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The role of engagement in immigrant students' academic resilience

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A R T I C L E I N F O

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A B S T R A C T

Academic resilience refers to academic success despite chronic socio-educational adversity. Given increases in immigration across the world in the past decade (including in Europe), there have been calls to identify factors (e.g., engagement) that can better support immigrant students' academic resilience. With a sample of $N = 17{,}241$ immigrant students from 18 European countries, the present investigation employed multi-level probit regression to determine the extent to which cognitive, behavioral, and social-emotional engagement predict academic resilience status at both the student- and school-level. Findings revealed that cognitive engagement and behavioral engagement, at both the student- and school-level, are positively associated with academic resilience (yielding moderate and large effect sizes), while the findings regarding social-emotional engagement were more equivocal.

1. Immigrant students and academic adversity

In the past decade, Europe has faced the challenge of integrating substantial numbers of newly arrived migrant and refugee students (herein referred to as "immigrant students") into its education systems. Large-scale international student assessments have highlighted significant gaps in achievement among disadvantaged immigrant learners (Cutmore et al., 2018). For example, data from the OECD's Programme for International Student Assessment (PISA) show that immigrant status is a highly influential factor determining educational success (European Commission, 2016). The ongoing socio-educational challenges experienced by immigrant students are a barrier to their upward social mobility (Crul et al., 2017). To better understand these challenges and how immigrant students deal with them, the Bertelsmann Foundation (2008) and OECD (2006, 2010) examined a new sub-group of interest: "academically resilient" students. These are students who academically succeed despite their unfavorable starting conditions and continued socio-educational adversity (Luthar et al., 2000; OECD, 2011). Building on this paradigm of resilience, Cutmore et al. (2018) conducted a major review and analysis of academic resilience among immigrant students in European Union Member States. That report identified many factors implicated in immigrant students' academic resilience and educational success. Of particular relevance to psycho-educational research and practice were aspects of engagement. However, in that report engagement was operationalized as part of a broader psycho-educational construct and not differentiated by its well-established cognitive, behavioral, and social-emotional dimensions (Fredricks et al., 2004; Martin, 2021). The present study extends Cutmore et al.'s (2018) research by modelling student and school-average cognitive, behavioral, and social-emotional engagement as predictors of immigrant students' academic resilience status and the proportion of academically resilient immigrant students in a school. In modelling multilevel multivariate academic engagement in this way, researchers and practitioners can gain a sense of the unique role of specific aspects of engagement in immigrant students' academic resilience at the student- and school-level. In turn, this can guide psycho-educational practice aimed at better supporting the educational development of immigrant students.

2. Theoretical backdrop to immigrant students' academic development

One of the more well-established youth-oriented frameworks centrally concerned with ethnic and cultural minority status—though, focused more on general child/adolescent development than educational development—is that proposed by Garcia Coll and colleagues

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(1996). Harnessing social stratification theory, Garcia Coll et al. (1996) reported, "social stratification deriving from prejudice, discrimination, racism, or segregation and the differential access to critical resources such as good schools, employment, and health care influence families and children of color to develop goals, values, attitudes, and behaviors that set them apart from the dominant culture" (p. 1904). In later work, Martin et al. (2012) drew on the Garcia Coll et al. framework to investigate problem solving among immigrant students. They found that it was not immigrant status per se that impacted problem solving, but other personal and contextual attributes that were key, including how immigrant students develop and engage at school. This being the case, it is vital to identify factors that may underpin immigrant students' ability overcome disadvantage and the negative forces that typically impact them—hence, our focus on engagement factors that predict the academic resilience of socio-educationally disadvantaged immigrant students.

3. Academic resilience and its operationalization

Academic resilience is conceptualized as "the heightened likelihood of success in school and other life accomplishments, despite environmental adversities brought about by early traits, conditions, and experiences" (Wang et al., 1994, p. 46). Academically resilient students are those who achieve highly despite the presence of conditions that place them at risk of academic underachievement (Alva, 1991). Examples of chronic academic-related adversities include poor early educational background, challenging learning conditions, and low socio-economic status (as relevant to educational opportunity; Cutmore et al., 2018). In large-scale international assessments, researchers have conceptualized academically resilient students as those who experience chronic socio-educational disadvantage and yet achieve highly (OECD, 2014). Based on this definition, academic resilience has recently been operationalized using empirically-driven approaches through the application of cut-off scores such as students who are in the lowest quartile (bottom 25%) of socio-educational status and the highest quartile (top 25%) of academic achievement (Cutmore et al., 2018; OECD, 2014). In PISA (the data used in this investigation), socio-educational status is represented by the index of economic, social, and cultural status (ESCS) which comprises data on parent education and occupation, family wealth, educational resources, and cultural resources (OECD, 2017). The present study follows this approach, seeking to identify the specific engagement factors that predict the academic resilience of immigrant students; that is, students demonstrating high levels of achievement (top 25%) in the face of high socio-educational disadvantage (bottom 25% of ESCS). Placing this operationalization into the more classic "risk" framework (e.g., Coleman & Hagell, 2007), we might consider the lowest quartile of ESCS as a form of socio-educational risk in the sense that it represents the lowest levels of parent education and occupation, family wealth, educational resources, and cultural capital (OECD, 2017). Moreover, given our focus on immigrant students, we might further consider that the joint operation of immigrant status and low-ESCS constitutes additional socio-educational risk. Bringing these factors together, in line with OECD's operationalization, we posit that students experiencing socio-educational adversity (low ESCS and migrant status) *and* who perform in the top quartile of PISA achievement can be deemed academically resilient (though in Discussion below, we identify other ways to further validate this approach to academic resilience).

4. Factors predicting academic resilience: academic engagement

In identifying potential predictors, we draw on prior research that has sought to isolate the various factors implicated in how students navigate academic adversity. This work has highlighted relevant factors that may be more immediately amenable to change and personal/institutional intervention (e.g., psycho-educational factors) and factors that may take longer to meaningfully address or are relatively fixed (e.g., SES, family structure; Cappella & Weinstein, 2001; Martin & Marsh, 2009). It is the factors that are more amenable to intervention that are the focus for our investigation. Of these, Martin and Marsh (2009) have described engagement as particularly important. Indeed, major theories of youth development highlight that student engagement critically contributes to students' resilience and ongoing development (Fredricks & Eccles, 2008; 2005Lerner).

Academic engagement is conceptualized as a multidimensional construct encompassing cognitive, behavioral, and social-emotional elements (Fredricks, 2011; Fredricks et al., 2004; Fredricks & McColskey, 2012; Martin, 2021). Cognitive engagement draws on concepts around being willing, thoughtful, and strategic as one invests academically and exerts scholarly effort (Fredricks et al., 2004; Martin, 2021; Martin et al., 2021). It refers to students' cognitive and attitudinal investment in their learning (Fredricks et al., 2004) that includes future-oriented cognitive representations such as educational aspirations, expectations, etc. (Martin, 2021). In the present study, and consistent with Burns et al. (2018) and Bostwick et al. (2020), we operationalize cognitive engagement by way of academic expectations. Behavioral engagement draws on concepts relevant to involvement and participation (Fredricks et al., 2004; Martin, 2021; Martin et al., 2021). It refers to students' actions and active participation in academic activities (Fredricks et al., 2004). Following Martin et al. (2017), we operationalize behavioral engagement by way of student attendance at school. Social-emotional engagement draws on concepts around negative and positive emotional and interpersonal responses implicated in learning (Fredricks et al., 2004; Martin, 2021; Martin et al., 2021). It refers to students' emotional reaction to their schoolwork and academic environment, such as their emotions (e.g., enjoyment) related to academic content and their affective responses to their peers (e.g., enjoying working with other students; Fredricks et al., 2004). The present study operationalizes social-emotional engagement by way of students' enjoyment working with others at school. It is important to account for all three components of engagement, as they are inter-related (Fredricks et al., 2004), and thus disentangling the unique effects of each component is vital to understand where and how future intervention efforts should be focused.

Research based on 'mainstream' populations has shown each of these engagement factors to be associated with students' achievement (e.g., Burns et al., 2018; Khattab, 2015; Martin et al., 2021). The question now is the extent to which engagement may support the achievement of immigrant students who experience socio-educational disadvantage—that is, the extent to which engagement predicts immigrant students' academic resilience. We used OECD PISA data to test this. Although we recognize these data are cross-sectional which limits causal claims, there is a long line of research placing academic engagement as a predictor of academic achievement (see Martin, 2013, 2021 for reviews). Many researchers identify academic engagement as a means by which learning and achievement occur. The agentic elements of various forms of academic engagement enable students to exert control over their learning and achieve more highly (Reeve, 2012; Schunk & Mullen, 2012). In the case of the three engagement factors in the present study, research suggests that behavioral engagement (such as attendance and participation) enables more instructional time and helps students to attain better understanding of a subject area or topic (Credé et al., 2010; Green et al., 2012). With respect to cognitive engagement, students' conceptions of their academic futures (such as the cognitive engagement construct in our study) impact their present learning (e.g., Burns et al., 2021; de Bilde et al., 2011; Kauffman & Husman, 2004). For social-emotional engagement, factors such as enjoyment involve affective/social connections and immersion with learning peers or with a topic that improve skill and knowledge acquisition (Burns et al., 2021; Nakamura & Csikszentmihalyi, 2009). All this being the case, we believe there are defensible grounds for modeling cognitive, behavioral, and social-emotional engagement as predictors of high achievement in the face of low socio-educational advantage—i.e., academic resilience. Notwithstanding this, we return to this issue and argue for due caution in our discussion of limitations later.

5. Relevant student and school attributes

In Garcia Coll et al.'s (1996) framework, the impact of ethnic and cultural minority status on developmental competencies is affected by many factors, including "social position" factors such as gender, "child characteristics" such as age, and "promoting/inhibiting environment" factors such as those related to their schooling environment. In seeking to understand the role of academic engagement in immigrant students' academic resilience, it is thus important to account for these student and school factors as covariates in the modeling. In doing so, we are able to identify the unique role of engagement in academic resilience, beyond other personal and contextual factors. Socio-demographics such as gender and age are relevant. Research has found immigrant girls generally outperform immigrant boys at school and demonstrate higher educational attainment (Baolian Qin, 2006); however, immigrant boys perform more highly in mathematics (Martin, 2004; OECD, 2004). Regarding age, Marsh (2016) identified age-within-cohort effects in PISA data, with students older in the cohort reporting higher levels of academic motivation. With regard to first- and second-generation immigrant students, Martin et al. (2012) identified significant differences in science achievement between first- and second-generation immigrant students relative to non-immigrant students. There are also school attributes to account for that can make a difference to students' outcomes (Hattie, 2009; Martin, 2016). In relation to school socio-economic status and school location, research has shown that immigrant students tend to be in urban and inner-city areas of lower SES standing (Meunier, 2011; Pong & Hao, 2007). Research has also suggested that immigrant students are more likely to attend larger schools (Meunier, 2011; Pong & Hao, 2007), but the impact of this is unclear.

6. Multilevel considerations: school-level engagement and academic resilience

In the present study, students are nested within schools; thus, we employ multilevel modeling (Goldstein, 2003) to account for the hierarchical nature of these data to understand the variance attributable to student- and school-levels. This addresses the question as to whether, beyond the effects of student-level engagement on student-level academic resilience, as well as school characteristics (e.g., location), school-average engagement may be associated with the proportion of immigrant students in a school who are academically resilient (indeed, this design also disentangles unique student-level effects from school-level effects). There is research showing that school-level engagement impacts school-level achievement. For example, Burns et al. (2020) found school-level social-emotional engagement (school belonging) predicted school-level achievement. Prior to that, Burns et al. (2019) found that school-level cognitive and social-emotional engagement (interest and enjoyment) in science predicted school-average science achievement. Recently, Bostwick et al. (2022) found that school-level (and student-level) school belonging (akin to social-emotional engagement) predicted academic resilience. However, those investigations did not assess all cognitive, behavioral, and social-emotional engagement factors, the Burns et al. (2019) study aggregated cognitive and social-emotional engagement, and the Bostwick et al. (2022) study operationalized academic resilience via a self-report of academic buoyancy. Thus, it is unclear what relative emphasis ought to be given to each school-level engagement factor in school-based interventions targeting academic resilience. Moreover, given that there can be significant differences between schools in immigrant student achievement (Dronkers et al., 2012), it is possible there may also be differences between schools in how academic engagement is associated with immigrant students' academic success.

7. Aims of the present study

Immigrant students in Europe have emerged as a particularly academically at-risk group, owing in large part to the socio-educational adversity they experience. Recently, academic resilience has been proposed as a factor that may assist their academic outcomes. With a focus on immigrant students in European Union Member States, the present study aimed to understand the role of academic engagement in predicting immigrant students' academic resilience (i.e., achievement in the face of socio-educational adversity). Specifically, the present study investigated (a) the role of student-level engagement in predicting students' academic resilience status and (b) the role of school-level engagement in predicting the proportion of academically resilient students in the school.

8. Methods

8.1. Participants and sampling

The investigation comprised students from 18 European Union Member States from PISA 2015 that Cutmore et al. (2018) identified as comprising sufficient numbers of immigrant students, and therefore representing large enough samples within PISA from which resilient students could be garnered.[1] PISA collects nationally representative samples from each country via a two-stage data collection process. The first stage is school selection and the second stage is student selection; schools are selected from a comprehensive national list of schools, and then students who are 15 years old are randomly selected from within those schools (OECD, 2017). In total, there were $N = 17{,}241$ immigrant students in our study. The students included in analysis were clustered in $N = 4253$ schools. Most schools (35%) from which students were sampled were located in a town (viz., 15,000–100,000 people) and were public (i.e., government funded) schools (82%). The average school size was $M = 820$ students ($SD = 515$).

Our immigrant student sample includes students who are classified as either first or second generation. First generation immigrant students are those whose parents (both) and themselves were born in a country different to the one in which the student sat the PISA test. Second generation immigrant students are those who were born in the country in which they sat the PISA test (i.e., an EU Member State) but whose parents (both) were born in a different country. Both generations were included to capture the complex movement histories of immigrant students and to maximize the students included in analysis. The sample was approximately evenly split by generation (44% first generation). Importantly, as is discussed below, immigration generation was included in the analysis as a covariate.

The average age was $M = 15.78$ years old ($SD = 0.29$; note the target age of PISA sampling is 15 years old). Approximately half of the sample was female (51%) and spoke a language other than the test language at home (56%).[2] Although socio-economic status was included in the identification of academic resilience status, and thus not included as a

[1] The European Union countries included were: Austria, Belgium, Croatia, Cyprus, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Lithuania, Luxembourg, Netherlands, Slovenia, Spain, Sweden, and United Kingdom. Following Cutmore et al. (2018), we excluded Member States where there were typically low shares of students with a migrant background in PISA 2015 and, as such, represented smaller samples within PISA from which resilient students could be identified. Member States excluded were: Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Malta, Poland, Portugal, Romania, and Slovakia. It is important to note that the exclusion of these Member States does not imply that academic resilience is absent in such contexts.

[2] Although information about language background is included for completeness in the description of the sample, it was not included as a covariate in analysis. It was initially included, but this resulted in suppression effects because of its collinearity with immigrant status.

covariate (discussed below), it is relevant to note the average socio-economic status of the immigrant sample. PISA assesses socio-economic status via the index of economic, social, and cultural status (ESCS; discussed above). The ESCS measure is standardized across all participating countries such that scores higher than zero indicate an above average socio-economic status for the whole PISA sample and scores below zero indicate a below average socio-economic status. The average ESCS score of the immigrant sample was $M = -0.26$ ($SD = 1.03$), indicating that, on average, immigrant students were below the OECD socio-economic average.

8.2. Materials

All measures included in this analysis were in either the 2015 Student Questionnaire or the 2015 School Questionnaire (OECD, 2017). Students completed the Student Questionnaire. The School Questionnaire was completed by the principal of the school from which students were sampled. Measures were modelled at the student/residual-level (L1) and/or the school-level (L2), as appropriate. The country-level was not explicitly modelled for analytical reasons (discussed in Data Analysis below).

8.2.1. Cognitive engagement

Cognitive engagement was measured via academic expectations (an indicator for future-oriented cognitive representations; Martin, 2021). The PISA survey asks students what level of education they expect to complete via a single item ("Which of the following do you expect to complete?"). This item was rated on a scale from 1 (*lower secondary school* [ISCED level 2]) to 6 (*bachelor's degree* [ISCED level 6]). At L1 (student-level), cognitive engagement was modelled via the single item of academic expectations and group-mean centered; at L2 (school-level), cognitive engagement was modelled as an aggregated mean score of academic expectations and grand-mean centered.

8.2.2. Behavioral engagement

Behavioral engagement was assessed via school attendance. This was measured with two items ("In the last two full weeks of school, how often: I <skipped> a whole school day" and "In the last two full weeks of school, how often: I <skipped> some classes"). These items were rated on a scale of 1 (*none*) to 4 (*five or more times*). The behavioral engagement factor was found to be reliable at L1 ($\omega_{L1} = 0.948$) and L2 ($\omega_{L2} = 0.951$). At L1 (student-level), behavioral engagement was modelled via an error-adjusted mean score and group-mean centered (Cole & Preacher, 2014). An error-adjusted mean score was selected as a preferable modelling solution to a two-item latent factor and to reduce the risk of inflated parameter estimates (Cole & Preacher, 2014). The following equation was used to calculate the error-adjusted mean score: $\sigma_h^2 * (1 - \omega_h)$, where σ_h^2 is the estimated variance of the substantive factor (h) and ω_h is the reliability estimate of (h) at either L1 or L2 (Hayduk, 1987; see also; Cole & Preacher, 2014). At L2 (school-level), behavioral engagement was modelled via an error-adjusted aggregated mean score and grand-mean centered.

8.2.3. Social-emotional engagement

Social-emotional engagement was measured via two items from the 4-item Enjoy Cooperation scale (OECD, 2017). The two items selected reflected a social-emotional connection with school via their peers ("To what extent do you disagree or agree about yourself? I enjoy cooperating with peers" and "To what extent do you disagree or agree about yourself? I prefer working as part of a team to working alone"). The two items dropped from the study related to a preference for aspects of cooperative learning which were not a reflection of a social-emotional engagement with school (viz., "I enjoy seeing my classmates be successful" and "I enjoy considering different perspectives"). The two selected items were rated on a scale from 1 (*strongly disagree*) to 4 (*strongly agree*). The social-emotional engagement factor was found to be reliable at L1 ($\omega_{L1} = 0.907$) and L2 ($\omega_{L2} = 0.882$). Social-emotional engagement was modelled via an error-adjusted group-mean centered score at L1 (student-level) and an error-adjusted aggregated grand-mean centered score at L2 (school-level).

8.2.4. Academic resilience status

In the present investigation, academic resilience was defined as "succeeding academically despite facing education-related adversity," with the primary education-related adversity indicator being socio-economic status (SES), in line with Cutmore et al. (2018). Thus, students were identified as academically resilient if they achieved in the top quartile of achievement but were included in the lowest quartile of SES. The socio-economic quartiles were identified via the quartiles of the ESCS measure (discussed above). To avoid biasing the quartiles by country-level SES (i.e., the majority of students included in lowest quartile are from low SES countries), SES quartiles were calculated within country. It is also important to note that, when calculated, the quartiles included immigrant and non-immigrant students.

The achievement quartiles were identified via the plausible values of the Science, Mathematics, and Reading Assessments that PISA administers. Details on this process are presented in Supplementary Materials. Academically resilient students were identified as those who were in both the lowest ESCS quartile and the highest achievement quartile of their country. For example, an academically resilient student from France was in the lowest French ESCS quartile and highest French achievement quartile (not the overall OECD quartiles). In total, 2.6% of students ($N = 449$) were identified as academically resilient. This figure varied to some extent across countries—for example, from 1.7% of students ($N = 27$) in Belgium to 4.6% of students ($N = 24$) in Greece (see Supplementary Materials for multi-country multilevel modeling). As discussed below, academic resilience status was included in analysis as a dichotomous outcome (not resilient vs. resilient). It is important to note that the outcome variable at L2 was not modelled with manifest aggregation, but rather latent aggregation with random intercepts.

8.2.5. Covariates

Student- and school-level background covariates were included in order to ascertain the role of engagement in predicting academic resilience, beyond variance explained by these background factors. Age, gender, and immigrant generation were included as student-level covariates. *Age* was measured as a continuous outcome, whereas *gender* (0 = female; 1 = male) and *immigrant generation* (0 = first generation; 1 = second generation) were both measured as dichotomous variables. The following were included as school-level covariates: school size, school location, economic disadvantage, and extracurricular activities offered. *School size* was assessed as a continuous measure. *School location* was measured on a scale from 1 (village fewer than 3000 people) to 5 (large city with over 1,000,000 people). *Economic disadvantage* was assessed as a continuous measure of the percentage of the student body from socio-economically disadvantaged homes. *Extracurricular activities* were measured via an index of extra-curricular activities offered by the school (e.g., sports teams, science club) and considered an indicator of school-level resourcing; the measure included in the analysis is the sum of this index (i.e., total number offered by the school).

8.3. Data Analysis

Data analysis proceeded through two stages: preliminary descriptive and correlational analysis and multilevel probit regression (ML-PR) using M*plus* version 8 (Muthén & Muthén, 2017). For preliminary analyses, the descriptive and distributional statistics of the substantive factors were first examined. Intraclass correlations (ICC) were inspected to assess variance at L2 (Byrne, 2012). Although researchers argue that ICCs >0.10 are preferable, others argue that factors that are below this value should still be modelled at L2 if there are valid theoretical and empirical reasons to do so (Byrne, 2012). The bivariate correlations among all covariates and substantive factors were also assessed. This was conducted via a multilevel confirmatory factor analysis (Kline, 2016).

In the ML-PR setup, Level 1 (L1) refers to students (and residual variance) and Level 2 (L2) refers to schools. At L1 student-level engagement predicted academic resilience status and at L2, school-level engagement predicted school-level academic resilience status. To control for variance attributable to background attributes at each point of the model, student-level (L1) and school-level (L2) covariates predicted (respectively) L1 and L2 engagement and academic resilience status. Because ML-PR is estimated with weighted least squares means and variance adjusted (WLSMV), Bayesian imputation was conducted to handle missing data at L1. It was not possible to include country level clustering (i.e., "type = twolevel complex" command in M*plus*) or to run multilevel multigroup models when using WLSMV. However, for completeness, a series of models were run in which country was included as a covariate at the student- or school-level to examine similarities and differences across countries; the findings of these models are presented in Supplementary Material (Table S2). Twenty multiply-imputed data sets were used. For the substantive factors, total missingness ranged from 0 to 1.3%. ML-PR was used to examine the predictive relationships among the covariates and substantive factors. Student- and school-level weights provided by PISA were included to avoid the influence of sample size and selection procedures on standard error estimation (OECD, 2017). The student-level weight (variable name in PISA dataset: W_FSTUWT) corrects for the influence of school cluster size and school-level weight (W_SCHGRNRABWT) corrects for the influence of likelihood of school selection on standard error estimation (OECD, 2017). Both weights were calculated by PISA via well-established methods used by other international survey agencies (e.g., TIMSS, PIRLS) and are readily available for use within the PISA dataset (OECD, 2017). It should also be noted that the OECD outlines that the weights must be used in analysis of PISA data to account for sampling error.

As noted above, because student-level (L1) predictors were group-mean centered and school-level (L2) predictors were grand-mean centered (e.g., Bliese et al., 2018; Kreft et al., 1995), we were also able to ascertain the unique effects of the L2 engagement factors on the outcome above and beyond that of L1 (viz., b_{L2}-b_{L1}; Caro & Lenkeit, 2012). These effects were calculated using the "model constraint" function in M*plus*; because of this, relevant estimates reported are unstandardized and are interpreted accordingly. Fit statistics are not reported due to the use of error-adjusted mean scores (viz., saturated fit). When we report on standardized path coefficients, we also indicate the size of that effect as per Keith (2019): standardized effects of $0.05 \leq ß < 0.10$ are considered small, $0.10 \leq ß < 0.25$ are considered moderate, and $ß \geq 0.25$ are considered large.

9. Results

9.1. Preliminary Data Analysis

All descriptive and distributional statistics are presented in Table 1. Regarding ICCs, behavioral and cognitive engagement were above the 0.10 threshold (Byrne, 2012). Although the ICCs for social-emotional engagement and resilience status were below 0.10, these estimates were significant at $p < .001$ (as were the estimates for behavioral and cognitive engagement), and there is sufficient prior research to support modelling these factors at L2 (see Introduction). The bivariate correlations among the substantive factors are presented in Table 2 (correlations among all factors, including covariates, are presented in Table S3 in Supplementary Materials). These show preliminary support for contended relationships in the predictive ML-PR model.

9.2. Multi-level probit regression

The significant ML-PR regression estimates among the substantive factors are the focus here (and shown in Fig. 1). All significant and non-significant estimates for substantive parameters are presented in Table 3. Estimates among all factors, including covariates, are presented in Table S4 in Supplementary Materials (along with a description of relatively notable covariate effects). At L1, cognitive engagement ($\beta = 0.05$, $p < .05$; small effect size), behavioral engagement ($\beta = 0.13$, $p < .01$; moderate effect size), and social-emotional engagement ($\beta = -0.09$, $p < .001$; small effect size) predicted academic resilience status. Thus, immigrant students who reported higher behavioral engagement (in this study, attendance) and students who reported higher cognitive engagement (in this study, academic expectations—though, a small effect size) were more likely to be resilient. In contrast (though, also a small effect size), immigrant students who reported higher social-emotional engagement (in this study, social-emotional connection with school via peers) were less likely to be academically resilient.

At L2, school-level cognitive engagement ($\beta = 0.70$, $p < .001$; large effect size) and behavioral engagement ($\beta = 0.28$, $p < .01$; large effect size) significantly predicted school-level academic resilience status. Moreover, when subtracting student- (L1) from school-level (L2) effects (e.g., Caro & Lenkeit, 2012; also see Data Analysis), a significant effect was derived for school-level cognitive engagement (but not behavioral or social-emotional engagement), suggesting that school-level cognitive engagement is positively related to students' academic resilience even after accounting for student-level cognitive engagement ($\Delta b = 0.19$, $p < .001$; moderate effect size). In other words, given two students with comparable levels of cognitive engagement, the one attending a school with higher school-average cognitive engagement is more likely to be academically resilient.

10. Discussion

The present investigation examined the extent to which immigrant students' cognitive, behavioral, and social-emotional engagement predicted their academic resilience. Findings revealed that cognitive engagement and behavioral engagement, at both the student- and school-level, are positively associated with academic resilience for immigrant students, but the findings regarding social-emotional engagement were more equivocal.

10.1. Findings of particular note and implications for practice and policy

At the student-level (L1), behavioral engagement (operationalized via school attendance) was a significant factor in students' academic

Table 1
Descriptive Statistics, Distributional Statistics, and ICC Estimates.

	Mean		SD		Skewness		Kurtosis		ICC
	L1	L2	L1	L2	L1	L2	L1	L2	
Cognitive Engagement	4.09	4.08	1.81	1.12	−0.29	−0.24	−1.41	−0.48	.32
Behavioral Engagement	3.64	3.64	0.63	0.35	−2.34	−2.47	5.77	10.81	.13
Social-emotional Engagement	2.97	2.97	0.70	0.33	−0.62	−0.66	0.41	4.05	.03
Academic Resilience Status	0.02	0.02	0.16	0.08	6.09	6.13	35.04	56.04	.02

Note: L1 = student/residual level; L2 = school level; SD = standard deviation; ICC = intra-class correlation.

Table 2
Standardized Bivariate Correlations Among Substantive Factors.

	Cognitive Engagement		Behavioral Engagement		Social-emotional Engagement		Academic Resilience Status	
	L1	L2	L1	L2	L1	L2	L1	L2
Cognitive Engagement	–	–						
Behavioral Engagement	.07***	.07***	–	–				
Social-emotional Engagement	−.04***	−.21***	.07***	−.08***	–	–		
Academic Resilience Status	.07***	.72***	.13***	.33***	−.08***	−.15*	–	–

Note: L1 = student/residual level; L2 = school level; Correlations among all factors (substantive and covariate) are in Table S3 of Supplementary Materials.
*$p < .05$, **$p < .01$, ***$p < .001$.

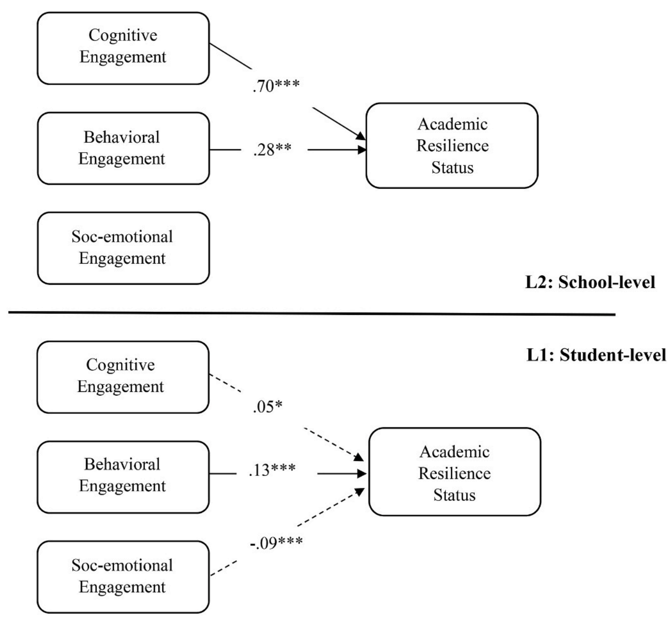

Fig. 1. Significant results of standardized multi-level probit regression.
* $p < .05$, **$p < .01$, ***$p < .001$; Dashed lines indicate paths with small effect sizes as per Keith (2019); See Results for contextual effects; L1 paths are controlled for variance attributable to student-level covariates (age, gender, immigrant generation) and L2 paths are controlled for variance attributable to school-level covariates (school size, school location, economic disadvantage, extracurricular activities offered).

Table 3
Substantive Path Coefficients of Multi-level Probit Regression Model.

	Academic Resilience Status			
	L1		L2	
	β	S.E.	β	S.E.
- Cognitive Engagement	.05*	.02	.70***	.09
- Behavioral Engagement	.13***	.03	.28**	.09
- Social-emotional Engagement	−.09***	.02	.01	.08
Variance Explained (R^2)	.05		.65	

Note: L1 = student/residual level; L2 = school level; S.E. = standard error; Paths for all factors (substantive and covariate) are in Table S4 of Supplementary Materials.
*$p < .05$, **$p < .01$, ***$p < .001$.

resilience. This is in line with suggestions that students who attend school are more likely to be resilient because they are better able to access supportive resources at school (e.g., support from teachers, academic resources) on a more frequent basis (Roby, 2003). Additionally, by being at school more, students receive more instructional time that positively impacts their achievement (Andersen et al., 2016). Increased instructional time means that students may not only receive more content-focused support but may also be afforded more opportunities to develop key relationships, such as with their teacher, that support their capacity for resilience (Battey et al., 2016; Bostwick et al., 2022; Granziera et al., 2022). Indeed, the joint benefits of resource support and instructional time may be key to buffering the negative effects of socio-educational adversity. We also cannot underestimate the role of the home when seeking to address students' attendance at school. In some homes, and possibly immigrant homes in particular, there are family duties (e.g., caring roles, work to earn money, attendance at cultural events) that may prohibit school attendance on occasions (Australian Institute of Family Studies, 2017). Thus, consistent with the Cutmore et al. (2018) report, policy and practice aimed at assisting immigrant families to support their child's school attendance or to develop flexible and accessible alternatives that help students manage these multiple demands is important.

Cognitive engagement (operationalized via academic expectations) was also a significant positive predictor of immigrant students' academic resilience at L1 (student-level), but it was a small effect size and we therefore do not give it undue attention at the student-level (though, it did yield a large effect size at the L2 school-level and we discuss this more fully below). Suffice to say, that personal expectations are a future-oriented cognitive engagement factor (Burns et al., 2021; Martin, 2021) that may help students commit to adaptive academic behaviors that assist them through adversity (Cutmore et al., 2018). Research has detailed the impact of teachers' expectations for student outcomes, especially for students from "minority" backgrounds (Rubie-Davies et al., 2006). Thus, providing teachers with strategies that help them to more clearly communicate positive expectations to immigrant students may help these students internalize and value these expectations (Rubie-Davies, 2006).

Interestingly, social-emotional engagement (operationalized via school and peer enjoyment) was found to negatively predict resilience status at the student-level (L1). As with cognitive engagement at L1 (above), because this was a small effect we do not give it undue weight but do offer some brief speculation. Perhaps this finding is not so surprising given our operationalization of social-emotional engagement via peer affiliation, cooperation, teamwork etc., which are important for personal wellbeing outcomes (e.g., mental health; Bonell et al., 2014), but perhaps not so directly important for academic achievement once the positive effects of behavioral and cognitive engagement are accounted for (as they were in our study). In addition, social-emotional engagement by way of cooperation is not necessarily an easy or straightforward interpersonal skill to develop (Warneken, 2018) and this may also explain why it is inversely associated with resilience. We therefore do not discourage efforts to promote social-emotional engagement—rather, we suggest educators and researchers need to be mindful of what aspects of social-emotional engagement are positively associated with various academic and personal wellbeing outcomes and target them accordingly.

At L2 (school-level), cognitive engagement (in this study, school-average student expectations) and behavioral engagement (in this study, school-average student attendance) were found to play significant positive roles. Specifically, schools with higher school-average academic expectations and higher attendance rates had higher proportions of academically resilient immigrant students. Thus, beyond student-level action to promote cognitive and behavioral engagement (see discussion of L1 findings above), creating a culture of cognitive engagement (by way of high academic expectations) and behavioral engagement (by way of whole-school approaches to attendance) may be beneficial to building school-level academic resilience. Moreover, school-level cognitive engagement was positively related to students' academic resilience even after accounting for student-level cognitive engagement. Thus, given two students with comparable levels of cognitive engagement, the student attending a school with higher school-average cognitive engagement is more likely to be academically resilient. This aligns with findings in Cutmore et al. (2018) suggesting a need for school-level preventative measures to offset the risk that immigrant students withdraw effort or give up at school by supporting them to integrate into their new education system. This includes creating conditions and opportunities in the school to actively involve immigrant parents and to build stronger connections between the school and child's community.

10.2. Limitations to consider

When interpreting the present findings, there are some limitations to consider. First, we used PISA data which are cross-sectional. Thus, our analyses could only highlight statistical associations, not causality. Having said this, engagement is often placed as a predictor of achievement in psycho-educational research (see Martin, 2012, 2021 for reviews) and so we believe we have reasonable grounds for modeling it as a predictor of academic resilience (high achievement in the face of socio-educational disadvantage) as we have. Nevertheless, we do advise caution pending empirical support using longitudinal data. Second, related to this is the limitation of using secondary data to assess target constructs. For example, in the Introduction we provided a detailed rationale for the three engagement measures used in the study, but we also recognize that some adaptation was required to fit the study (e.g., two items were dropped when forming the social-emotional engagement measure—see Materials). There are enormous efficiencies gained in harnessing existing large-scale datasets and researchers lament the under-utilization of these empirical resources (Bulmer et al., 2009), but at the same time caution must be exercised in mapping measures against hypothesized constructs and concepts. Third, much of the PISA student data are self-reported and we could not account for known issues of recall, bias, misinterpretation, etc. (Karabenick et al., 2007). Fourth, there was not a measure of cognitive ability available in the dataset. In 2015, the individual problem-solving assessment in PISA changed to a collaborative problem-solving assessment, the focus of which was on social problem-solving skills, such as communication and managing conflict, rather than cognitive ability skills. Analyzing the PISA 2003 data, Martin et al. (2012) found that immigrant students were slightly lower in problem-solving ability scores than non-immigrants, but the effect sizes were small relative to non-immigrants ($b = -0.05$ and $b = -0.06$ for 1st and 2nd generation immigrants respectively) and so we do not anticipate that cognitive ability (or similar) was a factor that would disproportionately affect immigrants in our study. Nevertheless, future research would do well to control for any potential source of heterogeneity such as this. Fifth, we applied the OECD's (2014; see also Cutmore et al., 2018) approach to operationalizing academic resilience (viz. students in the lowest quartile of socio-educational status and the highest quartile of academic achievement). Although this was appropriate given we were using OECD's PISA data, we recognize this is a somewhat inferred approach to academic resilience and future research might administer other approaches to validate academic resilience status, such as alternative combinations of high vs. low SES and achievement or other measures of academic resilience, such as the Academic Buoyancy Scale (Martin & Marsh, 2008) or the Academic Risk and Resilience Scale (Martin, 2013). This approach also meant we could not disentangle the effects of SES and immigrant status in the same way that we could if SES and immigrant status were alongside each other as correlated predictors of academic achievement. We also recognize that the ICC for academic resilience was low, which is interesting in that there was not much variation in academic resilience from school to school (though, there was more between-school variance for other substantive variables). We nevertheless pursued multilevel modeling as a conservative approach because even small ICCs can produce biased standard errors if non-independence at each level is not accounted for (Bliese et al., 2018). Related to this is the relative emphasis we give to findings yielding small, moderate, and large effect sizes. We applied Keith's (2019) guide for effect sizes, and in this context, some statistically significant paths yielding small effect sizes (e.g., student-level social-emotional engagement predicting academic resilience) may be considered borderline in terms of educational significance. That said, because no prior research has investigated student- and school-level engagement using our (and OECD's, 2014) upper (achievement) and lower (SES) quartile approach to operationalizing academic resilience, we cannot interpret our effects strictly in line with other research—but we do note that the recent Bostwick et al. (2022) study also found a small effect size for its form of social-emotional engagement predicting academic buoyancy. Sixth, we did not have between-class data, only between-student and between-school data. Thus, our analyses could only be conducted at the student- and school-levels. Finally, unregistered or undocumented immigrants can be difficult to include in PISA surveys. To the extent this is the case, such immigrants may not be adequately represented in our study. Also, we adopted the Cutmore et al. (2018) approach and excluded European nations where there were low numbers of immigrants in their PISA data (as this would yield too few academically resilient immigrants – see Footnote 1). It is important to note that the exclusion of these nations does not imply that academic resilience is absent in such contexts.

11. Conclusion

Immigrant students often present as an academically at-risk group, in large part due to the socio-educational adversity they experience. This study has revealed that cognitive engagement and behavioral engagement, at both the student- and school-level, were positively associated with academic resilience for immigrant students. Thus, student- and school-level actions targeting cognitive and behavioral engagement may particularly bolster academic resilience among immigrant students. In so doing, educators and policy-makers will be in a stronger position to support the educational development of immigrant students through school—and beyond.

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Appendix A. Supplementary data

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