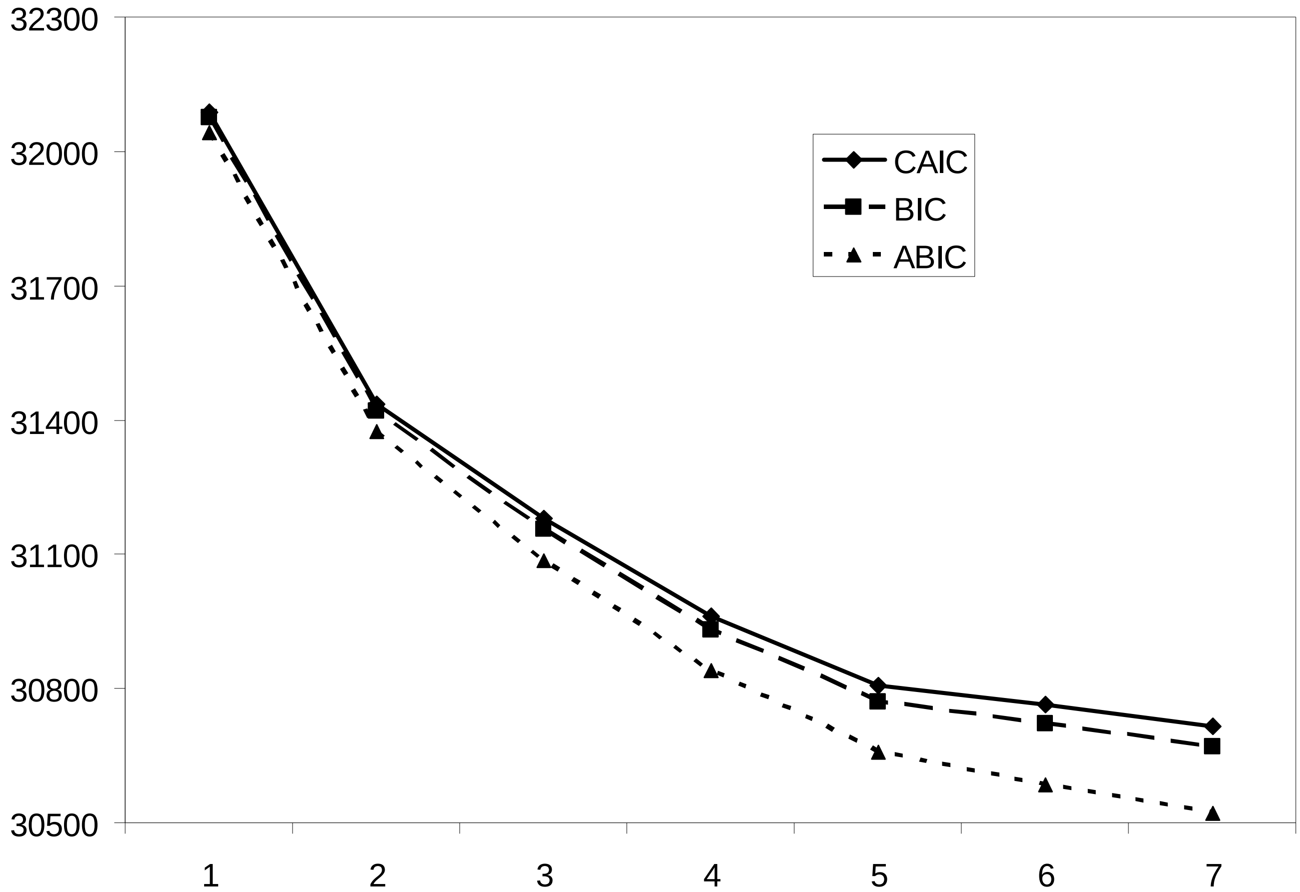

Figure 1. Elbow plot of the CAIC, BIC and ABIC indicators for the GGMA-LV models

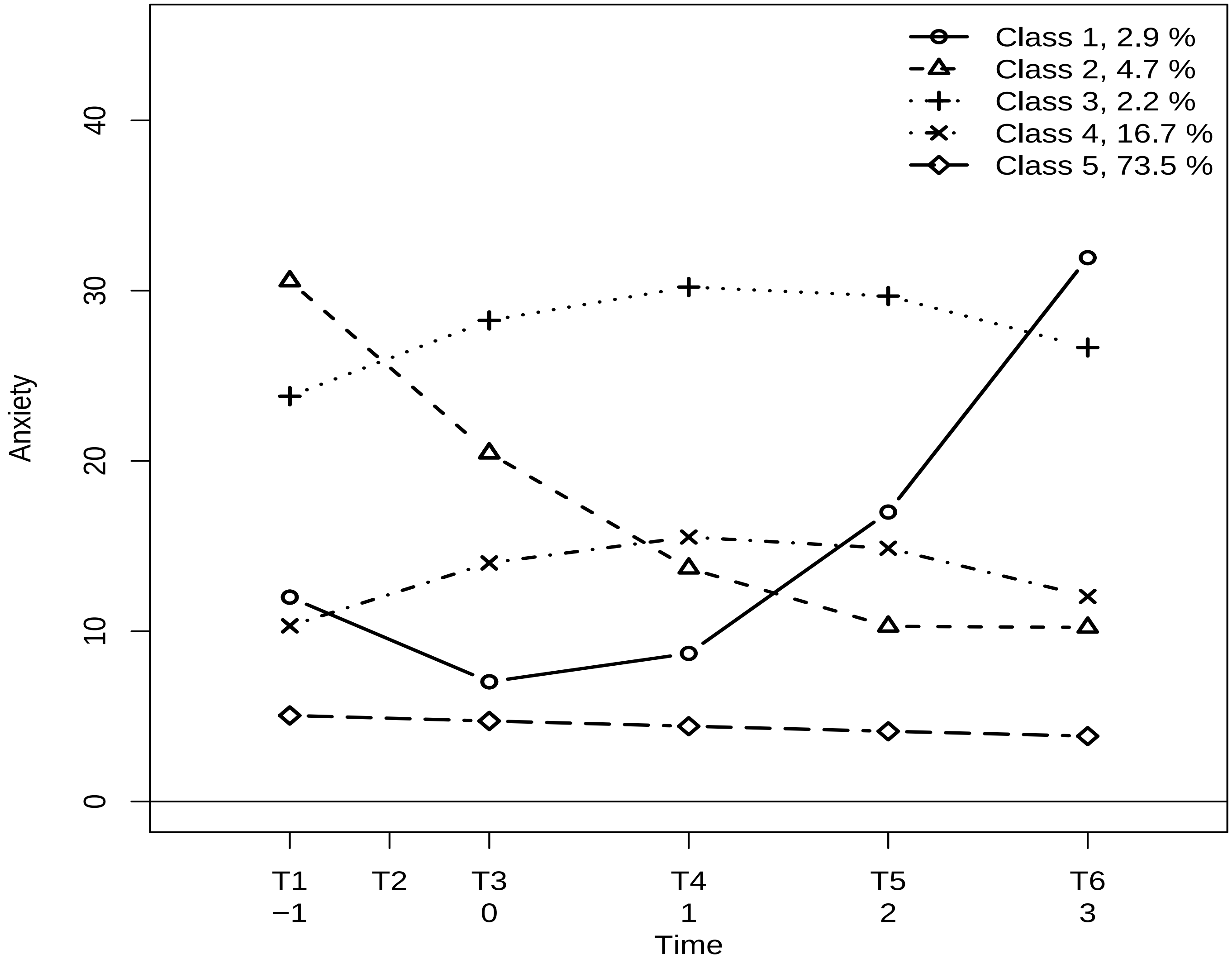

Figure 2a. Developmental Trajectories Estimated from the LCGA 5-Class Model.

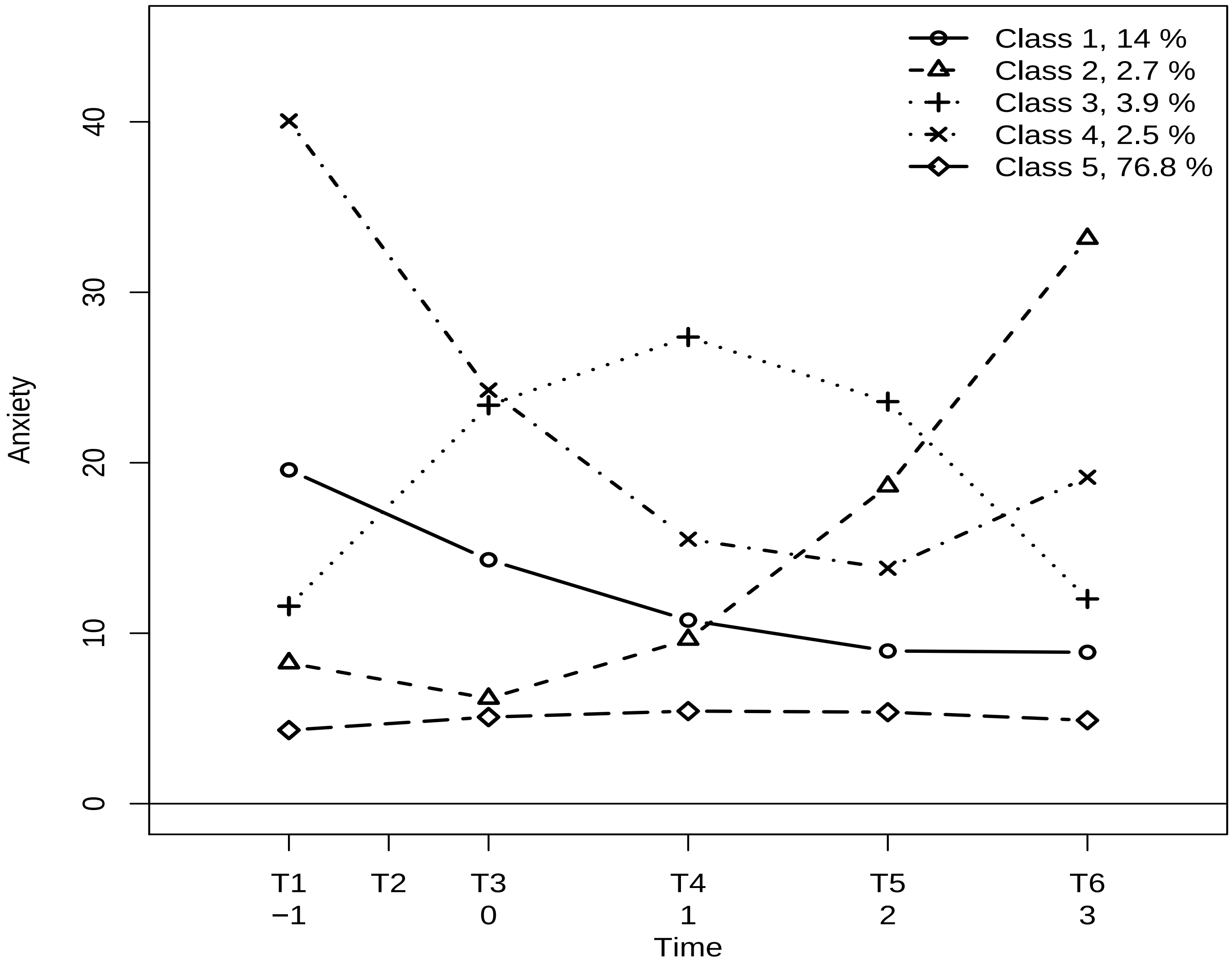

Figure 2b. Developmental Trajectories Estimated from the GGMA-MD 5-Class Model.

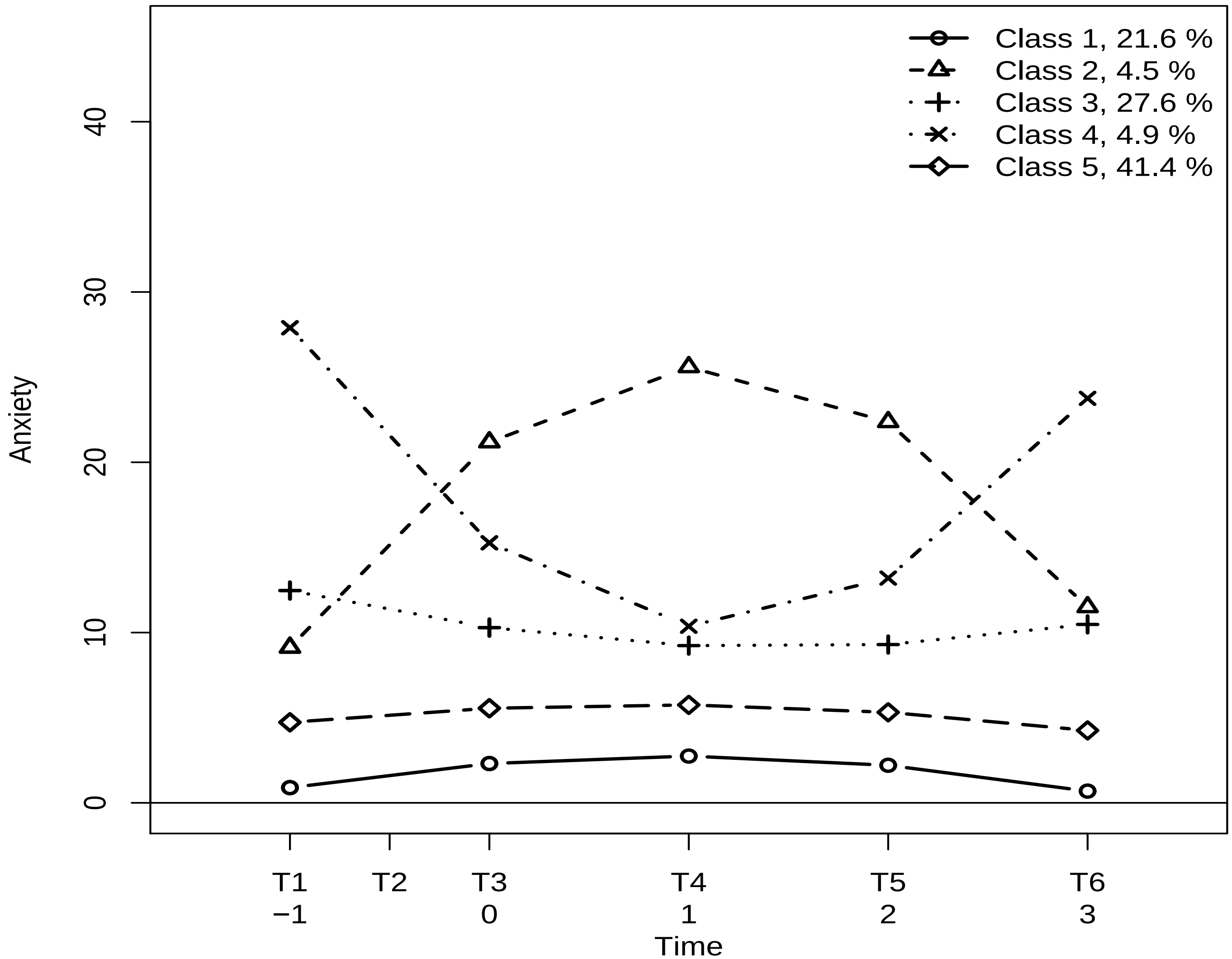

Figure 2c. Developmental Trajectories Estimated from the GGMA-LV 5-Class Model.

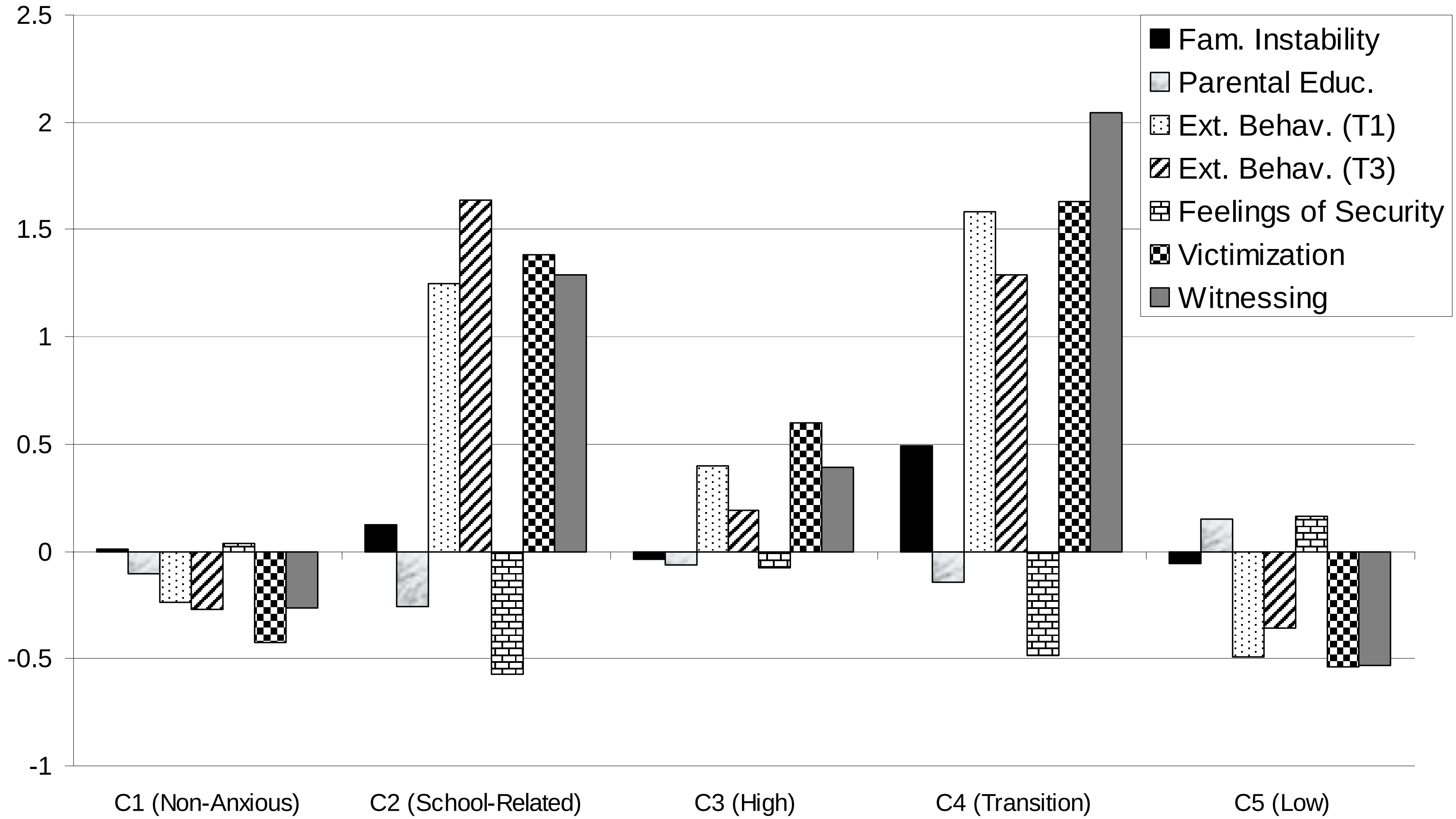

Figure 3. Characteristics of the Latent Trajectory classes on the Predictors.

Note. The results were standardized to help in the interpretation of this histogram.

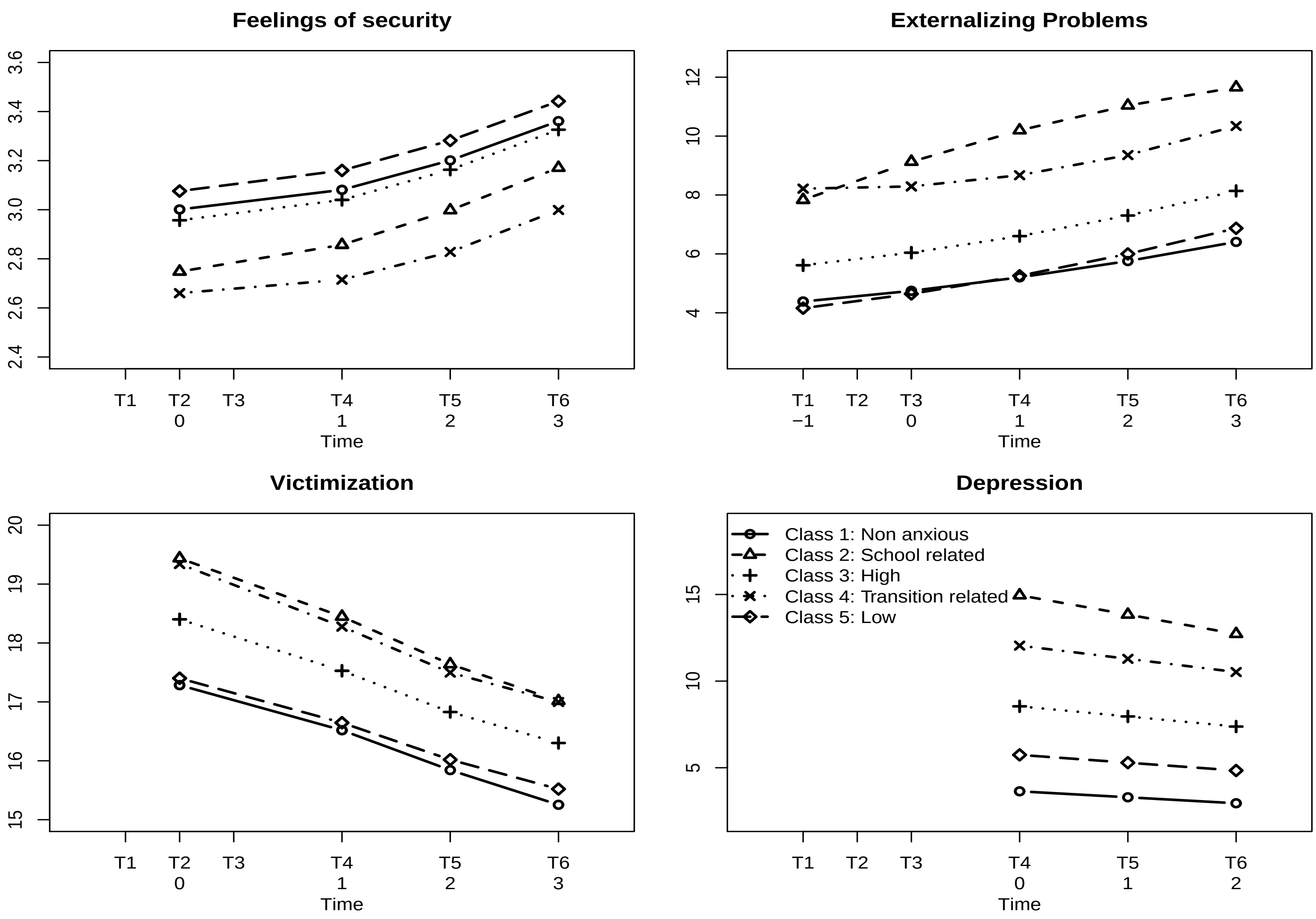

Figure 4. Class-specific trajectories of the covariates.

Appendix. Mplus input codes for the main models used in the present study.

LCGA input:

```
TITLE:  LCGA
DATA: FILE IS "anx_traj.dat";
VARIABLE:
NAMES ARE CI ANXT1 ANXT3 ANXT4 ANXT5 ANXT6;
IDVARIABLE = CI;
MISSING ARE ALL (999);
USEVARIABLES ARE ANXT1 ANXT3 ANXT4 ANXT5 ANXT6;
CLASSES = c (5);
ANALYSIS:
TYPE = MIXTURE;
STARTS = 1000 100;
LRTBOOTSTRAP = 100;
PROCESSORS = 2 (START);
MODEL:
%OVERALL%
i s q |  ANXT1@-1 ANXT3@0 ANXT4@1 ANXT5@2 ANXT6@3;
i@0 s@0 q@0;
OUTPUT:
SAMPSTAT STANDARDIZED RESIDUAL CINTERVAL MODINDICES (3.0);
TECH1 TECH2 TECH3 TECH4 TECH7 TECH11 TECH13 TECH14;
```

GGMA-MD input (model part only):

```
MODEL:
%OVERALL%
i s q |  ANXT1@-1 ANXT3@0 ANXT4@1 ANXT5@2 ANXT6@3;
q@0;
```

GGMA-LV input (with predictors and outcomes):

```
TITLE:  GGMA-LV
DATA: FILE IS "anx_traj.dat";
VARIABLE:
NAMES ARE CI SEX FAM SES ANXT1 ANXT3 ANXT4 ANXT5 ANXT6
FEELS1 EB1 EB3 VICT1 WITN1 GPAF DRUGF DEPF LONEF DROPF;
IDVARIABLE = CI;
MISSING ARE ALL (999);
USEVARIABLES ARE SEX FAM SES ANXT1 ANXT3 ANXT4 ANXT5 ANXT6
FEELS1 EB1 EB3 VICT1 WITN1;
AUXILIARY =  GPAF (e) DRUGF (e)  DEPF (e) LONEF (e) DROPF (e);
CLASSES = c (5);
ANALYSIS:
TYPE = MIXTURE; STARTS = 1000 100; LRTBOOTSTRAP = 100;
PROCESSORS = 2 (START);
MODEL:
%OVERALL%
c#1-c#4 ON  SEX FAM SES FEELSE EB1 EB3 VICT1 WITN1;
i s q |  ANXT1@-1 ANXT3@0 ANXT4@1 ANXT5@2 ANXT6@3;
q@0;
I ON SEX FAM SES FEELSE EB1 EB3 VICT1 WITN1;
%c#1%
i s;  i WITH s; [I S Q];  I@0; S@0;
%c#2% ! Use same specifications for %c#3%, %c#3%, and %c#5%
i s;  i WITH s; [I S Q];
OUTPUT:
SAMPSTAT STANDARDIZED RESIDUAL CINTERVAL MODINDICES (3.0);
TECH1 TECH2 TECH3 TECH4 TECH7 TECH11 TECH13 TECH14;
```