A Longitudinal Person-Centered Perspective on Youth Social Support: Relations with Psychological Wellbeing

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Abstract

Past research suggests that perceived social support from parents, teachers, and peers are all positively associated with wellbeing during adolescence. However, little longitudinal research has examined the implications of distinctive combinations of social support for developing adolescents. To address this limitation, we measured multiple dimensions of social support, psychological ill-health, and wellbeing in a sample of 2034 Australian adolescents (M_{age} = 13.7; 49.6% male) measured in Grades 8 and 11. Latent transition analyses identified a six-profile solution for both waves of data, and revealed substantial inequality in perceived social support. Two “socially rich” profiles corresponded to 7% of the sample and felt supported from at least two sources of social support 1 *SD* above the sample mean (*Fully Integrated; Parent and Peer Supported*). In contrast, 25% of the sample was “socially poor”, having support that was between -.65 to .-86 *SD* below the sample mean for all three sources (*Isolated* profile). None of the other profiles (*Peer Supported; Moderately Supported; Weakly Supported)* had levels of support below -.37 *SD* from any source. Furthermore, almost all wellbeing problems were concentrated in the *Isolated* Profile, with negative effects more pronounced in Grade 11 than Grade 8. Despite feeling low parent and teacher support, adolescents in the *Peer Supported* profile felt strong peer support and average to above-average levels of wellbeing in Grades 8 and 11. However, they also had an 81% chance of making a negative transition to either the *Isolated* or *Weakly Supported* profiles in Grade 11.

Keywords: Social support, Person-centered, Wellbeing ,Latent Transition Analysis

Social support can come from a wide variety of individuals, among which parents, teachers, and peers typically represent the foremost sources for developing children and adolescents (Chu et al., 2010; Parker, Ludtke, Trautwein, & Roberts, 2012). Past research has tended to examine different aspects of social support in isolation. That is, research has typically focused on the isolated role of parents, teachers, or friends in the promotion of youth wellbeing. Far fewer studies have focused on the combinations of multiple sources of social support, with very little research focusing on parents, teachers and peers simultaneously. Single source research is valuable, but makes it difficult to examine the possibility that distinct combinations of social support, or "social support profiles", may have different implications for wellbeing. Social support from parents, teachers, and peers may combine in various ways so that the consequences of support from any one source may depend on the context provided by the other sources. Feeling supported from one source may compensate for a lack of support from other sources. For example, having a highly supportive teacher could be particularly helpful for youth otherwise lacking in supportive relationships with peers and parents.

In addition to a focus on single sources of support, little research has examined the development of social support profiles across the high school period (for an exception, see Jager, 2011). This leaves three important questions unanswered. First, does the nature and structure of support profiles change during high school? Second, how do young people transition between different profiles? Third, does the effect of profiles on wellbeing differ across developmental periods? The present research addresses these questions by focusing on perceived support from multiple sources (teachers, parents, peers) at multiple time points (Grade 8 and 11), and using longitudinal latent profile analyses (i.e., latent transition analyses).

Social support and human thriving

Several decades of research have shown that supportive relationships are linked to a broad array of wellbeing and health benefits (Hawkley & Cacioppo, 2010; Heinrich & Gullone, 2006). For example, Holt-Lunstad, Smith, & Layton (2010) conducted a meta-analysis of 148 longitudinal studies involving over 300,000 people who were followed for an average of 7.5 years, and found that people with relatively strong social relationships had a 50% greater likelihood of survival compared to those with weaker social relationships. The health benefits of having strong social relationships are similar to the benefits of quitting smoking and exceed the benefits of having healthy weight and engaging in physical activity (Holt-Lunstad et al., 2010).

These benefits can be explained by two perspectives. The indirect , "stress buffering" perspective suggests that the provision of emotional, informational, or instrumental (e.g., resources) support helps people to successfully manage stressful life events (Cohen & Wills, 1985). The direct effect perspective suggests that social support provides benefits during both non-stressful and stressful times, such as when supportive relationships give one a sense of belonging and meaning. Research generally supports both of these perspectives (Taylor, 2011; Thoits, 1995).

The present paper focuses on perceived social support, which is defined as an individuals' subjective appraisal that people in their social network care for them and are willing to provide assistance when needed (Lakey & Scoboria, 2005). It is important to examine perceived social support because feeling supported is an inherently subjective judgment, and there may be a discrepancy between the extent that others think that they are being supportive and the extent to which adolescents perceive others' support. Indeed, perceptions of social support are more strongly linked to wellbeing than other indices of support (Chu, Saucier, & Hafner, 2010).

A Person-Centered Approach to Social Support

Many possible social support profiles could, in theory, occur in the population. For example, some adolescents may be characterized by high levels of support from adults (parents and teachers), but low levels of peer-support. Alternatively, some may present profiles characterized by high levels of support from their peers, but low levels of adult-support. This focus on subpopulations presenting quantitatively and qualitatively distinct profiles of social support requires the adoption of a *person-centered* approach (Marsh, Ludtke, Trautwein, & Morin, 2009; Morin, Morizot, Boudrias, & Madore, 2011). Whereas the traditional *variable-centered* approach used in research on social support has mainly focused on relations among sets of variables, and possible two or even three ways interactions among them, the *person-centered* approach adopts a more holistic perspective and focuses on the possibility that the sample under study may in fact reflect multiple subpopulations characterized by a different configuration on the set of variables under study (Morin & Wang, 2016).

Latent profile analysis (LPA) is a model-based approach to profiling which is integrated in the larger mixture modeling (or generalized structural equation modeling) framework (Muthén, 2002). This framework provides a flexible approach to person-centered analyses, allows for a direct incorporation of covariates, predictors, and outcomes in the model, and provides a way to adopt a longitudinal approach to the estimation of participants' profiles (Kam, Morin, Meyer, & Topolyntsky, 2016; Morin & Wang, 2016). Furthermore, a comprehensive approach has recently been proposed to guide a systematic investigation of the similarity of profile solutions across time points that is particularly relevant to the present study (Morin, Meyer, et al., 2016). The availability of this new approach to assess the stability of profile solutions across time points represent a key advantage for LPA given that many researchers have previously noted that a critical test of the meaningfulness of any LPA solution requires the demonstration that it generalizes across meaningful samples or time points (Meyer & Morin, 2016; Muthén, 2003; Solinger, van Olffen, Roe, & Hofmans, 2013).

Profile Structure: Convergence versus Divergence

It has been theorized that positive relationships give rise to other positive relationships (e.g., Dekovic & Meeus, 1997), and thus that profiles will tend to "converge" or be consistently high or low across types of relationships (Jager, 2011). Consistent with this view, support from one source is associated with support from other sources (Demaray, Malecki, Davidson, Hodgson, & Rebus, 2005; Malecki & Demaray, 2006; Scholte, Lieshout, & Aken, 2001). Therefore, **Hypothesis 1a** is that we will find at least one profile receiving high levels of felt social support from all sources (*Integrated*) and at least one profile receiving low levels of perceived support from all sources (*Isolated*).

We also have good reason to expect some profiles to show divergence, that is, high support from some sources, but low support from others. Divergence can occur because some possible support sources are in conflict (Barrerra, Chassin, & Rogosch, 1993; Montemayro, 1982), and young people feel like they have to choose between, for example, adults and peers. Divergence can also occur because some young people get their support needs met better by the adults in their lives than by their peers, or vice versa. Consistent with these ideas, prior person-centered research with youth has found evidence for divergence, with some profiles being characterized by high support from some sources and low support from others (Jager, 2011; Scholte et al., 2001). Specifically, both Jager (2011) and Scholte et al. (2001) identified adolescent profiles reporting good relationships with parents but not peers, and good relationships with peers but not parents. Therefore, **Hypothesis 1b** is that we will identify a peer-dominated profile (*Peers only*) and an adult-dominated profile (*Adults only*).

In addition to these hypotheses, we also pursue more exploratory research questions. Past person-centered social support research has failed to assess teacher support (e.g., Scholte et al., 2001) or assessed it with single-item measures (e.g., Jager, 2011). Given the importance of teacher support for otherwise isolated at risk students (Baker, 2006; Huber, Sifers, Houlihan, & Youngblom, 2012; Ladd & Burgess, 2001; Meehan, Hughes, & Cavvell, 2003; Mihalas, Witherspoon, Harper, & Sovran, 2012; Richman, Rosenfeld, & Bowen, 1998), we explored whether a profile dominantly supported by teachers would emerge (**Research Question 1**)? A second research question that we pursued was related to the identification of the relative size of each profile (**Research Question 2**). Given the rarity of previous research adopting a multiple-source configurational approach to social support, an answer to this question – particularly in terms of obtaining precise estimates of the relative size of Integrated, *Isolated*, *Peers only,* or *Adults only* profiles – is likely to be important for intervention purposes.

Profile Development and Change

While some research has sought to identify the structure of social support profiles in youth (Jager, 2011; Lausen, 2006; Scholte et al., 2001), little research has examined profile development and change during the high school period. For example, Jager (2011) and Sholte et al.(2001) derived profiles based on data aggregated across all years of high school. Lausen et al. (2006) conducted a two-year longitudinal study of social support profiles, but did not examine profile transitions, perhaps because of the relatively small sample size ($N < 200$). Jager's (2011) study is notable in that it used longitudinal data and examined how social support profiles during high-school predicted constellations of social support during young adulthood. For example, Jager (2011) found that adolescents characterized by the divergent "high parent, low romance profile" evolved for the better in young adulthood, such that the below average aspects of support become above average.

This past research offers important insights, but needs to be extended in two important ways. First, we need to examine the extent to which profile structure remains the same over time within a specific sample (within-sample stability; Morin, Meyer, et al., 2016). Second, we need to examine the extent to which, during the high school period, individual membership into specific profiles remains stable over time for specific individuals (within-person stability).

Early in life, social support begins in the family. Supportive parents teach children that others can be trusted and relied upon (Bowlby, 1969), and help them to manage stressful life events, to experience positive affect, and to develop emotion regulation skills, hope, and self-esteem (Heaven & Ciarrochi, 2008; Williams, Ciarrochi, & Heaven, 2012). As children get older, relationships between child and parents become more egalitarian (Sabatelli & Mazor, 1985), and levels of social support received from parents tend to either remain the same or to decrease over time (Cauce, Mason, Gonzales, Hiraga, & Liue, 1994; Furman & Buhmester, 1992; Meeus, 1989). As children enter adolescence, relationships outside of the family, such as those involving peers and teachers, become increasingly important as young people become introduced to new social roles and learn to cooperate with others (Eccles, 1999; Erikson, 1968). Indeed, one of the major adolescent tasks is to go beyond the familiar world of the family in order to build new relationships with peers (Hayes & Ciarrochi, 2015; Helsen, Vollebergh, & Meeus, 2000). Research shows that in Grade 4, parents tend to represent the number one source of social support for children, whereas by Grade 10 friends and parents tend to be equally important (Helsen et al., 2000). Adolescents spend increasing amounts of time with peers, with whom they develop intimate relationships (Clark & Ayers, 1992; Helsen et al., 2000).

Research confirms that supportive friendships help youth to successfully attain developmental milestones and to develop satisfactory levels of wellbeing. For example, close friendships promote the development of interpersonal skills, learning, and growth (Bukowski, 2001; Gifford-Smith & Brownell, 2003; Sullivan, 1953). Having friends has also been found to be linked to lower rates of depression and other mental health problems (Kiuru, 2008; Schaefer, Kornienko, & Fox, 2011), as well as to higher levels of subjective wellbeing (Bukowski, Newcomb, & Hartup, 1998).

Teachers may also come to represent a critically valuable source of social support for developing youth (Chu et al., 2010; Heaven, Leeson, & Ciarrochi, 2009). Teacher support is often deliberately developed through school-based social and emotional learning programs and has been shown to provide substantial benefit to students (Durlak, Weissberg, Dynmicki, Taylor, & Schellinger, 2011). Indeed, one meta-analysis suggests that teacher support may yield greater benefits in terms of student wellbeing than support from family and friends (Chu et al., 2010). Another meta-analysis concluded that the strength of the associations between the quality of students' relationships with their teachers and academic engagement tended to be medium to large, whereas similar associations were small to medium in relation to achievement-related outcomes (Roorda, Koomen, Splilt, & Oort, 2011). This second meta-analysis also suggested that the importance of teacher support seemed to increase with age, while remaining important across childhood and adolescence (Roorda et al., 2011).

In summary, past research raises the possibility that development might be accompanied by changes in profiles structure (within-sample instability) and membership (within-person change). Concerning structural change, we did not have a strong hypothesis, but sought to explore the possibility that some types of profile (e.g., *Peer only*) are more common in late than early adolescence. Concerning membership change, variable-centered developmental research suggests that perceived social support from a single source tends to be moderately stable, with approximately 25% of current social support being predicted by social support in the previous year (Marshall, Parker, Ciarrochi, & Heaven, 2014; Rowsell, Ciarrochi, Deane, & Heaven, 2016). Therefore, **Hypothesis 2a** is that adolescent membership into specific social support profiles will remain moderately stable between Grade 8 and Grade 11. When transitions occur in terms of profile membership, they should occur mainly across profiles presenting relatively similar levels of social support from multiple sources, rather than across drastically different profiles. Also, a substantial amount of research shows that a lack of supportive relationships with adults can hinder the development of social and emotional skills (Heaven & Ciarrochi, 2008; Williams et al., 2012), which are needed to build and maintain supportive social networks (Marshall et al., 2014; Rowsell et al., 2016). This leads to **Hypothesis 2b** that adolescents characterized by membership into profiles presenting poor adult support in Grade 8 will tend to either stay in the same profile or transition to weaker support profiles in Grade 11.

Profile Predictors and Wellbeing Outcomes

Construct validation, based on the demonstration that extracted latent profiles do relate to theoretically-relevant covariates in a meaningful manner, is critical to the demonstration that the profiles are practically meaningful (Marsh et al., 2009; Morin, Morizot, et al., 2011; Muthén, 2003). **Hypotheses 3a to 3c** relate to demographic predictions.

Hypothesis 3a: Given that parental divorce is associated with lower levels of parental support (Kalmijn, 2013), we predicted adolescents from separated or divorced families should be less likely to correspond to profiles characterized by high levels of social support from parents.

Hypothesis 3b: Adolescents from low SES or minority backgrounds show increased risk of being socially isolated (Demaray & Malecki, 2002; Ladd & Burgess, 2001; Richman et al., 1998) and receive less support from teachers (Hughes & Kwok, 2007; Ladd & Burgess, 2001). Therefore, they should be more likely to correspond to profiles characterized by low levels of perceived social support from a variety of sources, and particularly from teachers.

Hypothesis 3c: Past research suggests that adolescent males and females tend to receive similar levels of parental support, but that females tend to receive more peer support than males (Ciarrochi, Parker, Sahdra, Kashdan, et al., 2016; Helsen et al., 2000). Therefore, adolescent females should be more likely than males to correspond to profiles characterized by high levels of peer support.

Concerning the relations between profile membership and wellbeing outcomes, variable-centered research generally demonstrate clear positive relations between social support received from parents, peers and teachers, and levels of wellbeing (Chu et al., 2010). **Hypothesis 3d** is therefore that profiles with more support will generally experience more wellbeing than those with less support.

One of the strengths of LPA is to allow us to explore the possibility that some profiles are more strongly linked to wellbeing than other profiles, even if they do not differ in total amount of support. Furthermore, given our longitudinal design, we can also assess whether some profiles provide a greater boost to wellbeing in earlier adolescence (Grade8) than in later adolescence (Grade 11), or vice versa. Malecki and Demaray (2003) show that family, teachers, and peers may support young people in different ways: Parents most commonly provide emotional and informational support, teacher commonly provide informational support, and peers commonly provide emotional and instrumental support (e.g., material or financial). While this finding does not allow us to make concrete hypotheses, it does raise some interesting questions. Do young people who only have one source of support benefit more by having emotional support (parents or peers) than informational support (teachers)? If young people already have strong support from parents (emotional and informational), is the addition of teacher support (informational) redundant? That is, if a young person already has strong parent support, does it matter whether or not they have teacher support?

Method

Sample and Procedures

The sample consisted of Grade 8 students (M_{age} = 13.7, SD_{age} = .45, N= 2034, 49.6% male) and Grade 11 (M_{age} = 16.6, SD_{age} = .48, N= 1727, 47.9% male) students from sixteen secondary schools within the Cairns (Queensland) and Illawara (New South Wales) Catholic Dioceses. All schools within the Dioceses participated. This sample was part of the Australian Character Study, in which participants completed a battery of questionnaires. Paper-and-pencil questionnaires were administered using a similar procedure in all schools. Ethics approval was obtained from the University of Wollongong Human Research Ethics Committee (HE10/158) before data collection.

In total, 2510 students (49.2% males) completed at least one of the Grade 8 or 11 questionnaires, forming the main sample of this study (see the analysis section for additional details on missing data). The demographic makeup of this sample broadly reflects that of the Australian population in terms of ethnicity, employment, and religious belief (Australian Bureau of Statistics, 2010). The Australian Government provides a school socioeconomic index in which the average across Australia is 1000 (http://bit.ly/1mJK7KC). The schools in this sample had a similar average score of 1026 (SD = 43).

Measures

Demographic Predictors. Students' gender was obtained from self-reports, and was coded 0 for males (49.2%) and 1 for females (50.8%). Students were asked to report on their ethnicity and their parents' marital status. Ethnicity was recoded into two dummy variables. The first one reflected Australia's indigenous populations, comprising Aboriginal Australians and Torres Strait Islanders (5.0%), which were coded 1 while all other students were coded 0. The second one reflected ethnic minorities, including students of Asian, Arabic, African, South and Central American, or African-American origins (16.5%), which were coded 1, while all other students were coded 0. When these two dummy variables are included together in an analysis, the comparison group is thus formed of

Anglo Caucasian students (78.5%). Parents' marital status was coded 1 for married families and families in which both parents were still together (74.0%), and 0 otherwise. Finally, familial socio-economic status (SES) was measured by the highest of mother and father occupational prestige coded according to the International Socio-Economic Index of Occupational Status (ISEI; Ganzeboom, Graaf, & Treiman, 1992). SES was standardized prior to all analyses.

Perceptions of Social Support. We utilized three subscales of the Student Social Support Scale to assess close friend support, parent support, and teacher support (Malecki & Elliot, 1999; Nolten, 1994). Due to limitations in the time we were given to administer the questionnaire, we used seven items for each subscale, selected based on prior factor analysis results reported elsewhere (Malecki & Elliot, 1999). Participants utilized a six-point scale (1 = *never* to 6 = *always*) to rate social support from parents (α = .93 in Grade 8 and .94 in Grade 11; 7 items, e.g., "*Praise me when I do a good job*"), peers (α = .93 in Grade 8 and .94 in Grade 11; 7 items, e.g., "*Understands my feelings*"), and teachers (α = .93 in Grade 8 and .95 in Grade 11; 7 items, e.g., "*Cares about me*").

Subjective Wellbeing. The Mental Health Continuum – Short Form (MHC-SF) is a 12-item self-report questionnaire that assesses positive mental health (Keyes, 2006). Participants utilized a 6-point Likert scale (1= *never* to 6 = *every day*) to rate their emotional wellbeing (α = .85 in Grade 8 and .908 in Grade 11; 3 items, e.g., "*During the past month, have you felt happy*"), psychological wellbeing (α = .80 in Grade 8 and .81 in Grade 11; 4 items, e.g., "*During the past month, how often did you feel good at managing the responsibilities of your daily life*"), and social wellbeing (α = .84 in Grade 8 and .85 in Grade 11; 5 items, e.g., "*During the past month, how often did you feel that you belonged to a community like a social group, your school, or your neighbourhood*").

General Ill-Health. General ill-health was measured using the General Health Questionnaire (α = .89 in Grade 8 and .91 in Grade 11), which is a highly used, reliable, and valid measure of mental health (Golderberg & Hillier, 1979) that has been successfully used with adolescents (Ciarrochi, Parker, Sahdra, Marshall, et al., 2016; Tait, French, & Hulse, 2003). Participants were provided with the sentence stem, "Have you recently…" and then with 12 response-items including, "been feeling unhappy or depressed," "felt you couldn't overcome your difficulties," and "been able to face up to your problems." Ratings were made on a four-point scale, with labels such as "*not at all*" to "*much more than usual*." Higher scores are indicative of greater psychological distress.

Analyses

Preliminary Analyses

Confirmatory factor analyses (CFA) were first estimated to verify the adequacy of the a priori measurement models underlying the constructs assessed in this study and their measurement invariance across the two waves. These models were estimated using the MLR estimator available in Mplus 7.31 (Muthén & Muthén, 2015) in conjunction with the Mplus design-based correction of standard errors (Asparouhov, 2005) to take into account the nesting of students within schools. These models were estimated on the data from all respondents who completed at least one wave of data (corresponding to n = 2510), using Full Information MLR estimation (FIML)—rather than a listwise deletion strategy focusing only on participants having answered both two time waves (N = 1251) (Enders, 2010; Graham, 2009; more details on the robustness of FIML to missing data are provided in the online supplements).

Missing data in Grade 11 were mainly due to school "Leavers", that is to students who were present in Grade 8 but not Grade 11 (783 of the 2034 who completed Grade 8 questionnaires, or 38%). In contrast, missing data in Grade 8 were mainly due to "New Arrivals", that is to students who were not enrolled or absent in Grade 8, but were present in Grade 11 (476 of the 1727 who completed Grade 11 questionnaires, or 28%). Based on government statistics (Australian Bureau of Statistics, 2015; Department of Education and Communities, 2012), the natural attrition rate is about 25-30% between grade 8 to 11, as people transition out of school and into vocational training or employment in Australia at this time. Our "Leaver" group was slightly larger than that, due to people moving in and out of private catholic system, or who weren't present on the day or on an excursion at testing time. Conversely, our "New Arrivals" included natural transfers between schools as families move, and families moving their children from public education and into private catholic education for the senior high-school years (which occurs frequently in Australia). Refusal rates on the day of testing were negligible. We also noted that FIML relies on the assumption that missing data occur at random

(MAR), rather than completely at random (MCAR) (Enders, 2010; Graham, 2009). MAR allows missing data to be conditional on all variables included in the model – which in our study includes all of the variables themselves as measures at the other time points.

These models supported the adequacy of the a priori measurement models, their measurement invariance across time waves, the distinctiveness of the various constructs, their relative stability over time, and the fact that they were meaningfully related to one another. Supporting the strength of the measurement model, omegas (ω) revealed satisfactory levels of composite reliability for the social support (ω = 0.939 to 0.940) and outcomes (ω = 0.806 to 0.904) measures. Rather than using scale score to estimate the profiles and their relations with the outcomes, factor scores (estimated in standardized units with $M = 0$, $SD = 1$) from these preliminary models were used as inputs in the main analyses. To ensure comparability in the measures across time waves, these factors scores were saved from longitudinally invariant measurement models (Millsap, 2011). Although only strict measurement invariance is required to ensure stable measurement (e.g., Millsap, 2011), there are advantages to saving factors scores from a model of complete measurement. Thus, saving factor scores based on a measurement model in which both the latent variances and the latent means are invariant (i.e., respectively constrained to 1 and 0 in all time waves) provides scores on profile indicators that can be readily interpreted as deviation from the grand mean expressed in standard deviation units. Details on these measurement models and their longitudinal invariance are reported in the online supplements. For more discussion of the advantages of factor scores in LPA, see (Morin, Boudrias, Marsh, Madore, & Desrumaux, 2016; Morin, Meyer, et al., 2016).

Latent Transition Analyses

Prior to the estimation of the LTA (Collins & Lanza, 2010; Nylund, Asparouhov, & Muthén, 2007), LPA were conducted on the social support factors at each time wave separately. This was done to ensure that the same number of profiles would be extracted at each wave. For each wave, we examined solutions including 1 to 10 latent profiles, using the three social support dimensions as indicators. The variances of these indicators were freely estimated in all profiles (Morin, Maïano, et al., 2011).

A challenge in LPA is to determine the number of latent profiles in the data. Although the substantive meaning, theoretical conformity, and statistical adequacy (e.g. absence of negative variance estimates) of the solution are three critical elements to consider in this decision (Bauer & Curran, 2003; Marsh et al., 2009; Muthén, 2003). Statistical indices support this decision (McLachlan & Peel, 2000): (i) The Akaïke Information Criterion (AIC), (ii) the Consistent AIC (CAIC), (iii) the Bayesian Information Criterion (BIC), (iv) the sample-size Adjusted BIC (ABIC), (v) the standard and adjusted Lo, Mendel and Rubin’s (2001) LRTs (LMR/aLMR, as these tests typically yield the same conclusions, we only report the aLMR); and (iv) the Bootstrap Likelihood Ratio Test (BLRT). A lower value on the AIC, CAIC, BIC and ABIC suggests a better-fitting model. A significant *p* value for the aLMR and BLRT supports the model with one fewer latent profile. Simulation studies indicate that four of these indicators (CAIC, BIC, ABIC, and BLRT) are particularly effective and that when the indicators fail to retain the optimal model, the ABIC and BLRT tend to overestimate the number of classes, whereas the BIC, CAIC, and aLMR tend to underestimate it (Nylund et al., 2007; Peugh & Fan, 2013; Tein, Coxe, & Cham, 2013; Tofighi & Enders, 2008; Yang, 2006). However, these tests remain heavily influenced by sample size (Marsh et al., 2009), so that with sufficiently large sample sizes, they may keep on suggesting the addition of profiles without ever reaching a minimum. In these cases, information criteria should be graphically presented through “elbow plots” illustrating the gains associated with additional profiles (Morin, Maïano, et al., 2011). In these plots, the point after which the slope flattens indicates the optimal number of profiles. It is important to avoid confusion with a similar process typically used in the interpretation of scree plots produced in the context of traditional exploratory factor analyses. More precisely, whereas scree plots are typically utilized to identify the first “angle”, the elbow plot requires the identification of a plateau: the key issue is thus not to locate the “steeper” decrease, but rather to locate the point after which decreases become negligible. Finally, the entropy indicates the precision with which the cases are classified into the various profiles. The entropy should not be used to determine the optimal number of profiles (Lubke & Muthén, 2007), but summarizes the classification accuracy, varying from 0 to 1 (higher values indicating more accuracy).

Once the optimal number of profiles has been selected at each time point, we integrated the two retained LPA solutions (one at each time point) in a single LTA model, allowing for the estimation of transition probabilities between LPA solutions estimated across adjacent time waves. Following the strategy proposed by Morin 2016; Morin, Meyer et al., 2016), we tested the longitudinal similarity of the LPA solutions in the following sequence. The first step examines whether the same number of profiles can be identified across time waves (i.e., *configural* similarity). In the second step, the *structural* similarity of the profiles is verified by including equality constraints across time waves on the means of the profile indicators. The third step tests the *dispersion* similarity of the profiles by including equality constraints across time waves on the variances of the profile indicators. Fourth, starting from the most similar model from the previous sequence, the *distributional* similarity of the profiles is tested by constraining the class probabilities to equality across time waves. This sequence can then be extended to tests of "*predictive*" and "*explanatory*" similarity to test whether the associations between the profiles, predictors and outcomes remain the same across time waves.

As all models are all estimated using factor scores, no missing data were present. To avoid local maxima, all LPA were conducted using 5000 random sets of start values, 2000 iterations, and retained the 200 best solutions for final stage optimization (Hipp & Bauer, 2006; McLachlan & Peel, 2000). These values were respectively increased to 10000, 2000, and 400 for the LTA.

Predictors and Outcomes of Profile Membership

Multinomial logistic regressions were conducted to test the relations between the demographic predictors (sex, SES, parental marital status, and ethnicity) and the likelihood of membership into the various profiles. Three alternative models were contrasted. First, relations between predictors and profile membership were freely estimated at both time waves, and predictions of Grade 11 profile membership was further allowed to vary across Grade 8 profiles (providing a direct test of whether the effects of predictors on profile transitions differed from one profile to the other). In a second model, predictions were still estimated freely at both time waves, but not allowed to differ across Grade 8 profiles. Finally, we tested the *predictive* similarity of the profiles by constraining these logistic regressions coefficients to invariance across time waves.

Outcomes were incorporated into the final LTA solution. We used the MODEL CONSTRAINT command of Mplus to systematically test mean-level differences across pairs of profiles or time waves within any specific profile using the multivariate delta method (Kam et al, 2016; Raykov & Marcoulides, 2014). Following incorporation of these outcomes, we proceeded to tests of *explanatory* similarity by constraining the within-profile means of these outcomes to equality across time waves. Sample inputs for all LTA models are available in the online supplements.

Results

The fit indices of the LPA estimated at each time wave are reported in Table 1. These result reveals that the AIC, CAIC, BIC and ABIC keep on decreasing with the addition of latent profiles, the aLMR (an indicator with a known tendency for underextraction) supports the 3-profile solution at both waves, while the BLRT remains significant for all solutions. To complement this information, we relied on elbow plots, which are reported in Figures S1 and S2 of the online supplements. These figures show that the relative improvement in fit associated with the addition of latent profiles reached a relatively clear plateau around 6-7 profiles.

It is important to keep in mind that the process involved in the decision of the optimal number of profiles, despite being guided by these statistical indices, always needs to incorporate some degree of subjectivity where the researcher needs to carefully examine, and contrast, the meaningfulness, statistical adequacy, and theoretical conformity of the alternative solutions. In the present study, not only do the elbow plots suggest the presence of a plateau around 6-7 profiles, but the decrease in the statistical indicators observed before reaching this plateau remains substantial (e.g., Raftery, 1995). Based on this information, we decided to examine more carefully the 6-profile solution and of adjacent 5- and 7- profile solutions (naturally, all other solutions should also be examined). This examination first showed that all of these solutions were fully proper statistically. Perhaps even more importantly, these alternative solutions revealed profiles with the same general shape across time waves, thus providing initial support to the longitudinal generalizability of the estimated profiles. Indeed, all of the alternative solutions (including 2 to 8 profiles) proved to be highly similar across time waves, thus supporting the *configural* similarity of these profiles across time waves. Because this decision process was pretty straightforward in the present study, we do not need to report all of these alternative solutions to support our decision. As noted below, we decided to retain the 6-profile solution in the present study, which will later be illustrated in Figure 1. When we look at this Figure, profiles corresponding to Profiles 1, 2, 4, and 5 were already present in the 4-profile solution. Adding a fifth profiles resulted in the addition of Profile 4, which arguably brings valuable information to the model in presenting a profile characterized by high levels of supports from parents and peers, but lower levels of teacher support. Similarly, adding a sixth profile resulted in the addition of valuable information to the model through the addition of Profile 3 characterized by very high levels of social support from all sources, in particular their teachers. In contrast, adding a seventh profile simply resulted in the arbitrary division of Profile 5 into two highly similar profiles characterized by a moderate level of social support from all sources. On the basis of this information, we thus decided to retain the 6-profile solutions at both time waves for further analyses.

The fit indices from the final LPA and for all LTA are reported in Table 2. We next explored the possibility of changes in profile structure across time. A two-wave LTA of *configural* similarity including 6-profiles at each time wave was first estimated. From this model, we estimated a model of structural similarity by constraining the within-profile means on the social support dimensions to be equal across time waves. Compared to the model of *configural* similarity, this model resulted in a slightly higher value on the AIC and ABIC, but lower values on the BIC, and CAIC, thereby supporting the *structural* similarity of this 6-profile solution across times waves. We then estimated a model of *dispersion* similarity by constraining the within-profile variability of the social support dimensions to be equal across time waves. Compared to the model of structural similarity, this model resulted in a lower value on the CAIC, BIC, and ABIC, thereby supporting the *dispersion* similarity of the profiles. Finally, we estimated a model of *distributional* similarity by constraining the size of the latent profiles to be equal across time waves. Compared with the model of *dispersion* similarity, this model resulted in an increase in the value of all information criteria, and is thus not supported by the data. This result suggests that the size of the profiles differs across time waves. The model of *dispersion* similarity was thus retained for interpretation and for the next stages. This model results in a high classification accuracy (entropy =.821), and is illustrated in Figure 1. The exact within-profile means and variances are reported in Table 3, whereas the sizes of these profiles at the different time waves, and the transition probabilities across time waves, are reported in Table 4.

Consistent with the convergence hypothesis (1a), we found a generally very low (Profile 1) and a generally very high (Profile 3) social support profiles. Profile 1 describes students who perceive receiving low levels of social support from all three sources. The size of this *Isolated* profile remains fairly stable over time, characterizing 24.5% of the students in Grade 8, and 25% in Grade 11. Profile 2 describes students who perceive receiving slightly below average levels of social support from all three sources. This *Weakly Supported* profile remains relatively large over time, and grows larger as students get older, characterizing 26.4% of the students in Grade 8, and 31.8% in Grade 11. Profiles 3 and 4 are highly interesting, and both describe students who perceive that they receive very high levels of social support from a variety of sources. In Profile 3, social support emerges from all three sources, and is notably high from teachers. In contrast, in Profile 4, social support mainly emerges from parents and peers, although teacher support still remains above average. These two profiles are much smaller in size that the previous ones. Thus, the *Fully Integrated* Profile 3 characterizes 2.2% of the students in Grade 8, and remains stable in size in Grade 11 where it characterizes 2.8% of the students. The *Parent and Peer Supported* Profile 4 is slightly larger, characterizing 6.5% of the students in Grade 8, but tends to decrease in size in Grade 11, where it characterizes 3.8% of the students. Profile 5 is also a relatively large profile, characterizing 31.6% of the students in Grade 8 compared to a slightly lower proportion (28.9%) in Grade 11. This *Moderately Supported* profile perceives receiving moderately high levels of social support from their parents, teachers, and peers, although support from peers remains lower than support from parents and teachers.

The divergence hypothesis (1b) suggested the presence of adult-only and peer-only profiles. We did not find evidence for an adult-only profile; every profile with high adult support also had high peer support. However, Profile 6 describes students for whom the main source of support comes from their peers and who feel receiving only low levels of support from their parents and teachers. This *Peer Supported* profile is moderate in size, and tends to become slightly smaller over time, characterizing 8.8% of the students in Grade 8, compared to 7.7% in Grade 11. These results suggest that for a majority of students (82.5% in Grade 8 and 85.7% in Grade 11: corresponding to Profiles 1, 2, and 5), social support levels are well aligned across sources of support. However, 17.5% of the students in Grade 8 and 14.3% in Grade 11 receive social support dominated by peers (Profile 6), parents and peers (Profile 4), or teachers (Profile 3), although this last profile suggests that high levels of teacher support are reserved to students already well supported by other sources.

Hypothesis 2a, suggesting that profiles would be moderately stable over time, was supported for the three largest profiles. Profiles 1 (*Isolated*), 2 (*Weakly Supported*) and 5 (*Moderately Supported*) appear fairly stable over time, with probabilities of transitioning to the same profile varying between 57.3% and 69.9% for these three profiles. For students initially corresponding to Profiles 1 or 2 in Grade 8 and transitioning to a different profile in Grade 11, most of the transitions occur across these two profiles, with 36.4% of the *Isolated* students in Grade 8 transitioning to the *Weakly Supported* Profile in Grade 11, and 24.4% of the *Weakly Supported* students transitioning to the *Isolated* Profile in Grade 11. Interestingly, 12.3% of the *Weakly Supported* students in Grade 8 transition to the *Peer Supported* profile in Grade 11 as their relative levels of peer support increase. In contrast, membership into the *Moderately Supported* profile remains stable over time for most students (69.9%), showing no systematic pattern of change for those who transition to a new profile in Grade 11.

Membership into the smaller Profiles 3 (*Fully Integrated*), 4 (*Parent and Peer Supported*) or 6 (*Peer Supported*) was less stable, with probabilities of transitioning to the same profile varying between 10.2% and 21.2% for these three profiles. For *Fully Integrated* (Profile 3) students in Grade 8 transitioning to a different profile in Grade 11, most of the transitions (70.7%) involve the *Moderately Supported* Profile (5), thus reflecting a slight decrease in the relative level of social support received from all three sources. Similarly, 61.3% of the *Parent and Peer Supported* (4) students in Grade 8 also transition to the *Moderately Supported* Profile (5), although 12.7% of them lose support from their parents and teacher, and transition to the *Peer Supported* Profile (6) in Grade 11.

Hypothesis 2b suggested that transitions from profiles with weak adult support should be generally downwards, that is, towards less supported profiles. This hypothesis was supported in that *Peer Supported* students (Profile 6) in Grade 8 had an 80% chance of transitioning to a worse group in Grade 11, with 18.5% transitioning to the *Isolated* profile and 61.6% transitioning to the *Weakly Supported* (Profile 2: 61.6%) profile in Grade 11. In contrast, *Peer Supported* students only had a 5.3% chance of transitioning to a better profile in Grade 11 (Profiles 3, 4 or 5).

Demographic Predictors of Profile Membership (Predictive Similarity)

Starting from the model of *dispersion* similarity, predictors were then added to the model. We estimated a model in which the effects of the predictors was freely estimated across time waves and profiles, and contrasted this model with one in which these paths freely estimated across time waves only, and then with a model in which these were constrained to be invariant across time waves and profiles (i.e., *predictive similarity*). As shown in Table 2, the model of *predictive* similarity resulted in lower values for the BIC, CAIC, and ABIC when compared to both alternative models. These results thus support the *predictive* similarity of the model, and show that the effects of the predictors on profile membership remains stable across time waves, and thus unrelated to specific profile transitions. The results from this multinomial logistic regression are reported in Table 5.

As expected (Hypothesis 3a), young people from separated or divorced families presented a higher likelihood of membership into profiles with low adult support (Profile 6 *Peer supported* and Profile 1 *Isolated*) relative to the *Parent and Peer Supported* (4) and *Moderately Supported* (5) profiles. Minority status (Hypothesis 3b) failed to predict profile membership, thus suggesting that profile membership is independent of ethnic minority status. Similarly, relatively few differences were related to SES, which only predicted a slightly increased likelihood of membership into Profile 5 (*Moderately Supported*) relative to Profiles 4 (*Parent and Peer Supported*) and 6 (*Peer Supported*), suggesting that higher levels of SES tend to be accompanied by slightly lower levels of peer support.

Finally, we found some support for Hypothesis 3c that females would be more likely than males to correspond to high support profiles, especially in profiles involving peer support. Females were more likely than males to be members of Profile 6 (*Peer Supported*) relative to Profiles 1 (*Isolated*), 2 (*Weakly Supported*), 3 (*Fully Integrated*), and 5 (*Moderately Supported*). Females also presented a higher likelihood than males to be members of Profile 4 (*Parent and Peer Supported*) relative to Profiles 1 (*Isolated*), 2 (*Weakly Supported*) and 5 (*Moderately Supported*). These results thus suggest that females are less likely than males to be members of the *Isolated* or *Weakly Supported* profiles, and more likely to receive high levels of social support from their peers.

Outcomes of Profile Membership (Explanatory Similarity)

To test for *explanatory* similarity, outcomes were added to the model of *dispersion* similarity described earlier. We first estimated a model in which the within-profile levels of outcomes were freely estimated across time waves, and contrasted this model to one in which these levels were constrained to be equivalent across time waves (i.e., *explanatory* similarity). As shown in Table 1, compared with the model where the relations between profiles and outcomes were freely estimated across time waves, the model of *explanatory* similarity resulted in a lower value for the CAIC, but in higher values for the AIC, BIC, ABIC, thus failing to support the *explanatory* similarity of the model. This suggests that the relations between profiles and outcomes differ across time waves.

The within-profile means of each outcome, together with tests of significance, are reported in Table 6, and graphically illustrated in Figure S3 of the online supplements. We found clear support for the prediction that higher support profiles are linked with higher wellbeing (Hypothesis 3d). The results regarding Emotional, Psychological, and Social Wellbeing are highly consistent across outcomes and time waves. In Grade 8, levels of Emotional, Psychological, and Social Wellbeing were highest in Profile 3 (*Fully Integrated*), followed in order by Profile 4 (*Parent and Peer Supported*), 5 (*Moderately Supported*), 6 (*Peer Supported*), and 2 (*Weakly Supported*), with the lowest levels observed in Profile 1 (*Isolated*). All differences between profiles proved to be significant, except for the level of Emotional Wellbeing which did not differ between Profiles 2 and 6. In Grade 11, the results followed the same pattern, but showed no differences between Profiles 3 (*Fully Integrated*) and 4 (*Parent and Peer Supported*) on any of the wellbeing dimensions, and no differences between profiles 5 (*Moderately Supported*) and 6 (*Peer Supported*) in terms of emotional and psychological Wellbeing. The results further show that levels of emotional and social wellbeing decreased over time in Profile 1 (*Isolated*), whereas levels of psychological and social wellbeing increased over time in Profile 5 (*Moderately Supported*). Levels of psychological wellbeing also increased over time in Profiles 4 (*Parent and Peer Supported*) and 6 (*Peer Supported*), suggesting that the role of peer support in psychological wellbeing tends to increase with age.

Results regarding General Ill-Health show a similar, albeit reversed, pattern. In both Grades, levels of General Ill-Health were highest in Profile 1 (*Isolated*), followed by Profiles 6 (*Peer Supported*) and 2 (*Weakly Supported*) which were indistinguishable from one another, followed by Profile 5 (*Moderately Supported*), with the lowest levels observed equally in Profiles 3 (*Fully Integrated*) and 4 (*Parent and Peer Supported*). Finally, levels of General Ill-Health tended to increase over time in Profiles 1 (*Isolated*), 2 (*Weakly Supported*), and 5 (*Moderately Supported*).

Supplementary Analyses of Missing Data Patterns

In order to more specifically investigate how missing data related to the profiles estimated at each of the two waves of the study, we finally investigated the extent to which Grade 8 profile membership was associated with being a member of the "Leavers" group (present in Grade 8 but not in Grade 11) and how profile membership in Grade 11 was associated with being a member of the "New Arrival" group (not present in Grade 8, but present in Grade 11). There were no significant associations between Grade 11 profile membership and the New Arrival group [$\chi^2(5) = 4.048$, $p >$ .05], but there was a significant association between Grade 8 profile membership and the "Leaver" group [$\chi^2 (5) = 90.62$, $p <$. 001]. More precisely, "Leavers" were more likely to be correspond to the Isolated (47.2%) and Peer-Only profiles (55.5%) in Grade 8 than to the other profiles (27% to 37.4%).

Discussion

Our findings suggest that only certain social support profiles naturally occur in adolescence. Specifically, our results revealed that every profile that was above average in terms of parent support was also above average in peer and teacher support. Thus, if a young person perceived high levels of parental support, they also tended to perceive higher than average levels of peer and teacher support. However, the reverse was not true. Having high levels of peer support did not guarantee high adult support, as evidenced by the identification of a profile whose social support mainly emerged from the peer group (the *Peer Supported* profile). We found no evidence for a teacher only support profile; suggesting that high levels of perceived teacher support appeared to be reserved to students who already perceived receiving satisfactory levels of support from their parents and peers.

Our results further revealed an inequality in perceived social support. Like wealth, perceived social support was not evenly distributed. A small percentage of the socially "rich" students (*Integrated*: ~2.5%) reported receiving substantial support from teachers, parents, and peers. A slightly higher percentage of students felt enriched with social support from their peers (~8%), or from their parents and peers (~5%). As with wealth distribution, the "middle classes" were more numerous, with a third of students reported moderately low and moderately high levels of social support from all sources. In contrast, a considerably large "poor" group (*Isolated*: ~25%) reported little support from parents, teachers or peers. This *Isolated* profile appeared to be particularly concerning, as it characterized adolescents who were at least .5 *SD* under the mean in terms of social support from *all* sources. None of the other profiles had *any* source of support that fell as low below the sample mean.

Change in Profile Membership

Our analyses established that profile structure was stable over time, and thus that the same profile structure could be identified in Grade 8 and 11. This finding allowed us to focus on two other aspects of development: Change in profile membership and change in the consequences of this membership. Regarding the first of these changes (the second is discussed in the next section), our results showed that profile membership changes did occur, but that the transitions were not encouraging for the "middle class" or "poor" social support profiles. In fact, for those profiles, the results showed that profile membership remained relatively stable over time. More precisely, adolescents corresponding to the *Isolated*, *Weakly Supported*, or *Moderately Supported* profiles in Grade 8 had ~60% chance of exhibiting the same profile in Grade 11. Further, when these youth transitioned to a different profile, downward transitions to "lower" social support profiles appeared to be more frequent than "upward" transitions, with observed "upward" transitions occurring across adjacent profiles rather than toward more highly desirable profiles. For example, if adolescents were *Isolated* in Grade 8, they had a 93.7% chance of staying in the *Isolated* (57.3%) or of moving to the *Weakly Supported* (36.4%) profile three years later. Similarly, *Weakly Supported* students in Grade 8 had an 84.7% chance of staying in the same profile (60.3%) or moving to the *Isolated* (24.4%) profile in Grade 11.

In contrast, adolescents with a profile characterized by above average levels of adult support in Grade 8 tended to experience the most positive transitions to Grade 11, having a 90% chance of being in the three groups characterized by the highest levels of adult support (*Fully Integrated*, *Parent and Peer Supported*, and *Moderately Supported*). In particular, adolescents from the "richest" *Fully Integrated* profile had a 100% chance of transitioning into a profile characterized by above average levels of perceived support from adults three years later. This research is consistent with past research which highlights the role of supportive parenting for positive development and social integration in adolescence (Heaven & Ciarrochi, 2008; Williams et al., 2012). In our study, each of the profiles characterized by higher than average levels of adult support was also characterized by similarly high levels of peer support. Thus, adolescents who felt highly supported by their parents also felt supported by their peers, suggesting peer integration that may, at least in part, benefit from supportive relationships with parents. Similarly, support from teachers dovetailed with support from parents: all the profiles with above average teacher support also had above average parent support. Taken together, these results suggest that feeling supported by parents, presumably due to positive parenting, may expand adolescents' capacity to feel supported by others outside home, thus helping them get integrated into the social world beyond the immediate social environment at home.

On the flip side, peer support in the absence of adult support may have risks. Although the *Peer Supported* profile was associated with higher than average levels of peer support, and higher than average to average levels of wellbeing at each time point, it also appeared to be associated with less desirable transitions. More precisely, *Peer Supported* adolescents in Grade 8 had only a 14.6% chance of remaining in that profile three years later, and a much higher (81%) chance of undergoing a downward transition to the *Isolated* or *Weakly Supported* profiles in Grade 11. Research on peer group influence on social behavior may provide one framework for understanding this effect. Adolescent peer groups may increase antisocial behavior through "deviance training" opportunities, where peers reinforce deviant attitudes and behaviors (Dishion, McCord, & Poulin, 1999; Dishion, Nelson, Winter, & Bullock, 2004; Patterson, Dishion, & Yoerger, 2000). Such deviance training may be particularly likely to occur in situations that are unstructured and unsupervised by adults or within peer groups that serve to compensate for a lack of adult support (Rorie, Gottfredson, Cross, Wilson, & Connel, 2011). Rejection of adult rules and other forms of deviance may be initially reinforcing, and may help boost the wellbeing of adolescents who otherwise feel unsupported by adults in their lives. However, despite the wellbeing benefit in the short-term, support from peers but not adults may lead to increasing social isolation in the long run, as suggested by the current results.

Wellbeing Consequences of Profile Membership: Consistency and Change

Our results provided clear support to the notion that profiles characterized by higher levels of support tended to be associated with higher levels of wellbeing at both time waves. What was striking was that almost all of the problems involving poor wellbeing and ill mental health where concentrated in the *Isolated* profile. This profile appears to experience well below average levels of emotional, psychological, and social wellbeing, and substantially above average levels of ill-health, with levels varying from 1.1 to 1.7 *SD* below the sample average on these indicators. In contrast, the next best profile (*Weakly Supported*) was only about a third of a *SD* under the sample average on these same indicators of wellbeing. Furthermore, the negative developmental consequences of corresponding to this *Isolated* profile appeared to become even more severe in Grade 11 when compared to Grade 8.

The *Fully Integrated* and *Parent and Peer Supported* profiles mostly differ in terms of the former having higher teacher support than the latter. Being *Fully Integrated* conferred a wellbeing advantage over the *Parent and Peer Supported* in Grade 8, but this advantage disappeared in Grade 11, when the two profiles had similar levels of wellbeing. We do not believe that this result contradicts past research showing the value of teacher support (Chu et al., 2010; Durlak et al., 2011), or teacher's ability to compensate for a lack of support from other sources. Rather, our results suggest that when adolescents feel satisfactory levels of parental and peer support, they also tend to perceive satisfactory levels of teacher support, which does not appear to carry a substantial added value for these already well-supported adolescents. Assuming that perceived support is a reasonably good proxy for actual support, adolescents' levels of perceived parental support may reflect the quality of parenting they receive. Thus, it may be that supportive parents influence teachers to support their children. That is, teacher support may, to some extent, mediate the link between parent support and wellbeing. Future longitudinal research is needed to test this interesting possibility.

Past research suggests that teacher support is particularly helpful for at-risk, or otherwise socially-isolated, adolescents (Baker, 2006; Crosnoe & Elder, 2004; Huber et al., 2012; Meehan et al., 2003; Mihalas et al., 2012). Similarly, intervention research suggests that connecting adolescents with a supportive adult mentor, such as a teacher, can increase engagement and positive academic outcomes (Biglan, 2015; Sinclair, Christenson, & Thurlow, 2005). Our research suggests that such interventions do not occur frequently enough in the natural setting to be picked up by our person-centered approach. That is, we were unable to identify a group that was supported exclusively by teachers. Would the 25% *Isolated* or the 30% *Weakly Supported* students benefit from an intervention aiming to increase teacher support? We believe future research is needed to test this possibility.

Our results also suggested that peers were able to compensate, to some extent, for a lack of adult support. For example, the *Peer Supported* profile perceived lower levels of parental support than the *Weakly Supported* profile, and yet scored significantly higher in emotional (Grade 11), psychological (Grades 8 and 11) and social (Grades 8 and 11) wellbeing. This observation is consistent with past research suggesting that peers can be a valuable source of support (Chu et al., 2010). However, our data highlights that consequences of a particular profile cannot be entirely assessed at a single time point. Longitudinally, peer support in Grade 8 in the absence of adult support predicted negative profile transitions in Grade 11, with most peer-supported young people transitioning to the *Isolated or Weakly Supported* profile. Future research is needed to achieve a clearer understanding of the costs and benefits associated with peer support as a compensatory mechanism for a lack of adult support.

Demographic Characteristics of the Profiles

Among the various demographic predictors of profile membership that we considered, divorce and gender appeared to be the most reliable. Adolescents from separated or divorced families were more likely to belong to profiles characterized by low levels of perceived support from adults, consistent with the literature on divorce (Kalmijn, 2013). We also found that females were more likely than males to correspond to profiles of high support, especially those involving peer support. This is consistent with past research suggesting that females are more likely than males to affiliate with females, who generally have higher empathy than males, and are also more likely to affiliate with empathic males than unempathic ones (Ciarrochi, Parker, Sahdra, Kashdan, et al., 2016). Thus, females may feel more supported simply because they affiliate with more empathic peers. Finally, we found that youth characterized in Grade 8 by the *Isolated* or *Peer-only* profiles were more likely to no longer be in the study in Grade 11, suggesting that these profiles may indicate risk for leaving school. Clearly, future research should more thoroughly investigate this possibility.

Limitations and Future Directions

We examined perceived social support profile transitions across a substantial time frame (3 years), and showed that a profile that is beneficial in the short-term may have negative long-term consequences. Specifically, the *Peer Supported* group appeared to have satisfactory, i.e., average levels of wellbeing, despite having poor support from parents or teachers. However, most of the adolescents corresponding to this profile in Year 8 transitioned to a worse profile in Year 11. Our research looked at only one transition period. Future research should examine if the *Peer Supported* profile has negative consequences in the transition from high school to university and the workforce. Furthermore, although our research considered predictors of profile membership, these predictions were found to be equivalent across time waves, and unrelated to profile transitions per se. Although this could be expected given our focus on time-invariant demographic predictors, this also reinforces the need for future research to consider a greater variety of time invariant psychosocial predictors, more naturally suited to the investigation of how transitions occur. A particularly interesting approach, in this regard, would be to incorporate a latent change approach to the assessment of predictors (e.g., McArdle, 2009), so as to be able to directly test the effects of changes in predictors' levels on profile transitions. In addition, our research focused on self-reported support. Future research should include informant measures of support from parents, teachers, and peers, to examine the extent that effects of informant and perceived support correspond.

We found that severe wellbeing problems were concentrated in a single profile of adolescents receiving very poor support from parents, teachers, and friends. This group was sizeable, about 25% of our sample. However, our data does not allow us to argue that a particular profile caused problems with wellbeing. It may be that young people who struggle with social and emotional problems also tend to push social support away (Ciarrochi, Deane, Wilson, & Rickwood, 2002). Research is needed to experimentally increase social support (Hogan, Linden, & Najarian, 2002) and examine its effects on perceived support and wellbeing in different profiles. We hypothesize that social support interventions would be most efficient and effective if they specifically targeted adolescents who lack support from parents, teachers, and friends, with a specific focus on school-based programs aiming to increase adult awareness of the importance their support could have for otherwise socially isolated students. Unfortunately, the current results are also limited by current possibilities provided by the analytical framework presented here, which does not yet allow for systematic test of relations between changes in profile membership and changes in outcomes levels over time. Future research is needed to assess the possibility that providing isolated adolescents with even a single positive source of support could make a sizeable difference to their lives. Once again, the incorporation of a latent change approach to the measure of outcomes would provide an interesting perspective on the effects of profile membership on changes in outcomes levels. Unfortunately, convergence issues precluded the incorporation of this approach to the current study.

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Table 1

Results from the Latent Profile Analysis Models Estimated Separately at Each Time Wave.

Model	LL	#fp	Scaling	AIC	CAIC	BIC	ABIC	Entropy	aLMR	BLRT
Grade 8 (N = 2034)										
1 Profile	-8311.463	6	4.407	16634.926	16674.632	16668.632	16649.570	–	–	–
2 Profiles	-7379.747	13	3.538	14785.493	14871.524	14858.524	14817.222	.976	.002	≤ .001
3 Profiles	-6787.324	20	2.289	13614.648	13747.004	13727.004	13663.462	.807	.001	≤ .001
4 Profiles	-6572.190	27	2.196	13198.380	13377.060	13350.060	13264.279	.810	.098	≤ .001
5 Profiles	-6422.016	34	1.825	12912.031	13137.035	13103.035	12995.015	.834	.074	≤ .001
6 Profiles	-6304.772	41	1.869	12691.544	12962.873	12921.873	12791.613	.781	.424	≤ .001
7 Profiles	-6191.450	48	1.996	12478.900	12796.553	12748.553	12596.053	.815	.142	≤ .001
8 Profiles	-6115.120	55	1.749	12340.241	12704.217	12649.217	12474.479	.766	.306	≤ .001
9 Profiles	-6054.051	62	1.537	12232.102	12642.403	12580.403	12383.425	.771	.209	≤ .001
10 Profiles	-6001.488	69	1.567	12140.976	12597.601	12528.601	12309.383	.775	.483	≤ .001
Grade 11 (N = 1727)										
1 Profile	-7280.986	6	1.934	14573.972	14612.696	14606.696	14587.635	–	–	–
2 Profiles	-6515.842	13	2.222	13057.685	13141.589	13128.589	13087.289	.989	≤ .001	≤ .001
3 Profiles	-6071.012	20	2.027	12182.025	12311.107	12291.107	12227.570	.791	.032	≤ .001
4 Profiles	-5802.044	27	1.750	11658.008	11832.270	11805.270	11719.494	.812	.055	≤ .001
5 Profiles	-5621.019	34	1.399	11310.037	11529.478	11495.478	11387.464	.836	.009	≤ .001
6 Profiles	-5499.664	41	1.672	11081.329	11345.949	11304.949	11174.696	.838	.161	≤ .001
7 Profiles	-5411.564	48	1.434	10919.128	11228.926	11180.926	11028.435	.843	.111	≤ .001
8 Profiles	-5339.788	55	1.339	10789.576	11144.554	11089.554	10914.824	.827	.239	≤ .001
9 Profiles	-5273.439	62	1.423	10672.723	11072.880	11010.880	10813.912	.831	.250	≤ .001
10 Profiles	-5218.079	69	1.422	10574.158	11019.494	10950.494	10731.288	.841	.570	≤ .001

Note. LL: Model LogLikelihood; #fp: Number of free parameters; Scaling = scaling factor associated with MLR loglikelihood estimates; AIC: Akaïke Information Criteria; CAIC: Constant AIC; BIC: Bayesian Information Criteria; ABIC: Sample-Size adjusted BIC; aLMR: Adjusted Lo-Mendel-Rubin likelihood ratio test; BLRT: Bootstrap Likelihood ratio test.

Table 2

Results from the Final Grade-Specific Latent Profile Analyses and from the Latent Transition Analyses Estimated on the Full Sample

Model	LL	#fp	Scaling	AIC	CAIC	BIC	ABIC	Entropy
Final Latent Profile Analyses								
Grade 8 (*N* = 2034)	-6304.772	41	1.8690	12691.544	12962.873	12921.873	12791.613	.781
Grade 11 (*N* = 1727)	-5499.664	41	1.6715	11081.329	11345.949	11304.949	11174.696	.838
Latent Transition Analyses (*N* = 2510)								
Configural Similarity	-14262.541	107	1.6107	28739.083	29469.683	29362.683	29022.716	.849
Structural Similarity	-14319.940	89	1.6113	28817.880	29425.575	29336.575	29053.800	.824
Dispersion Similarity	-14346.649	71	1.9184	28835.299	29320.090	29249.090	29023.504	.821
Distributional Similarity	-14379.683	66	1.8390	28891.366	29342.016	29276.016	29066.317	.811
Predictive Similarity								
Profile-Specific Free Relations with Predictors	-10330.967	246	1.0801	21153.934	22754.285	22508.285	21726.754	.829
Free Relations with Predictors	-10391.087	121	1.4756	21024.175	21811.339	21690.339	21305.928	.820
Invariant Relations with Predictors	-10424.671	96	1.4978	21041.342	21665.869	21569.869	21264.881	.816
Explanatory Similarity								
Free Relations with Outcomes	-31653.055	127	2.2432	63560.111	64427.272	64300.272	63896.760	.924
Invariant Relations with Outcomes	-31756.309	103	2.3297	63718.619	64421.907	64318.907	63991.649	.925

Note. LL: Model LogLikelihood; #fp: Number of free parameters; Scaling = scaling factor associated with MLR loglikelihood estimates; AIC: Akaïke Information Criteria; CAIC: Constant AIC; BIC: Bayesian Information Criteria; ABIC: Sample-Size adjusted BIC.

Table 3

Detailed Results from the Final Latent Transition Solution (Dispersion Invariance)

	Profile 1		Profile 2		Profile 3		Profile 4		Profile 5		Profile 6	
	Mean	CI	Mean	CI	Mean	CI	Mean	CI	Mean	CI	Mean	CI
Support: Parents	-.714	-.794; -.635	-.177	-.278; -.075	1.145	1.140; 1.150	1.090	1.075; 1.105	.574	.517; .630	-.264	-.464; -.065
Support: Teachers	-.646	-.773; -.518	-.141	-.218; -.064	1.378	1.374; 1.381	.546	.363; .729	.539	.452; .625	-.365	-.554; -.176
Support: Peers	-.862	-.989; -.735	-.130	-.239; -.022	1.034	1.015; 1.052	1.024	1.022; 1.026	.322	.263; .380	.957	.945; .969
	Var.	CI	Var.	CI	Var.	CI	Var.	CI	Var.	CI	Var.	CI
Support: Parents	.981	.889; 1.073	.210	.143; .276	.000	.000; .001	.004	.002; .006	.122	.107; .137	1.027	.789; 1.266
Support: Teachers	.853	.734; .972	.254	.207; .302	.000	.000; .000	.482	.291; .674	.224	.178; .271	1.347	1.160; 1.534
Support: Peers	1.020	.890; 1.150	.201	.137; .265	.001	-.001; .002	.000	.000; .001	.182	.148; .217	.003	.002; .003

Note. CI = 95% Confidence Interval.

Table 4

Relative Size of the Profiles and Transitions Probabilities for the Latent Transition Analyses

		Transition Probabilities to Grade 11 Profiles					
	Relative Size	P1: Isolated	P2: Weakly Supported	P3: Fully Integrated	P4: Parent- Peer Supported	P5: Moderately Supported	P6: Peer Supported
Grade 8 Profiles							
P1: Isolated	24.5%	**57.3%**	36.4%	0.3%	0.3%	1.8%	3.8%
P2: Weakly Supported	26.4%	24.4%	**60.3%**	0.0%	0.7%	2.2%	12.3%
P3: Fully Integrated	2.2%	0.0%	0.0%	**21.2%**	8.1%	70.7%	0.0%
P4: Parent-Peer Supported	6.5%	7.1%	1.2%	7.5%	**10.2%**	61.3%	12.7%
P5: Moderately Supported	31.6%	7.6%	4.6%	5.4%	8.1%	**69.9%**	4.5%
P6: Peer Supported	8.8%	18.5%	61.6%	0.5%	2.0%	2.8%	**14.6%**
Relative Size		25.0%	31.8%	2.8%	3.8%	28.9%	7.7%

Note. P1-P6: Profile 1 to Profile 6.

Table 5

Results from Multinomial Logistic Regressions for the Effects of the Demographic Predictors on Profile Membership.

	Isolated (1) vs. Peer (6)		Weak (2) vs. Peer (6)		Full (3) vs. Peer (6)		Parent-Peer (4) vs Peer (6)		Moderate (5) vs Peer (6)	
	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR
Sex	-0.938 (0.178)**	0.391	-0.961 (0.145)**	0.382	-0.573 (0.242)*	0.564	-0.434 (0.239)	0.648	-1.023 (0.193)**	0.359
SES	0.108 (0.055)	1.114	0.019 (0.076)	1.019	-0.049 (0.121)	0.952	-0.035 (0.074)	0.966	0.152 (0.033)**	1.164
Marital Status	0.111 (0.199)	1.117	0.148 (0.277)	1.159	0.411 (0.231)	1.508	0.692 (0.276)**	1.997	0.474 (0.155)**	1.607
Aboriginal	0.195 (0.532)	1.215	-0.118 (0.300)	0.889	0.331 (0.722)	1.393	0.157 (0.499)	1.170	0.443 (0.522)	1.557
Minority	-0.266 (0.176)	0.766	-0.442 (0.177)	0.643	-0.446 (0.363)	0.640	-0.258 (0.273)	0.773	-0.313 (0.238)	0.731
	Isolated (1) vs. Moderate (5)		Weak (2) vs. Moderate (5)		Full (3) vs. Moderate (5)		Parent-Peer (4) vs Moderate (5)		Isolated (1) vs Parent-Peer (4)	
	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR
Sex	0.086 (0.190)	1.089	0.062 (0.177)	1.064	0.450 (0.289)	1.569	0.590 (0.199)**	1.804	-0.504 (0.222)*	0.604
SES	-0.044 (0.061)	0.957	-0.132 (0.079)	0.876	-0.201 (0.105)	0.818	-0.187 (0.068)**	0.830	0.143 (0.084)	1.154
Marital Status	-0.363 (0.119)**	0.695	-0.327 (0.171)	0.721	-0.064 (0.26)	0.938	0.217 (0.232)	1.243	-0.581 (0.276)*	0.560
Aboriginal	-0.248 (0.362)	0.780	-0.561 (0.470)	0.571	-0.112 (0.37)	0.894	-0.286 (0.314)	0.751	0.038 (0.405)	1.039
Minority	0.046 (0.142)	1.047	-0.129 (0.234)	0.879	-0.133 (0.355)	0.875	0.055 (0.192)	1.056	-0.008 (0.176)	0.992
	Weak (2) vs. Parent-Peer (4)		Full (3) vs. Parent-Peer (4)		Isolated (1) vs. Full (3)		Weak (2) vs. Full (3)		Isolated (1) vs. Weak (2)	
	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR	Coef. (SE)	OR
Sex	-0.528 (0.184)**	0.590	-0.140 (0.233)	0.870	-0.365 (0.214)	0.695	-0.388 (0.232)	0.678	0.024 (0.166)	1.024
SES	0.054 (0.101)	1.056	-0.014 (0.115)	0.986	0.157 (0.131)	1.171	0.068 (0.146)	1.071	0.089 (0.080)	1.093
Marital Status	-0.544 (0.298)	0.581	-0.281 (0.300)	0.755	-0.300 (0.273)	0.741	-0.263 (0.358)	0.769	-0.037 (0.178)	0.964
Aboriginal	-0.275 (0.506)	0.760	0.175 (0.515)	1.191	-0.136 (0.465)	0.873	-0.449 (0.652)	0.638	0.313 (0.472)	1.367
Minority	-0.184 (0.249)	0.832	-0.188 (0.385)	0.829	0.180 (0.316)	1.197	0.004 (0.454)	1.004	0.176 (0.182)	1.192

Notes. **: $p < .01$; *: $p < .05$; Note. P1-P6: Profile 1 to Profile 6; SES: Socio-Economic Status; SE: standard error of the coefficient; OR: Odds Ratio. The coefficients and OR reflects the effects of the predictors on the likelihood of membership into the first listed profile relative to the second listed profile.

Table 6

Time-Varying Associations between Profile Membership and the Outcomes

	Isolated (P1)	Weakly Supported (P2)	Fully Integrated (P3)	Parent-Peer Supported (P4)	Moderately Supported (P5)	Peer Supported (P6)	Summary of Significant Differences
Emotional Wellbeing							
Grade 8	-1.460	-0.172	1.074	0.876	0.543	-0.065	1<2=6<5<4<3
Grade 11	-1.728	-0.179	1.030	1.053	0.528	0.360	1<2<5=6<4=3
Difference Grade 8-11	Grade 8 > 11	Grade 8 = 11	Grade 8 = 11	Grade 8 < 11	Grade 8 = 11	Grade 8 < 11	-
Psychological Wellbeing							
Grade 8	-1.438	-0.274	1.455	1.177	0.628	0.211	1<2<6<5<4<3
Grade 11	-1.617	-0.281	1.304	1.188	0.550	0.339	1<2<6=5<4=3
Difference Grade 8-11	Grade 8 = 11	Grade 8 = 11	Grade 8 = 11	Grade 8 = 11	Grade 8 > 11	Grade 8 = 11	-
Social Wellbeing							
Grade 8	-1.273	-0.255	1.473	1.098	0.621	0.072	1<2<6<5<4<3
Grade 11	-1.483	-0.315	1.193	1.020	0.495	0.121	1<2<6<5<4=3
Difference Grade 8-11	Grade 8 > 11	Grade 8 = 11	Grade 8 = 11	Grade 8 = 11	Grade 8 > 11	Grade 8 = 11	-
Global Ill-Health							
Grade 8	1.095	0.094	-0.888	-0.798	-0.550	0.258	3=4<5<6=2<1
Grade 11	1.505	0.205	-0.731	-0.781	-0.351	-0.010	3=4<5<6=2<1
Difference Grade 8-11	Grade 8 < 11	Grade 8 < 11	Grade 8 = 11	Grade 8 = 11	Grade 8 < 11	Grade 8 = 11	-

Note. P1-P6: Profile 1 to Profile 6.

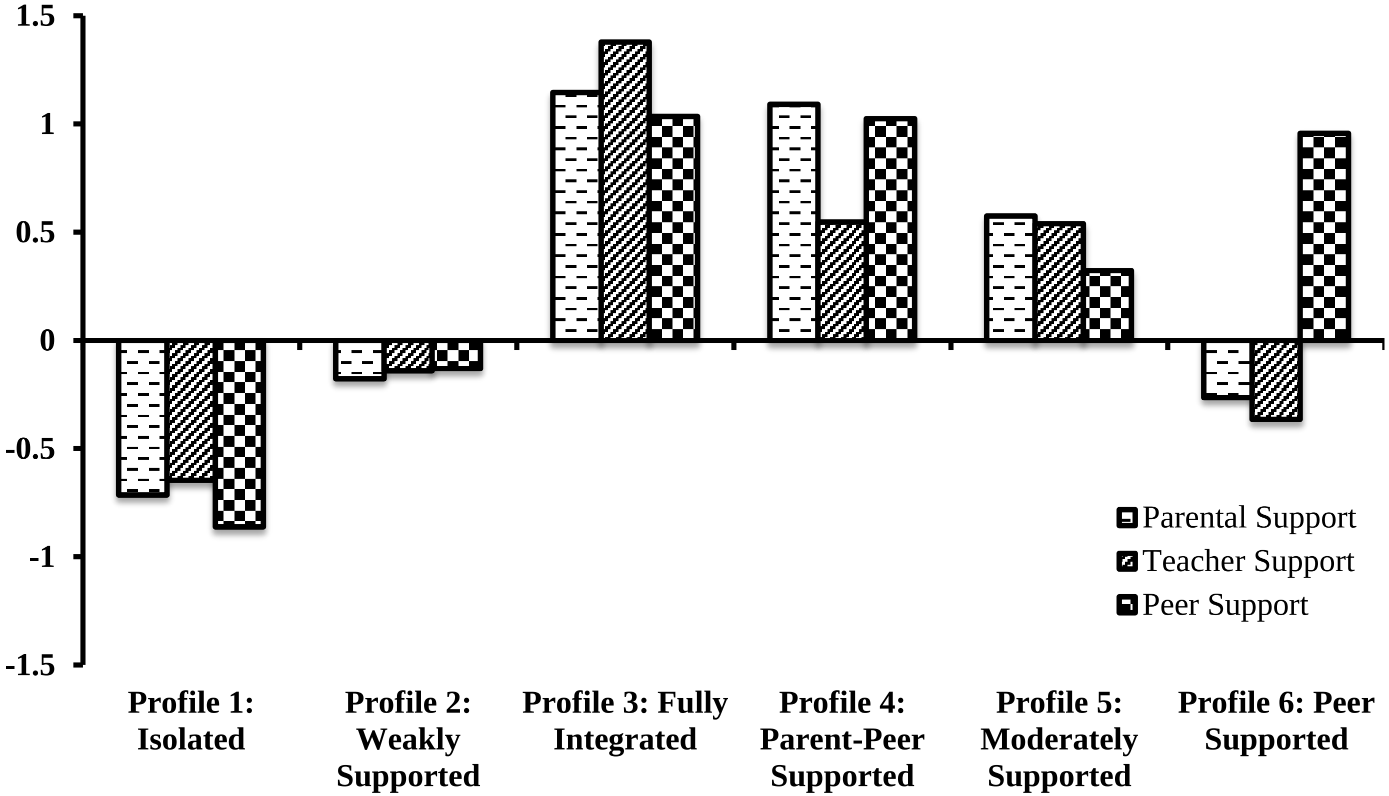

Figure 1. Final 6-Profile Solution Identified in this Study at Both Time Waves.

Online Supplemental Materials for:

A Longitudinal Person-Centered Perspective on Youth Social Support: Relations with Psychological Wellbeing.

Preliminary Confirmatory Factor Analyses

Confirmatory factor analysis (CFA) models were estimated using Mplus 7.31 (Muthén & Muthén, 2015). These models were first estimated separately for each time point (Grade 8: n = 2034; Grade 11: n = 1727), and included three factors for the perceived social support measure (Parents, Teachers, Peers), three factors for the wellbeing measure (Emotional, Psychological, Social) and one factor for the General Health Questionnaire (GHQ) representing global symptoms of ill-health. Then, complete longitudinal models were estimated across both time waves including a total of 14 factors (7 factors X 2 time waves). One orthogonal method factor was also included at each time wave to take into account the methodological artefact due to the negative wording of six GHQ items (e.g., Marsh, Scalas, et al., 2010). In the longitudinal models, these method factors were allowed to correlate with one another, but not with the substantive factors. All models were specified as congeneric, with each item allowed to load on a single factor, and all factors freely allowed to correlate within and across time-points. In the longitudinal models, a priori correlated uniquenesses between matching indicators of the factors utilized at the different time-points were also included to ensure that these longitudinal models did not converge on biased and inflated stability estimates (e.g., Marsh, 2007). For all models, these correlated uniquenesses reflected the fact that unique variance of these indicators was known to emerge, in part, from shared sources of influences over time (e.g., Marsh, Abduljabbar et al., 2013; Marsh, Scalas, et al., 2010)

CFA models were estimated using the robust maximum Likelihood (MLR) estimator. This estimator provides standard errors and tests of fit that are robust in relation to non-normality and the use of ordered-categorical variables involving at least four response categories (Finney & DiStephano, 2013), as well as to the nesting of students within schools when used in conjunction with the Mplus design-based correction of standard errors (Asparouhov, 2005). Longitudinal CFAs were conducted using the data from all respondents who completed at least one wave of data (corresponding to n = 2510), using Full Information MLR estimation (FIML)—rather than a listwise deletion strategy focusing only on employees having answered both two time waves—(Enders, 2010; Graham, 2009). FIML estimation has been found to result in unbiased parameter estimates under even a very high level of missing data (e.g., 50%), in the context of longitudinal studies with missing time points, under Missing At Random (MAR) assumptions, and even in some cases to violations of this assumption (e.g. Enders, 2001, 2010; Graham, 2009; Larsen, 2011; Shin, Davidson, & Long, 2009).

Before saving the factor scores for our main analyses, we verified that the measurement model operated in the same manner across time waves, through sequential tests of measurement invariance (Millsap, 2011): (1) configural invariance, (2) weak invariance (loadings), (3) strong invariance (loadings and intercepts), (4) strict invariance (loadings, intercepts and uniquenesses); (5) invariance of the latent variance-covariance matrix (loadings, intercepts, uniquenesses, and latent variances and covariances); (6) latent means invariance (loadings, intercepts, uniquenesses, latent variances and covariances, and latent means). In tests of the invariance of the latent variance and covariance, covariances within each set of latent variables (the three social support factors representing the profile indicators or the four wellbeing and health factors representing the outcomes) were constrained to equality across time waves.

Given the known oversensitivity of the chi-square test of exact fit (χ^2) to sample size and minor model misspecifications (e.g., Marsh, Hau, & Grayson, 2005), we relied on goodness-of-fit indices to describe the fit of the alternative models (Hu & Bentler, 1999): the comparative fit index (CFI), the Tucker-Lewis index (TLI), as well as the root mean square error of approximation (RMSEA) and its 90% confidence interval. Values greater than .90 for the CFI and TLI indicate adequate model fit, although values greater than .95 are preferable. Values smaller than .08 or .06 for the RMSEA respectively support acceptable and excellent model fit. Like the chi square, chi square difference tests present a known sensitivity to sample size and minor model misspecifications so that recent studies suggest complementing this information with changes in CFIs and RMSEAs (Chen, 2007; Cheung & Rensvold, 2002) in the context of tests of measurement invariance. A ΔCFI of .010 or less and a ΔRMSEA of .015 or less between a more restricted model and the previous one supports the invariance hypothesis.

The results from these models are reported in supplementary Table S1. These results clearly support the a priori measurement models (at each time wave separately, and longitudinally), as well as their complete measurement invariance (weak, strong, strict, latent variance-covariance, and latent means) across time waves as none of the goodness-of-fit indices exceeding the recommended cut-off scores (ΔCFI ≤ .010; ΔTLI ≤ .010; ΔRMSEA ≤ .015; and overlapping RMSEA confidence intervals). To ensure that the latent profiles estimated at each time wave were based on fully comparable measures of social support and could be compared on the basis of fully equivalent outcome measures, the factor scores used in main analyses were saved from the model of complete measurement invariance (loadings, intercepts, uniquenesses, latent variance-covariance, and latent means). Although only strict measurement invariance is required to ensure that measurement of the constructs remains equivalent across time waves for models based on factor scores (e.g., Millsap, 2011), there are advantages to saving factors scores from a model of complete measurement invariance for use in latent profile analyses. Indeed, saving factor scores based on a measurement model in which both the latent variances and the latent means are invariant (i.e., respectively constrained to take a value of 1 and 0 in all time waves) provides scores on profile indicators that can be readily interpreted as deviation from the grand mean expressed in standard deviation units.

The parameter estimates from these models are reported in Table S2 (factor loadings and uniquenesses) of these online supplements, and in Table 1 (factor correlations) of the main manuscript. These parameter estimates were used to compute composite reliability coefficients associated with each of the a priori factors using McDonald (1970) omega (ω) coefficient:

$$\omega = \frac{(\sum|\lambda_i|)^2}{[(\sum|\lambda_i|)^2 + \sum\delta_i]}$$

where $|\lambda_i|$ are the standardized factor loadings associated with a factor in absolute values, and δi, the item uniquenesses. The numerator, were the factor loadings are summed, and then squared, reflects the proportion of the variance in in indicators that reflect true score variance, whereas the denominator reflects total amount of variance in the items including both true score variance and random measurement errors (reflects by the sum of the items uniquenesses associated with a factor). These coefficients are all satisfactory (ω = .806 to .939), and reported in Tables S2 and 1.

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Table S1.

Goodness-of-Fit Statistics of the Longitudinal Confirmatory Factor Analytic (CFA) Models

Description	$R\chi^2(df)$	CFI	TLI	RMSEA	90% CI	$\Delta R\chi^2$ (df)	ΔCFI	ΔTLI	ΔRMSEA
Grade 8 (N = 2034)	3091.971 (918)*	.950	.946	.034	[.033; .035]	–	–	–	–
Grade 11 (N = 1727)	3758.575 (918)*	.936	.931	.042	[.041; .044]	–	–	–	–
Configural invariance (N = 2510)	9533.631 (3766)*	.941	.937	.025	[.024; .025]	–	–	–	–
Weak Invariance	9643.827 (3810)*	.940	.937	.025	[.024; .025]	90.495 (44)*	-.001	.000	.000
Strong Invariance	10214.468 (3848)*	.934	.932	.026	[.025; .026]	494.025 (38)*	-.006	-.005	+.001
Strict Invariance	10588.231 (3893)*	.931	.929	.026	[.026; .027]	318.273 (45)*	-.003	-.003	.000
Variance-Covariance Invariance	10653.418 (3909)*	.931	.929	.026	[.026; .027]	62.904 (16)*	.000	.000	.000
Latent Mean Invariance	10950.756 (3916)*	.928	.926	.027	[.026; .027]	233.639 (7)*	-.003	-.003	+.001

Note. *$p < .01$; $R\chi^2$: Robust chi-square test of exact fit; *df*: Degrees of freedom; CFI: Comparative fit index; TLI: Tucker-Lewis index; RMSEA: Root mean square error of approximation; 90% CI: 90% confidence interval of the RMSEA; $\Delta R\chi^2$: Robust chi-square difference tests (calculated from loglikelihoods for greater precision) (Satorra & Bentler, 2001).

Supplementary Table S2

Standardized Parameter Estimates from the Fully Invariant Longitudinal Confirmatory Factor Analytic (CFA) Model

	Parental Support		Teacher Support		Peer Support		Emotional WB		Psychological WB		Social WB		General Ill Health	
Items	λ	δ	λ	δ	λ	δ	λ	δ	λ	δ	λ	δ	λ	δ
Item 1	.872	.240	.819	.329	.812	.340	.819	.330	.743	.447	.714	.491	.480	.677
Item 2	.903	.185	.831	.310	.870	.243	.838	.298	.746	.444	.719	.483	.611	.627
Item 3	.857	.266	.866	.250	.842	.291	.888	.211	.627	.607	.722	.478	.562	.580
Item 4	.792	.374	.818	.331	.811	.343			.737	.457	.753	.434	.467	.596
Item 5	.783	.386	.855	.270	.841	.293					.705	.503	.642	.588
Item 6	.870	.243	.814	.337	.834	.305							.660	.564
Item 7	.721	.480	.800	.359	.806	.351							.551	.549
Item 8													.536	.543
Item 9													.824	.321
Item 10													.844	.287
Item 11													.819	.329
Item 12													.627	.504
ω	.939		.939		.940		.885		.806		.845		.904	

Note. All loadings and uniquenesses are significant ($p < .01$); WB= Wellbeing; λ = Loadings; δ = Uniquenesses; ω = omega coefficient of reliability.

Table S3.

Latent Correlations from the Fully Invariant Longitudinal Confirmatory Factor Analytic (CFA) Model

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1- Parent Support (G8)	*.939*													
2- Teacher Support (G8)	.378**	*.939*												
3- Peer Support (G8)	.373**	.280**	*.940*											
4- Emotional WB (G8)	.537**	.334**	.329**	*.885*										
5- Psychological WB (G8)	.580**	.406**	.505**	.794**	*.806*									
6- Social WB (G8)	.498**	.363**	.389**	.684**	.865**	*.845*								
7- Ill Health (G8)	-.471**	-.267**	-.207**	-.693**	-.642**	-.572**	*.904*							
8- Parent Support (G11)	.460**	.309**	.205**	.259**	.301**	.259**	-.233**	*.939*						
9- Teacher Support (G11)	.174**	.474**	.146**	.144**	.237**	.199**	-.099**	.378**	*.939*					
10- Peer Support (G11)	.169**	.183**	.379**	.211**	.257**	.207**	-.155**	.373**	.280**	*.940*				
11- Emotional WB (G11)	.222**	.187**	.088**	.395**	.352**	.324**	-.332**	.458**	.328**	.352**	*.885*			
12- Psychological WB (G11)	.281**	.207**	.162**	.354**	.385**	.359**	-.329**	.515**	.424**	.490**	.794**	*.806*		
13- Social WB (G11)	.189**	.221**	.105**	.292**	.324**	.393**	-.258**	.459**	.385**	.399**	.684**	.865**	*.845*	
14- Ill Health (G11)	-.145**	-.107**	.017	-.230**	-.154**	-.153**	.299**	-.376**	-.207**	-.253**	-.693**	-.642**	-.572**	*.904*

Note. ** $p < .01$; WB = Wellbeing; G8 = Grade 8; G11 = Grade 11; Composite reliability coefficients reported in the diagonal (italicized).

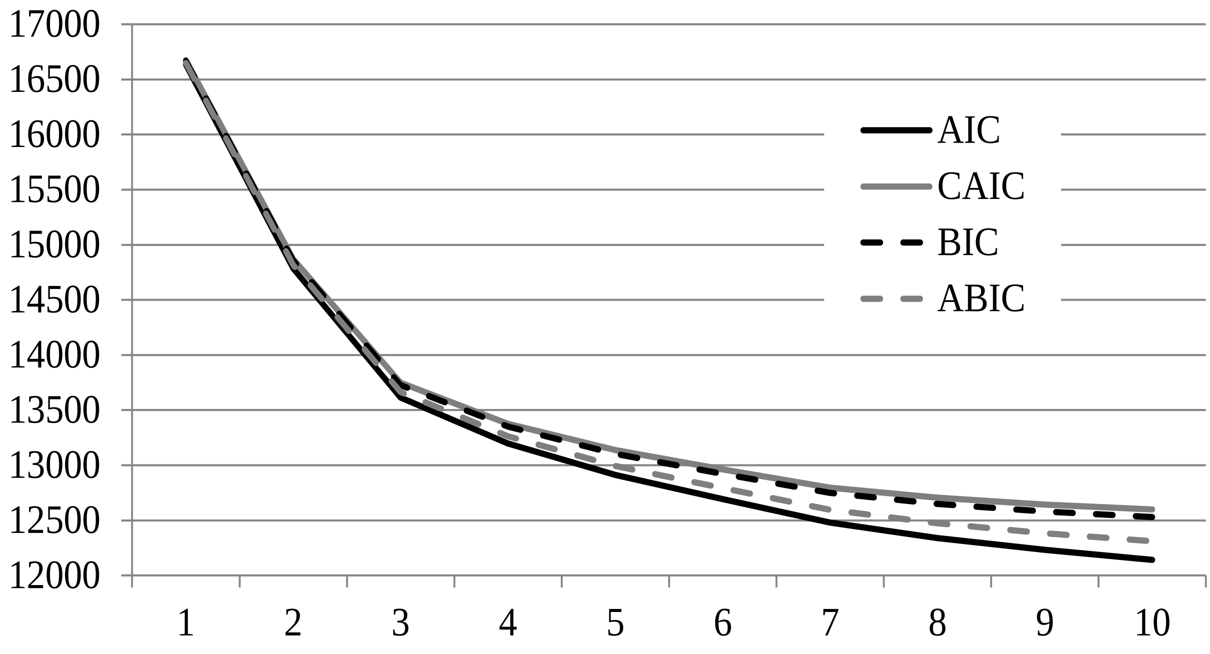

Figure S1. Elbow Plot of the Information Criteria for the Latent Profile Analyses (Grade 8).

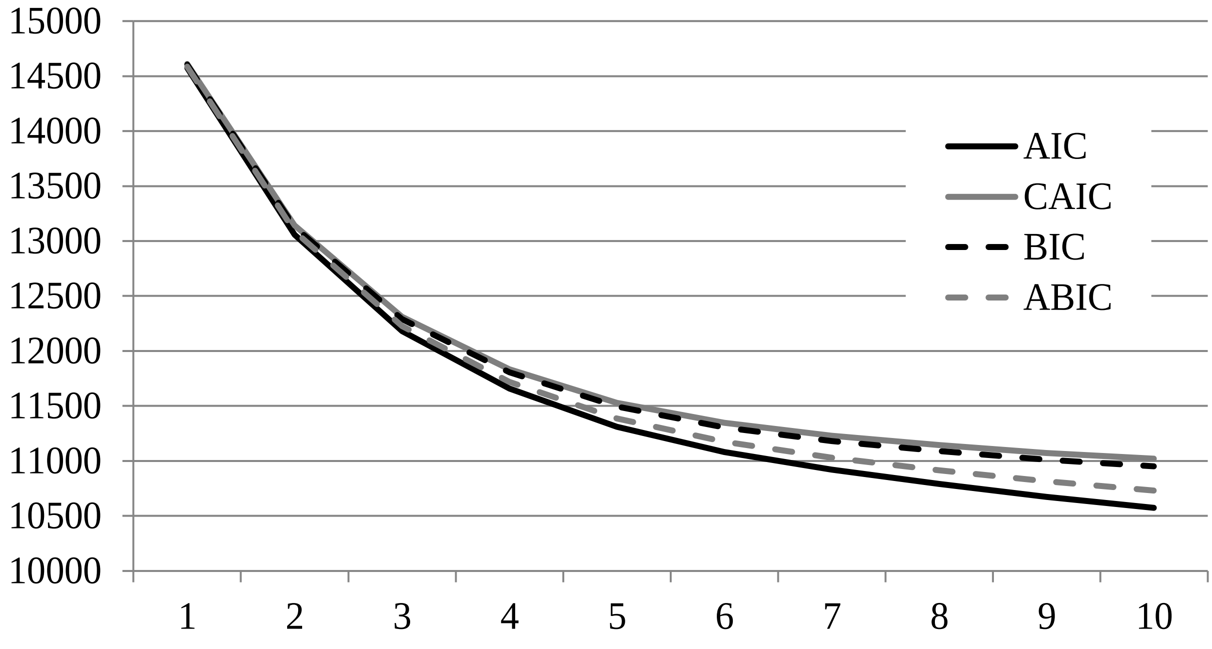

Figure S2. Elbow Plot of the Information Criteria for the Latent Profile Analyses (Grade 11).

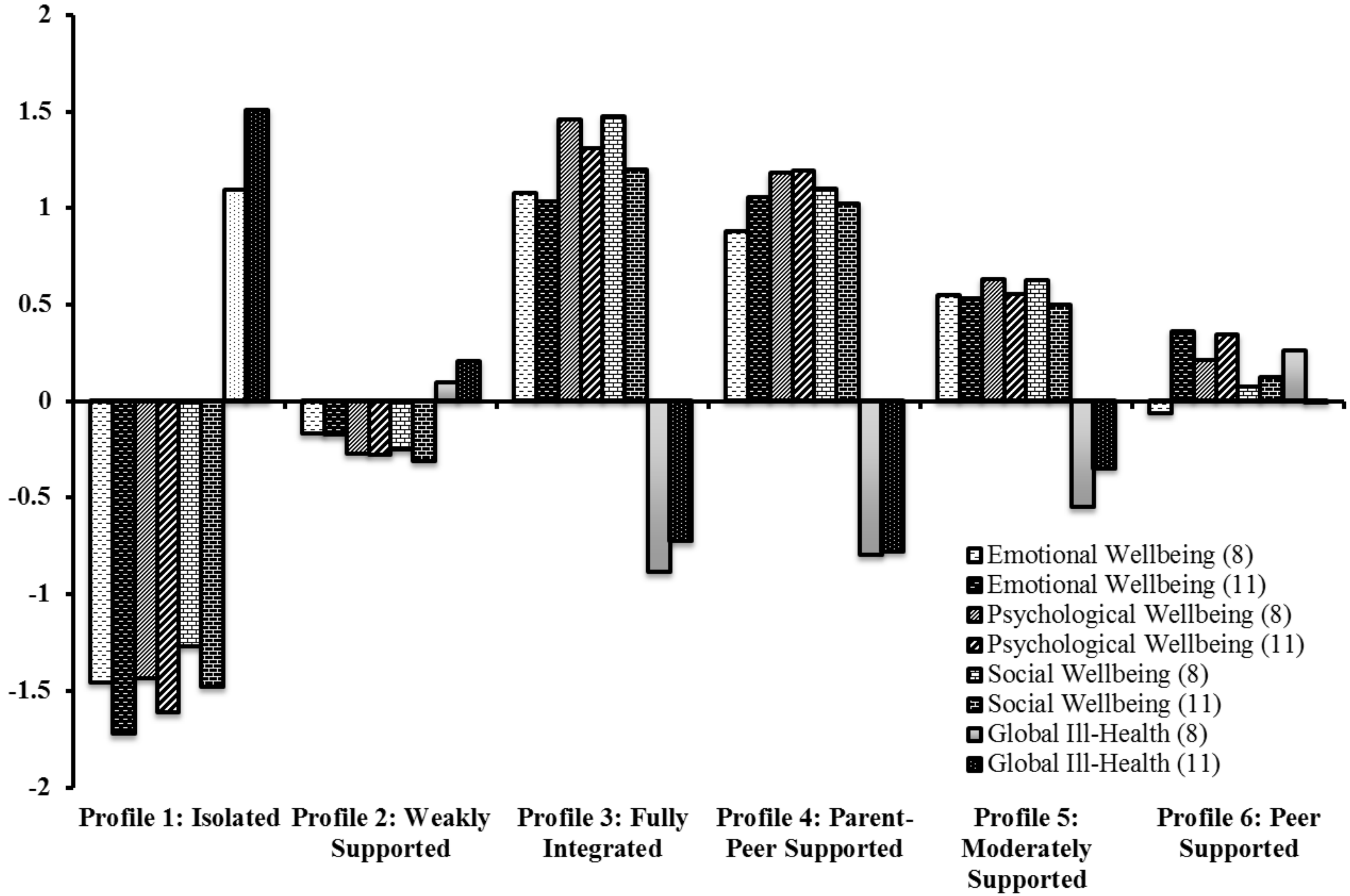

Figure S3. Outcome levels in each of the estimated latent profiles are each time points.

Mplus Input to Estimate a 6-Profile Latent Profile Analysis (Wave 1)

```
! In all input files, statements preceded by ! are annotations.
! Use the following statement to identify the data set. Here, the data set is labelled Data.dat.
DATA:
FILE IS Data.dat;
! The variables names function identifies all variables in the data set, in order of appearance,
! whereas the usevariable command identifies the variables used in the analysis.
VARIABLE:
NAMES = SSP1Y8 SSP2Y8 SSP3Y8 SSP4Y8 SSP5Y8 SSP6Y8 SSP7Y8 SSP1Y11 SSP2Y11
SSP3Y11 SSP4Y11 SSP5Y11 SSP6Y11 SSP7Y11 SST8Y8 SST9Y8 SST10Y8 SST11Y8 SST12Y8
SST13Y8 SST14Y8 SST8Y11 SST9Y11 SST1011 SST1111 SST1211 SST1311 SST1411
SSF15Y8 SSF16Y8 SSF17Y8 SSF18Y8 SSF19Y8 SSF20Y8 SSF21Y8 SSF1511 SSF1611
SSF1711 SSF1811 SSF1911 SSF2011 SSF2111 SWB1Y8 SWB2Y8 SWB3Y8 SWB4Y8 SWB5Y8
SWB6Y8 SWB7Y8 SWB8Y8 SWB9Y8 SWB10Y8 SWB11Y8 SWB12Y8 SWB1Y11 SWB2Y11
SWB3Y11 SWB4Y11 SWB5Y11 SWB6Y11 SWB7Y11 SWB8Y11 SWB9Y11 SWB1011 SWB1111
SWB1211 GH1Y8 GH2Y8 GH3Y8 GH4Y8 GH5Y8 GH6Y8 GH7Y8 GH8Y8 GH9Y8 GH10Y8
GH11Y8 GH12Y8 GH1Y11 GH2Y11 GH3Y11 GH4Y11 GH5Y11 GH6Y11 GH7Y11 GH8Y11
GH9Y11 GH10Y11 GH11Y11 GH12Y11 ID SEX SESZ MARIT DUM1IND DUM2MIN
PY8 PY11 PTOT PAR8 PAR8_SE TEA8 TEA8_SE PEER8 PEER8_SE PAR11 PAR11_SE
TEA11 TEA11_SE PEER11 PEER11_SE EMWB8 EMWB8_SE PSYWB8 PSYWB8_SE
SOCWB8 SOCWB8_SE EMWB11 EMWB11_SE PSYWB11 PSYWB11_SE SOCWB11
SOCWB11_SE GHQ8 GHQ8_SE MF8 MF8_SE GHQ11 GHQ11_SE MF11 MF11_SE SCHL ;
USEVARIABLES ARE
PAR8 TEA8 PEER8;
! The following is used to select only participant who completed questionnaires in Grade 8. The
! subpopulation function is required (rather than the USEOBSERVATION function) due to the use of
! design-based correction of standard errors to account for students nesting into schools.
SUBPOPULATION = PY8 EQ 1;
! Missing data are identified with the following (the same code * is used for all missing).
MISSING ARE ALL *;
! The following identifies the unique identifier for participants
IDVARIABLE = ID;
! The following identifies the variable including the nesting information (here, the school).
CLUSTER = schl;
! The following identifies the number of latent profiles requested in the analysis.
CLASSES = c (6);
Analysis:
! The following identifies that mixture modeling is requested in conjunction with the design-based
! correction of standard errors to account for students nesting into schools (COMPLEX).
type = mixture COMPLEX;
estimator = MLR;
! The following set up is to estimate the model using 3 processors, 5000 starts values, 200 final stage
optimizations, and 2000 iterations.
Process = 3;
STARTS = 5000 200;
STITERATIONs = 2000;
! In this input, the overall model statement defines sections that are common across profiles.
! Here, there is no need to include anything in this section.
! The %c#1% to %c#6% sections are class-specific statement to specify which part of the
! model is freely estimated in each profile.
! For a simple latent profile model, include the means of the indicators (using []) in all profiles.
! To also freely estimate all variances, the following is added in each class-specific statement:
! PAR8 TEA8 PEER8;
MODEL:
%OVERALL%
```

```
PAR8 TEA8 PEER8; [PAR8 TEA8 PEER8];
%c#1%
PAR8 TEA8 PEER8; [PAR8 TEA8 PEER8];
%c#2%
PAR8 TEA8 PEER8; [PAR8 TEA8 PEER8];
%c#3%
PAR8 TEA8 PEER8; [PAR8 TEA8 PEER8];
%c#4%
PAR8 TEA8 PEER8; [PAR8 TEA8 PEER8];
%c#5%
PAR8 TEA8 PEER8; [PAR8 TEA8 PEER8];
%c#6%
PAR8 TEA8 PEER8; [PAR8 TEA8 PEER8];
! Specific sections of output are requested. TECH11 estimates LMR, and TECH14 estimates BLRT.
OUTPUT:
SAMPSTAT STANDARDIZED RESIDUAL CINTERVAL MODINDICES (3.0) TECH2 TECH4 ;
svalues TECH11 TECH13 TECH14;
! The bootstrap LRT (BLRT) indicator (requested with TEC14) is not available with TYPE =
! COMPLEX. To obtain it, the “CLUSTER = schl;” statement need to be taken out, the
! “SUBPOPULATION = PY8 EQ 1;” statement needs to be replaced by “USEOBS = PY8 EQ 1;”
! and the “COMPLEX” statement needs to be taken out.
```

See the following webnote for an updated analytical sequence:

Morin, A.J.S., & Litalien, D. (2017). Webnote: Longitudinal tests of profile similarity and latent transition analyses. Montreal, QC: Substantive Methodological Synergy Research Laboratory. http://smslabstats.weebly.com/uploads/1/0/0/6/100647486/lta_distributional_similarity_v02.pdf