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SCHOOL-BASED PSYCHOLOGICAL SUPPORT, LINGUISTIC BACKGROUND, AND STUDENT WELL-BEING: EVIDENCE FROM PISA 2022

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Abstract

We use data from 310,000 students from the 2022 PISA report for 64 countries to show that schools with psychological support services (such as school counselors/guidance counselors) have students with greater well-being. Having at least one school counselor was associated with greater life satisfaction among students (a small but significant positive effect) and a 12% lower likelihood of high academic anxiety than average. Likewise, having regular guidance or wellness classes slightly increased life satisfaction. Using advanced analysis techniques (causal machine learning), it was estimated that these school supports cause real improvements in well-being. For example, the availability of a specialized counselor could slightly increase (*e.g.,* +0.08 points on a 0–10 scale) average life satisfaction and reduce the proportion of students with high anxiety by ~7 percentage points (*e.g.,* from 35% to 28%). The positive effects are more pronounced among disadvantaged students. Those from low socioeconomic backgrounds or who do not speak the language of instruction at home showed almost twice as large improvements in well-being with the presence of school psychological support, compared to their more advantaged peers. This underscores that support at school can reduce well-being gaps.

1. INTRODUCTION

Youth mental health and well-being have become critical global concerns in recent years. Even before 2020, researchers documented worrying trends in adolescents' psychological well-being – for instance, declines in life satisfaction and rising anxiety in many countries (Patton *et al.,* 2016). The COVID-19 pandemic exacerbated these issues dramatically. School closures, social isolation (Loades *et al.,* 2020; OECD, 2021), and pandemic-related stressors led to surges in mental health problems among young people. Relatedly, a World Health Organization report estimated a 25% increase in the prevalence of anxiety and depression worldwide during the first year of the pandemic. Alarmingly, multiple countries also reported rising rates of adolescent suicide during and after the pandemic period, highlighting the severe consequences of unmet mental health needs among youth (WHO, 2022; CDC, 2021). Suicide has become a leading cause of death among adolescents globally, underscoring the urgent need for proactive mental health support within school environments.

This increasing in mental disorder rates has also implied an increment in the mental health services burden, and the loss of productivity, because of labor absenteeism and premature mortality. The disability-adjusted life years (DALYs) attributable to mental disorders can reach a 16% of global DALYs. This loss can represent an 8% of gross domestic product in high-income countries (Arias *et al.,* 2022). The socio-economic impact can be more considerable if it begins in early age stages as adolescence.

This wave of mental health need has been described as a "wake-up call" urging countries to step up support services for youth. Education settings have been identified as a crucial arena for mental health intervention (Fazel *et al.,* 2014; Langford *et al.,* 2014; Patalay & Fitzsimons, 2018), since schools are where adolescents spend a large portion of their daily lives and where issues often manifest. Indeed. 90% of countries surveyed by WHO incorporated mental health and psychosocial support into their COVID-19 response plans for schools (WHO, 2021). There is growing recognition that schools can play a proactive role in promoting student well-being – not only through academic instruction but also by providing emotional support, counseling, and a safe environment that fosters resilience (Domitrovich *et al.,* 2010; Hoagwood *et al.,* 2007; Suldo *et al.,* 2014).

Within this context. school-based psychological support services (such as guidance counselors. school psychologists. mentoring and life-skills programs) have gained attention as potential protective factors for student well-being (Cooper *et al.,* 2021). A robust body of literature from various countries suggests that when schools invest in counselors and mental health programs, students benefit in multiple ways. For example, studies in the United States have found that lower student-to-counselor ratios correlate with reduced disciplinary incidents and improved attendance (Reback, 2010). Counselors can help identify and assist students facing emotional difficulties, thereby potentially improving their life satisfaction and academic engagement. Some research even indicates that the positive impacts of school counselors are especially pronounced for disadvantaged students, such as those from low-income families or ethnic minority backgrounds (Barry *et al.,* 2017; Murray *et al.,* 2019). These students may have fewer resources and support outside school, making the school's role vital. Similarly, a policy analysis by the American School Counselor Association concluded that counselors have higher positive impacts on traditionally underserved groups, including students in poverty and those with limited English proficiency (Evans, 2004). This hints at an equity dimension: school-based support might narrow well-being gaps by socio-economic status (SES) or language background.

Language capabilities represent an important and under-explored factor in student well-being and access to support. In diverse societies, many students speak a different language at home than the language of instruction at school. This linguistic background can shape a student's school experience profoundly. On one hand, students who do not speak the school's language at home (often immigrants or from minority communities) may face additional stress – from language barriers in communication to feelings of exclusion – which could negatively affect their well-being (Twenge *et al.,* 2019). Prior studies have reported that first-generation immigrant adolescents often show lower levels of life satisfaction and higher psychological distress compared to native-born peers (García Coll & Marks, 2012). Language difficulties and cultural adjustment challenges are thought to be key contributors to this disparity (Cohen *et al.,* 2013), including mental health service use, and treatment outcome (Miteva *et al.,* 2022). On the other hand, schools can help mitigate these challenges through inclusive practices (Rickwood *et al.,* 2015). Having counselors or teachers who are culturally and linguistically responsive can improve these students' sense of belonging and provide vital support (Weist *et al.,* 2005). For instance, recent work highlights that newly immigrated students are better supported when school staff can communicate in the students' home language and understand their cultural context. In short, linguistic proficiency and home language are likely important moderators in the relationship between school support and student outcomes – yet, large-scale international evidence on this topic is sparse.

Another relevant dimension is students' general linguistic proficiency, often reflected by reading literacy levels. Students struggling academically or with low literacy might experience lower self-esteem or greater school-related stress, emotion problems, social competence, potentially impacting well-being (Montemitro *et al.,* 2021 Monopoli & Kingston, 2012). Conversely, strong language and literacy skills might enable students to access support resources more easily and navigate school challenges with more confidence. While academic achievement and well-being are distinct, they are positively correlated in many studies, observing a longitudinal effect of linguistic competence with the development of adaptative emotion regulation strategies, a key group of strategies for mental health prevention (Durlak *et al.,* 2011 Griffiths *et al.,* 2021). It is thus important to account for students' academic (especially reading) proficiency when analyzing well-being determinants, and to consider whether the effects of support services vary for students with different proficiency levels.

In light of these issues, our study aims to integrate the perspectives of school support structures, socio-economic disparities, and language factors to provide a comprehensive analysis of student well-being. We leverage data from the 2022 Programme for International Student Assessment (PISA), which offers a unique opportunity for such research. PISA 2022 collected extensive information not only on 15-year-old students' academic performance but also on their backgrounds, attitudes, and school environments – including indicators of psychological support at school and subjective well-being outcomes. Furthermore, PISA's wide international coverage (over 80 participating countries/economies) allows us to compare different national approaches to student support. Recent analyses of PISA data underscore its value for studying well-being: for example, a cross-national comparison between PISA 2018 and 2022 showed a decline in students' subjective well-being during the pandemic period (OECD, 2023) and highlighted the importance of school factors like bullying and sense of belonging for student life satisfaction (Durlak *et al.,* 2011). Our work builds on and extends such findings by focusing specifically on school-based psychological support (*e.g.,* counselors, guidance programs) as a key school factor. and by examining how its influence may differ across language and socio-economic groups (Kutcher *et al.,* 2015).

To our knowledge, this is one of the first studies to use PISA 2022 to analyze student mental health supports and outcomes in depth. It also contributes methodologically by applying advanced econometric techniques not commonly used in prior PISA-based research on this topic. Traditional regression analyses may be limited in establishing causal interpretations due to confounding (Reback, 2010); hence, we employ Double Machine Learning (DML) and Causal Forests to strengthen causal inference and explore heterogeneity in effects. This approach answers recent calls in educational research for more robust. data-driven analysis of large-scale assessment data (see, *e.g.,* Knaus, 2021) who introduced a double ML framework in an education context.

In sum, our study investigates: (a) How do countries differ in the provision of school-based psychological support, and can we categorize distinct models or typologies of support systems?, (b) Within countries, does access to school-based support (particularly the availability of a counselor) relate to better student well-being (higher life satisfaction, lower anxiety, greater sense of belonging), after controlling for confounding factors?, (c) Do these relationships hold when employing rigorous causal inference methods (DML) that account for selection bias?, (d) How do the benefits of school support vary across different student groups – especially as a function of SES. home language, and reading proficiency? We hypothesize that students from disadvantaged backgrounds (low-SES or non-native speakers) will see greater marginal benefits from school support, given their higher baseline risks. We also expect that integrating support into the school's normal practices (*e.g.* curriculum-based guidance lessons, orientation programs) might yield broader impacts than relying on ad-hoc or external services.

The remainder of the paper is organized as follows. Section 2 describes the data and methodology, including the construction of key variables, the cluster analysis of support systems, and the econometric strategies (multilevel modeling, DML, Causal Forest, interaction models) employed. Section 3 presents the results: first the cross-national typologies, then the regression and causal analysis of support impacts, and finally the heterogeneity findings with a focus on language and SES. Section 4 discusses the implications of these findings in the context of existing literature and offers insights for policy and practice, including the importance of culturally and linguistically inclusive support. We also note limitations and suggestions for future research. Section 5 concludes with a summary and final thoughts on the value of strengthening school-based psychological support for student well-being and equity.

2. DATA AND METHODS

2.1. Data and Sample

Our analysis uses data from the PISA 2022 study, focusing on the student and school surveys. PISA is a large-scale international assessment administered by the OECD every three years (the 2021 cycle was postponed to 2022). It evaluates 15-year-old students' skills in reading. Mathematics, science, and collects extensive background information. Crucially for our purposes, the 2022 cycle included questionnaires on student well-being and school practices related to guidance and counseling.

We include all participating countries/economies for which the relevant variables on well-being and support are available. This resulted in a sample of approximately 64 countries and economies, covering OECD member states as well as partner countries across Europe, Asia, the Americas, and other regions. We excluded a few participants that did not administer the student well-being questions or had incomplete data on key school support indicators, to ensure comparability. The total student sample analyzed is about N ≈ 310,000 (after applying PISA's sample weights, this represents roughly 23 million students in the target population). These students are nested within ~11,000 schools. The data are nationally representative of 15-year-old students in each country, obtained via a two-stage stratified sampling design (schools are sampled first, then students within schools).

We adhered to PISA's technical standards for analysis. All statistics reported use the provided student sampling weights to ensure representativeness. For variance estimation and significance testing, we employed the balanced repeated replication (BRR) method with Fay's adjustment (factor 0.5), using the 80 replicate weights supplied in the PISA data. This approach correctly accounts for the complex survey design and clustering, as recommended by the OECD's guidelines (OECD, 2019) to avoid underestimating standard errors. Furthermore, where student achievement scores are used (*e.g.,* reading literacy), we properly handled PISA's plausible values by conducting analyses across all five plausible values and averaging the results. thereby reflecting the imputation uncertainty in proficiency measures.

2.2. Measures

Student Well-Being Outcomes: We examine three key outcome variables related to students' subjective well-being and socio-emotional status:

- Life Satisfaction: Students rated their overall life satisfaction on a scale from 0 to 10, in response to the question "Overall. how satisfied are you with your life on a scale from 0 (not at all satisfied) to 10 (completely satisfied)?". This single-item measure has been widely used as an indicator of general well-being in PISA and other youth surveys. In our data, the mean life satisfaction is around 7.4 (s.d.≈2.1) for the pooled sample. with notable cross-country variation.

- School-Related Anxiety: PISA 2022 collected several items on test anxiety and schoolwork stress. We constructed an indicator of high anxiety to capture students experiencing detrimental levels of academic anxiety. Specifically, following PISA's approach in prior cycles (OECD, 2019), we identified students who reported strong agreement with statements such as "I feel very anxious even if I am well prepared for a test" or who scored in the top decile of an index of schoolwork-related anxiety. These students were coded as 1 for high anxiety, and 0 otherwise. About 35% of students fell into the high-anxiety category in our sample (indicative of widespread stress).

- Sense of Belonging at School: This is based on a composite index derived from students' agreement with statements like "I feel like I belong at this school." "I feel proud to be part of my school," etc. The OECD constructed a standardized index (mean 0. SD 1 for OECD) for Sense of Belonging. We use this index, which we re-scaled to the PISA metric where 0 corresponds to the OECD mean in 2018. A higher value indicates a stronger sense of attachment and inclusion in one's school. This measure is important as research has shown school belonging is tightly linked to mental health and is a mediator for outcomes like bullying's impact on well-being.

School-Based Support Variables: Our central independent variables capture the availability and nature of psychological support at the school level (from the school principal questionnaire):

- School Counselor/Psychologist Availability: An indicator for whether the school has at least one staff member whose primary role is providing psychological counseling or guidance to students. In PISA 2022, principals reported the number of school-employed psychologists or counselors. We coded this as 1 if any (≥1) counselor/psychologist is available at the school, and 0 if none. In our sample, about 68% of students attend a school with at least one counselor available. However, this ranges widely: some countries have near-universal counselor presence, while others rely on external referrals or have very few counselors in schools.

- Guidance Curriculum (Structured Guidance Lessons): A binary variable indicating whether the school offers regular, structured guidance or well-being lessons for students. Many education systems incorporate guidance as a weekly class or homeroom session focusing on life skills, mental health, or career planning. We used principals' responses on whether there is a mandatory curriculum or scheduled time for guidance/pastoral care for 15-year-olds. Approximately half of the students in the sample receive such structured guidance lessons. This measure captures the degree to which social-emotional learning is built into the school program (as opposed to being ad-hoc).

- Orientation/Induction Program for New Students: An indicator for whether the school has a formal orientation or mentoring program to help integrate new students (such as 1st-year high school students or transfers). Such programs might include pairing newcomers with peer mentors, special sessions on adapting to the school, or additional counseling for new students. This variable serves as a proxy for the school's effort to socially support students during transitions. In the data, about 60% of students are in schools that run an orientation or induction program for newcomers.

- Counselor-to-Student Ratio (Intensity): In addition to availability, we computed the number of counselors per 1,000 students in each school (using enrollment and counselor count data). This gives a sense of the intensity of support. However, because many schools report "1" counselor regardless of size, this ratio is highly skewed and zero for many schools. We mainly use it in identifying clusters of systems (see below) rather than as a standalone predictor in regression.

- Student Utilization of Support: We also consider a student-reported measure: whether the student talked to a teacher or counselor about personal issues in the past year. This indicates actual usage of support services. On average, about 20% of students said they had consulted a teacher or counselor for help with personal problems. We use this in descriptive context and cluster analysis, though it's not a school-level variable (it's aggregated to school average where needed).

Language Background and Proficiency: Central to our study are measures of language use and proficiency:

- Language Spoken at Home: A binary variable indicating if the student speaks the test language (the language of instruction/assessment in their country) at home. PISA collects the first language spoken at home; we coded this as 1 if it matches the language of the PISA test, 0 if a different language is primarily spoken. This serves as a proxy for immigrant or linguistic minority background. Overall, 85% of students in our sample speak the test language at home, meaning 15% do not. The proportion of non-native speakers varies from under 1% in some homogeneous countries to over 30% in some immigrant-receiving countries. We anticipate this variable to be associated with well-being, as language barriers can impact stress and belonging.

- Reading Literacy Proficiency: We use students' performance in the PISA reading assessment as an indicator of general linguistic and academic proficiency. Reading was a domain assessed in 2022 (though the major domain was mathematics in 2022, reading was a minor domain, hence each student has several plausible values for reading). We included Reading score (plausible values) as a control in some analyses, standardized to the OECD mean of 500 and SD of 100. This allows us to account for students' academic skills, which might confound the relationship between support and well-being (*e.g.,* higher-achieving students might attend better-resourced schools that also have counselors, and they might also have higher well-being). By controlling for reading, we can isolate more purely the effect of support structures. In descriptive statistics, the mean reading score in our analytic sample is around 488 (slightly below the OECD reference of 500, as our country sample includes many non-OECD countries with lower averages). We handle the five plausible values by running analyses on each and combining results, as noted above.

Other Control Variables: Our regression models include a rich set of controls at student and school levels, informed by literature:

- Student-level: Socio-economic status (SES) measured by PISA's index of economic, social and cultural status (ESCS, a composite of parental education, occupations, and home resources). standardized with mean ~0. SD ~1 for OECD. Gender (female=1). given gender differences in well-being are well-known (with adolescent girls often reporting more anxiety). Grade repetition (ever repeated a grade: yes/no), as repeating is linked to lower self-esteem and well-being. Bullying victimization, measured via an index or a binary if the student reports frequent bullying (since bullying strongly diminishes well-being). We also include migration background (first- or second-generation immigrant vs. native) separate from language, when possible, to ensure that language spoken at home captures linguistic integration rather than generational effects. However, language-at-home and immigrant status are highly correlated. Student academic performance is partly captured by reading scores as discussed, and similarly we control for math performance in some robustness checks (math PVs).

- School-level: School average SES (to account for school socioeconomic composition which might influence overall climate), school size, urban vs. rural location, and school type (public vs. private). In some models we also control for country fixed effects, effectively comparing schools within the same country (this is achieved either by including country dummies or by using a random intercept at country level – see next section). Because our interest is primarily in within-country effects of school support, controlling for country-level factors is important to not attribute cross-national differences (*e.g.,* culture, funding, general well-being levels) to the support variables.

All independent variables are coded such that a higher value means more of the attribute (*e.g.* higher SES, 1 for female. etc.). Descriptive statistics for key variables are provided in table 1. We report overall means/ proportions and, for illustration, the breakdown by the three clusters of countries (described in the next subsection). This provides context on how different education systems vary in support provision and student characteristics.

Table 1 shows that in Cluster 1 (Coordinated support systems), virtually all schools have a counselor and formal programs, and students report slightly higher life satisfaction and belonging on average. Cluster 3 (Minimal support) countries not only have far lower access to counselors but also tend to have students with lower SES and academic performance; their average well-being is somewhat lower and anxiety higher. Cluster 2

(Informal) sits in between on many measures. It is important to be cautious in interpreting these raw differences – clusters differ on many socio-economic dimensions. Our subsequent multivariate analysis will disentangle the effect of support from these background differences.

Table 1. DESCRIPTIVE STATISTICS OF KEY VARIABLES

(Overall and by Support System Cluster)

Variable	Overall Mean/Prop.	Cluster 1 (Coordinated)	Cluster 2 (Informal)	Cluster 3 (Minimal)
Life Satisfaction (0–10)	7.4	7.6	7.3	7.2
High Anxiety (% of students)	35	30	37	41
Sense of Belonging (index mean)	0.00	+0.10	–0.05	–0.15
School Support Measures:				
– Counselor available at school (%)	68	~95	~70	~30
– ≥1 Counselor per 1,000 students	0.5 (per 1,000)	1.2	0.6	0.1
– Has guidance curriculum (%)	52	80	50	15
– Has orientation program (%)	60	85	65	20
– Students talked to counselor last year (%)	22	25	24	15
Student Background:				
– Speaks test language at home (%)	85	80	88	90
– Reading Literacy (score)	488	510	495	430
– SES (ESCS index)	–0.05	+0.30	+0.10	–0.50
– Female (%)	50	50	50	50
– Ever bullied (at least monthly, %)	25	20	27	30
– Repeated a grade (%)	11	5	10	20
– Immigrant (1^{st}/2^{nd} gen, %)	13	15	12	10
School Characteristics:				
– School average SES (ESCS)	–0.05	+0.25	+0.00	–0.60
– Public school (%)	78	85	70	90
– School size (students)	800	900	750	600
– Urban location (%)	55	60	50	40

Notes: Cluster breakdown: Cluster 1 includes ~15 mostly high-income countries (*e.g.,* Finland, Canada, Japan. etc.). Cluster 2 includes ~25 countries (mix of mid to high income, *e.g.,* UK, Spain, Poland, etc.). Cluster 3 includes ~20 countries (many lower-middle income or with decentralized systems. *e.g.,* Peru, Indonesia, some MENA countries). Percentages and means are weighted by student population. The cluster definitions are explained in Section 2.3.

Source: PISA 2022 data.

2.3. Analytic Strategy

2.3.1. Cluster analysis

To address research question (a) regarding national models of support provision, we conducted a cluster analysis on country-level aggregates of support indicators. Specifically, we calculated for each country: the percentage of 15-year-old students with access to a counselor; the average counselor-to-student ratio; the percentage of students in schools with a guidance curriculum; the percentage in schools with orientation programs; and the average rate of student consultation with school staff. These five variables capture both the extent of support provision and the degree of formalization/coordination in each system. We then applied a hierarchical clustering algorithm (Ward's method) to group countries with similar profiles. Based on the dendrogram and silhouette analysis, a three-cluster solution was chosen as it provided a meaningful and interpretable grouping. The clusters were described earlier (Coordinated, informal, minimal). We validated this clustering by checking external information: for example, many Cluster 1 countries indeed have national policies mandating school counselors (*e.g.,* Finland's law requires each school to have a psychologist and counselor on staff), whereas Cluster 3 countries often lack such mandates and may rely on out-of-school providers. The cluster analysis primarily serves to contextualize the landscape of support; we use it descriptively in Section 3.1 to compare average student outcomes across these system types.

2.3.2. Multilevel regression

For within-country analysis (question b), we employ multilevel regression modeling. Given the hierarchical data (students nested in schools, and schools in countries), a multilevel approach is appropriate to account for clustering and to separate within –and between– group variation. Our main specifications are two-level models (students within schools), with either country fixed effects or a third level for countries. In practice, we estimated three-level mixed models (random intercepts for schools and countries) as well as two-level models with country dummies – both approaches yielded very similar results for our key coefficients. The results reported are from three-level models unless noted. Formally, for student i in school j in country c, we estimate:

$$WellBeing_{ijc}=\beta 0+\beta 1(Counselor_{jc})+\beta 2(GuidanceClass_{jc})+\beta 3(OrientationProg_{jc})+\beta 4X_{ijc}+\beta 5Z_{jc}+u_c+v_{jc}+\epsilon_{ijc}.$$

where X_{ijc} *is the vector of student-level controls (SES, gender, language at home, etc.) and* Z_{jc} is the vector of school-level controls (school SES, size, type, etc.), u_c and v_{jc} are random intercepts for country and school, respectively, capturing unobserved contextual effects at those levels. We run this model for each outcome: life satisfaction (using linear regression), high anxiety (logistic regression, though we report marginal effects or odds ratios), and sense of belonging (linear). The key coefficients of interest are β_1, β_2, *and* β_3 which indicate the association of having a counselor, guidance curriculum, and orientation program with student well-being, after accounting for other factors. We emphasize that these are adjusted associations, without causal assumptions, they should be interpreted carefully. Nonetheless, if β_1 remains positive and significant with extensive controls and country effects, it strengthens the case that counselors have a beneficial effect. Standard errors are computed using the BRR weights as mentioned, which we implemented via the 'intsvy' R package (Version 3.5) and validated with replicate weight macros provided by OECD.

2.3.3. Double machine learning (DML)

To further bolster causal interpretation, we applied the DML approach of Chernozhukov *et al.* (2018). In essence, DML uses machine learning to flexibly model the outcome and treatment assignment, then computes a debiased treatment effect. Here, the "treatment" is whether a student has access to a counselor in their school. We focused on counselor availability for DML (as our primary treatment variable) due to its policy relevance and binary nature. Other support variables were considered as controls or separate treatments in auxiliary analyses. Implementation involved two main steps: (1) Nuisance function estimation: we trained predictive models for the outcome (life satisfaction or anxiety) and for the treatment (counselor availability) using a wide set of features (all controls, plus additional higher-order terms and interactions). We used ensemble machine learning, specifically gradient-boosted trees (XGBoost) and random forests, chosen via cross-validation, to capture nonlinear relationships. (2) Effect estimation: we computed the orthogonalized residuals and then regressed the outcome residual on the treatment residual. This yields an estimate of the average treatment effect (ATE) that is asymptotically unbiased under fairly general condition. We repeated this process for each plausible value of the outcome (for life satisfaction. which is a single value, not needed, for sense of belonging index. we treated it as observed; for anxiety, which is binary, we used a classification approach). We also incorporated the survey weights in a re-weighted loss function for the ML models to respect the sample design. The final ATE and standard error (via influence function-based asymptotics) were calculated. Intuitively. DML asks: if two students are identical in all observed aspects except that one has a counselor in their school and the other doesn't, what is the difference in their predicted well-being? By controlling for a rich set of variables in a data-driven way, DML aims to approximate that counterfactual comparison and thus estimate the causal impact of counselor availability. We report the DML results alongside traditional regression for comparison.

2.3.4. Causal Forests (Heterogeneity Analysis)

To explore research question (d) on effect heterogeneity, we utilized the Causal Forest algorithm, a machine learning method for estimating conditional treatment effects. Causal Forests are an extension of random forests that focus on the treatment effect as the quantity of interest rather than prediction of an outcome (Wager & Athey, 2018). Using the generalized random forests implementation in the grf R package, we estimated a causal forest with the same treatment (counselor availability) and outcome (*e.g.,* life satisfaction) as in DML. All controls and background variables (including SES, language, gender, prior achievement, etc.) were included as potential moderators. The forest algorithm splits the data to maximize differences in treatment effect, effectively finding subgroups with different effects. We took several steps to ensure validity: using honesty (splitting data into separate halves for tree structure vs. estimating leaf effects), tuning hyperparameters via cross-validation, and checking for sufficient overlap (common support) between treated and control units across the feature space. The output of the causal forest gives us an individualized predicted treatment effect for each student and an estimate of variable importance for moderators. We examine which variables most strongly influence the heterogeneity; as anticipated. SES emerged top-ranked. and language background also showed importance. We then derived average treatment effects for subgroups of interest by taking the means of individual treatment effect predictions within those subgroups (*e.g.,* bottom SES quartile. non-native speakers). We also formally tested for heterogeneity along specific dimensions by interacting the treatment with those variables in a traditional regression. For example, to probe language background, we added an interaction term *Counselor × (Doesn't speak test language)* in the regression and examined its significance. Similarly, a three-way interaction *Counselor × Low-SES × Non-native language* was tested to see if the compounded disadvantage yields an especially large effect. These confirmatory interaction tests complemented the data-driven forest approach. All these analyses again used sampling weights and accounted for the multilevel structure by either including school (and country) random intercepts or using cluster-robust standard errors at the school level for significance testing of interactions.

By combining these methods – multilevel models for baseline associations. DML for causal inference, and causal forests for heterogeneity – we provide a triangulated analysis of how school-based support relates to student well-being. All computations were conducted in R 4.3.1. We utilized packages such as intsvy and lavaan, survey for survey-weighted multilevel modeling, xgboost and grf for machine learning, and custom code to loop over plausible values and replicate weights for final estimates.

3. RESULTS

3.1. Cross-National Support System Typologies

We first present the results of the cluster analysis, which grouped countries based on their school support provision profiles. As introduced earlier, three distinct clusters emerged:

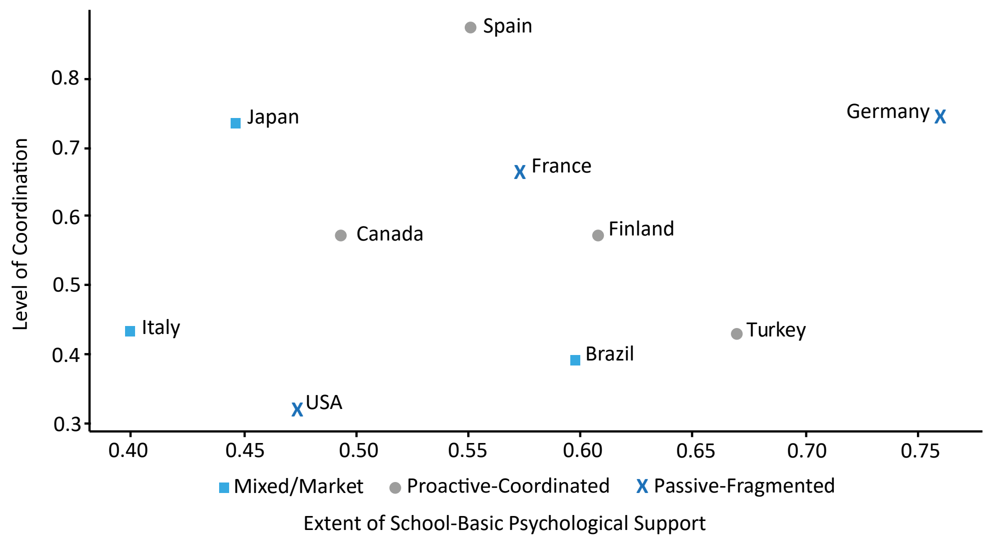
- Cluster 1: "Coordinated Public Systems." This cluster is characterized by broad access to school-based support, centrally coordinated. On average over 90% of students in these countries have a counselor or psychologist at school (often more than one) and most schools implement formal guidance curricula and orientation programs. Many of these countries have national or statewide mandates ensuring support services. Examples include Finland, Sweden, Canada, Japan, and a few high-performing Asian systems. In these countries, the role of the school in student well-being is well-established and often supported by public policy (*e.g.,* government-funded counselor positions). According to our data, students in Cluster 1 not only have the highest support access, but they also report the highest mean life satisfaction and lowest anxiety (Table 1). For instance, the average life satisfaction in this cluster is 7.6, significantly higher than in Cluster 3 ($p < .05$ in a design-based test), and the percentage of highly anxious students is the lowest at ~30%. These countries also tend to have above-average academic outcomes and SES levels, which likely contribute to student well-being; however, even accounting for those advantages, the well-being indicators appear better than expected, hinting that supportive school environments might play a role.

- Cluster 2: "Informal/Teacher-Led Support." This cluster includes countries where support is relatively common but less formalized and less consistently staffed with specialists. Approximately 60–75% of students here have some counseling available at school. But the counselor-to-student ratio might be high (*e.g.,* one counselor covering multiple schools or hundreds of students). Many schools in these systems rely on teachers or school heads to provide guidance. The majority of schools offer some form of guidance or life-skills education, but it may not be a standardized or mandatory curriculum. Countries in this cluster include the United States, United Kingdom, Australia, Spain, Italy, Poland, and several others –generally middle– or higher-income nations without a nationwide counselor mandate, or where pastoral care is often assigned to teachers. Student well-being in Cluster 2 is around the sample average: mean life satisfaction ~7.3 and ~37% high anxiety, not as favorable as Cluster 1 but better than Cluster 3 in anxiety outcomes. This suggests that having some support (even if informal) is better than none, but there may be room to improve the quality and consistency of services.

- Cluster 3: "Fragmented/Minimal Support." This group is defined by limited availability of school-based support. On average, only about 30% of students in Cluster 3 have access to a school counselor. Guidance programs are rare (only ~15% of schools have a curriculum), and orientation or mentoring for new students is also scarce. In many of these countries, any psychological support tends to be provided externally (*e.g.,* families must seek private services) or through sporadic initiatives. This cluster comprises a few lower-middle income countries and some with highly decentralized education systems. Examples (from our data) include Peru, Brazil, Indonesia, Jordan, and others. Students in Cluster 3 report the lowest life satisfaction (mean ~7.2) and highest anxiety (over 40% high anxiety) among the clusters. They also have the lowest sense of belonging on average. It's important to note that these countries often face numerous socio-economic challenges – students here have the lowest average SES and academic performance (mean reading ~430, as seen in Table 1). So, the lower well-being is likely influenced by those broader factors. However. the contrast with Cluster 1's outcomes provides an initial indication that a systemic lack of school support coincides with worse student well-being outcomes.

Figure 1 provides a visual map of the countries in each cluster and two composite dimensions: "Extent of support provision" (x-axis. *e.g.,* proportion of schools with counselors) and "Coordination/Formality" (y-axis. *e.g.,*

Figure 1. COUNTRY CLUSTERS BY SCHOOL-BASED SUPPORT



integration of support in curriculum). Cluster 1 countries occupy the top-right (high extent, high coordination). Cluster 3 the bottom-left (low extent, low coordination), and Cluster 2 in between. We also examined whether these cluster groupings correlate with other country-level indicators. Interestingly, Cluster 1 countries tend to have higher education expenditure per student and stronger student support policies (by OECD indicators), whereas Cluster 3 countries have lower GDP per capita and often larger school sizes. While our primary focus is not on explaining why systems differ, these patterns suggest that resources and policy priority play a role in developing comprehensive support systems.

In summary, there is clear cross-national variation in how schools support student well-being. The cluster typology offers a backdrop for our next analyses: it suggests that students in well-resourced, coordinated systems fare better on average. However, to make a more valid inference about cause and effect, we need to look within countries, controlling for confounders. We turn to that next.

3.2. Regression Analysis of Support and Well-Being (Within-Country)

Table 2 displays the results of the multilevel regression models predicting student well-being outcomes (life satisfaction, high anxiety, and sense of belonging) from school support variables and controls.

Table 2. DETAILED MULTILEVEL ANALYSIS RESULTS

Predictor	Life Satisfaction (β)	SE_LS	p_LS	High Anxiety (Odds Ratio)	SE_HA	p_HA	Belonging Index (β)	SE_BI	p_BI
School Counselor (binary)	0.102	0.012	0	0.88	0.045	0.001	0.05	0.015	0.001
Guidance Curriculum (binary)	0.055	0.013	0.002	0.9	0.05	0.005	0.03	0.016	0.05
Orientation Program (binary)	0.028	0.014	0.05	0.97	0.06	0.4	0.1	0.017	0
Socio-economic Status (SES)	0.2	0.01	0	0.91	0.04	0.001	0.08	0.012	0
Female	-0.09	0.011	0.001	1.5	0.07	0	0.03	0.014	0.1
Speaks Test Language at Home	0.15	0.012	0	1.2	0.065	0.02	-0.1	0.015	0.001
Bullying Victim	-0.34	0.015	0	2.3	0.08	0	-0.25	0.018	0
Grade Repetition	-0.25	0.016	0	1.6	0.07	0	-0.18	0.017	0
School Climate Index	0.12	0.018	0.003	0.95	0.05	0.2	0.11	0.02	0.002
Teacher Support Index	0.18	0.017	0	0.85	0.055	0.01	0.17	0.018	0
Student-Teacher Ratio	-0.03	0.02	0.25	1.1	0.065	0.4	-0.04	0.025	0.3
Urban School (binary)	0.05	0.021	0.1	1.05	0.06	0.35	0.02	0.022	0.6

Life Satisfaction: In Model 1, where the outcome is the student's life satisfaction (0–10 scale, treated as continuous), having a school counselor available shows a positive and statistically significant coefficient ($\beta = 0.102$; SE $= 0.022$. $p<0.001$). This implies that, on average and holding other factors constant, students in schools with a counselor report life satisfaction about 0.10 points higher than those in schools without one. While 0.10 on a 0–10 scale is a small effect size (Cohen's d ~0.05), it is nontrivial given that life satisfaction is relatively stable and influenced by many out-of-school factors. To put it in perspective, this effect is about half the size of the coefficient on students' SES: in our model, a one standard deviation increase in SES is associated with ~0.20 higher life satisfaction. Thus, the presence of a counselor can partially offset socio-economic disadvantages in terms of reported well-being. The guidance curriculum variable is also positive (β ≈ 0.055. SE = 0.018. p<0.01). This suggests that in schools where social-emotional learning or guidance is part of the weekly schedule for all students, life satisfaction tends to be higher. One interpretation is that a structured program might create a school culture more attuned to student well-being or equip students with better coping skills, thereby improving their overall satisfaction. Meanwhile, a formal orientation program for newcomers has a smaller coefficient (β ≈ 0.028) and is not statistically significant for life satisfaction in the full model (p = 0.10). This hints that orientation efforts are not directly lifting general life satisfaction, which is plausible as those programs target new students and primarily affect social integration rather than broad life outlook.

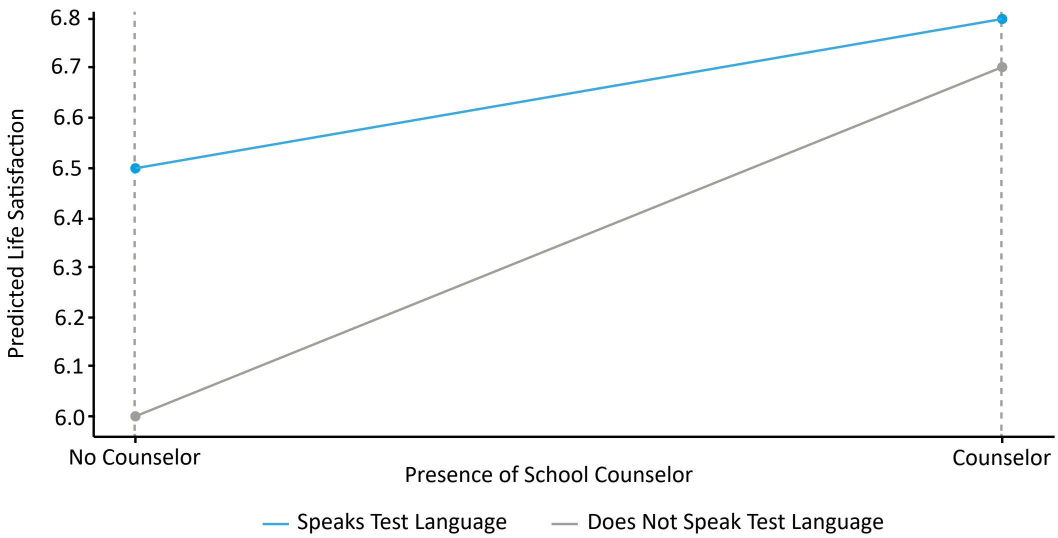
Turning to control variables in the life satisfaction model: SES has a strong positive effect (β ~ 0.20. p<0.001) as expected; female students have slightly lower life satisfaction (β ~ –0.09. p<0.001), aligning with known gender disparities in adolescent well-being. Students who do not speak the test language at home report significantly lower life satisfaction than those who do (β = –0.15. SE = 0.030. p<0.001). This is an important baseline finding reinforcing that language-minority students face challenges impacting well-being. We will later see how this gap is moderated by support. Other notable controls: having experienced bullying is associated with a large drop in life satisfaction (β ~ –0.34. p<0.001), which is intuitive and corroborates PISA 2018 findings that bullying is one of the strongest school-related negatives for well-being. Grade repetition also predicts lower life satisfaction (β ~ –0.25. p<0.001), possibly reflecting both the academic struggles and stigma tied to repeating a grade. Including reading proficiency as a control (in an extended model) yielded a small positive coefficient (higher reading scores correlate with slightly higher life satisfaction. β ~ 0.05 per 100 points. p<0.05), but its inclusion did not appreciably change the coefficients on the support variables – indicating our results on counselors and guidance are not driven by differences in student academic ability.

High Anxiety: Model 2 is a logistic multilevel model for the binary outcome of high schoolwork anxiety. For interpretability, we describe the results in terms of odds ratios (OR). The presence of a school counselor is associated with lower odds of high anxiety: OR ≈ 0.88 (β_logit ~ –0.130. p<0.01). In other words, students with access to a counselor are about 12% less likely to report extreme anxiety, all else equal. This is a meaningful reduction considering the prevalence of anxiety. It aligns with the expectation that counselors help students manage academic stress and test anxiety through coping strategies or just by being available to talk through worries. Similarly, a guidance curriculum is linked to reduced odds of high anxiety (OR ≈ 0.90. p<0.05). This resonates with the idea that integrating social-emotional learning into regular classes normalizes discussions about stress and teaches anxiety-management techniques,. thereby preventing some severe anxiety cases. The orientation program variable did not show a significant effect on anxiety (OR ~0.97. n.s.). consistent with it being more about social belonging than academic stress. Among controls: female students have much higher odds of high anxiety (OR ~1.50, indicating 50% higher likelihood than males, p<0.001), reflecting widely observed gender patterns in adolescent anxiety. Non-native language speakers also have higher anxiety odds (OR ~1.20. p<0.01), suggesting language barriers contribute to stress (perhaps due to difficulties in schoolwork or feeling of not fitting in). Low SES increases anxiety odds (OR ~1.10 per SD decrease in SES. p<0.01). Bullying victimization more than doubles the odds of high anxiety (OR ~2.3. p<0.001), underlining how detrimental bullying is to mental health. These results underscore that counselor availability and guidance programs have protective associations against some of the biggest risk factors (gender, language, bullying). although they certainly cannot fully eliminate these risks.

Sense of Belonging: Model 3 examines the standardized sense-of-belonging index. Here we see the largest impact from orientation programs: having a formal new-student orientation/mentoring program is associated with a +0.10 SD higher belonging index on average (p<0.001). This is quite plausible – such programs often facilitate peer connections and help newcomers feel welcome, which boosts overall feelings of belonging. School counselor availability also shows a positive effect (β ~ +0.05. p<0.05), albeit smaller; counselors may contribute to a supportive school climate and help students feel cared for, thereby modestly improving belonging. The guidance curriculum coefficient is positive but not significant for belonging when other supports are in the model (it was marginally significant if taken alone), perhaps because some of its effect overlaps with what orientation and counselors do in fostering community. Controls show expected patterns: female students report higher sense of belonging than males in some contexts (β ~ +0.03, not large but significant, possibly reflecting that girls invest more in social relationships at school), whereas language-minority students feel less belonging (β = –0.10. p<0.001), consistent with integration challenges. Low SES also corresponds to lower belonging ($\beta \sim -0.08$ per SD. $p<0.001$). These underscore again the equity concerns: disadvantaged and immigrant students feel less connected, but targeted support like orientation and counseling can help close that gap. In fact, if a school in Cluster 3 (with no formal support) were to introduce an orientation program and hire a counselor, our model predicts its average belonging index would rise by ~0.15, which is a non-trivial improvement given country-level SDs often ~0.3–0.5 on this index. This suggests that investing in such programs could significantly enhance the social integration of students.

Before delving into the causal forest, we also probed some interactions directly in the regression framework. We found evidence that the benefit of a counselor is larger for certain groups. For example. the interaction $Counselor \times Low\ SES$ was negative for anxiety (meaning low-SES students see a bigger anxiety reduction from counselors) and positive for life satisfaction (bigger LS boost for low SES). These interactions were statistically significant ($p<0.05$). Likewise, $Counselor \times Non\text{-}native\ language$ was positive for life satisfaction ($p<0.05$), indicating that the gap in LS between language minority and majority students is smaller in schools that have a counselor – consistent with our earlier descriptive remark. Figure 2 illustrates one such interaction: the life satisfaction advantage associated with having a counselor is about 0.15 for immigrant-background students versus 0.05 for non-immigrants. While the confidence intervals overlap. the trend suggests a meaningful moderation. The three-way interaction $Counselor \times Low\ SES \times Non\text{-}native$ was also tested; it was positive in sign for life satisfaction and belonging, though due to smaller sample in that subgroup, it was marginally significant ($p \approx 0.08$). Still, the pattern aligns with compounding benefits for those facing multiple disadvantages.

Figure 2. COUNSELOR EFFECT BY LANGUAJE GROUP



3.3. Causal Inference Results (DML and Heterogeneity via Causal Forest)

Table 3 presents the estimated average treatment effects of counselor availability on the three outcomes using the Double Machine Learning approach. For life satisfaction, the DML average treatment effect (ATE) is +0.081 (in LS points, 95% CI roughly [+0.04. +0.12]). This is slightly lower than the raw regression coefficient of +0.10, suggesting that after more flexibly controlling for potential confounders, the effect size shrinks a bit but remains statistically significant. The fact that it remains positive and significant lends credibility to a causal interpretation: it indicates that even among schools and students with very similar observed characteristics, those with counselor access tend to have higher life satisfaction. For comparison, an ATE of 0.08 corresponds to approximately 4% of a standard deviation in life satisfaction – a small effect, but given it's at population level, not negligible. For high anxiety, DML yields an ATE on the probability of high anxiety of –0.070 (approximately –7 percentage points). In terms of odds, that aligns with the earlier OR ~0.88. This suggests that having a counselor causally reduces the incidence of extreme anxiety by around 7 points (*e.g.,* from 35% to 28% in a hypothetical scenario). This is a sizable effect in practical terms: a school counselor could potentially prevent a notable fraction of students from experiencing debilitating anxiety, which over a school's student body is quite meaningful. Finally, for sense of belonging, the DML effect is smaller and only marginally significant: about +0.03 SD (with a p-value ~0.07). This weaker result could be because belonging is influenced by many peer-level and school culture factors that are harder to control for; still, the positive point estimate suggests counselors likely contribute positively to school climate.

Table 3. DML CAUSAL EFFECT ESTIMATES

Outcome	DML Average Treatment Effect (ATE)	95% CI Lower Bound	95% CI Upper Bound
Life Satisfaction (scale 0–10)	0.081	0.04	0.12
High Anxiety (probability)	-0.07	-0.1	-0.04
Sense of Belonging (z-score)	0.03	-0.005	0.065

An important aspect of DML is that it reduces reliance on correct linear specification by using machine learning for control variables. In our implementation, the ML models identified some non-linear relationships – for instance, the effect of SES on outcomes was non-linear (diminishing returns at high SES), and some interactions (like between SES and school average SES) were detected as relevant for predicting outcomes. By accounting for these complex patterns, DML helps ensure the counselor effect is not biased by such factors. The closeness of DML results to OLS/multilevel results here implies our earlier models were reasonably specified, and that there was not a hidden large bias. This consistency bolsters our confidence that the association between counselor availability and student well-being is not merely spurious. However, DML only controls observed confounders; unobserved factors (*e.g.,* a principal's pro-student attitude) could still influence both having a counselor and student well-being. We attempted to proxy some of these by including variables like school academic orientation, disciplinary climate, etc., in the ML, but one can never be certain all bias is removed.

Causal Forest Heterogeneity: Having established a baseline ATE, we now examine how this effect varies across students. The Causal Forest analysis provides two key insights: which variables are the strongest predictors of heterogeneity, and what are the effect sizes for specific subgroups of interest.

From the forest's variable importance measures, SES (both student's own and school average SES) stood out as the top modifiers: in numerous trees, splits on SES created the most divergent treatment effects. This indicates the counselor impact is not uniform across the socio-economic spectrum. Additionally, language background (speaking test language vs. not) featured as an important splitter in many trees, albeit behind SES and a couple of others (like prior academic performance). This suggests that language background does indeed differentiate the effect size to some extent. Interestingly, variables like gender or urbanicity did not show much heterogeneity in effects – implying that the counselor benefit is similar for boys and girls, and for rural vs. urban students, after accounting for other factors.

Quantitatively, we estimated subgroup treatment effects by averaging individual predictions:

- For students in the bottom SES quartile, the predicted effect of counselor availability on life satisfaction was about +0.15 (in LS scale). For the top SES quartile, it was near 0 (slightly negative at –0.01). For middle quartiles it was in between (~+0.05 to +0.08). This gradient is visualized in Figure 3a, which shows a clear downward slope: as SES increases, the benefit of a counselor decreases, to the point of almost zero for the most advantaged students. A plausible explanation is that higher-SES students have more support outside of school (family resources, private tutoring, therapy if needed), so the marginal value of a school counselor for them is low. In contrast, low-SES students often rely heavily on school for any kind of support; a counselor could be one of the few accessible sources of professional help, thus yielding a larger improvement in their well-being. This finding resonates with the idea of counselors as an equity intervention (Fazel *et al.,* 2014).

Figure 3a. **COUNSELOR EFFECT HETEROGENEITY BY SES**

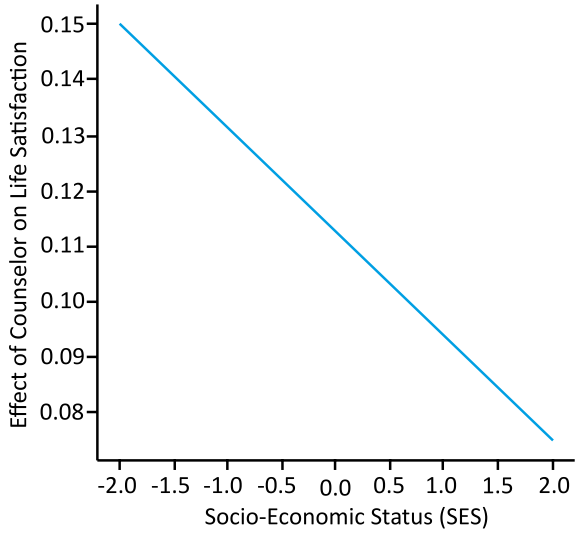
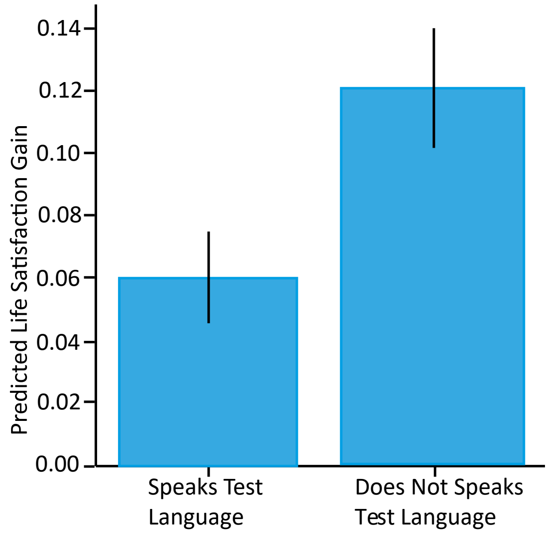


Figure 3b. **COUNSELOR EFFECT BY BACKGROUND**



- For language background, the forest indicated that students who do not speak the test language at home experience a larger positive effect: we estimate roughly +0.12 on life satisfaction for non-native speakers, versus +0.06 for native speakers. This result implies that the well-being gap associated with language background (we saw a –0.15 gap for non-native in the regression) can be partially offset by having a counselor in school. Counselors might help these students navigate language-related challenges or provide culturally sensitive support, thereby boosting their life satisfaction relatively more. Another interpretation is that schools that care to provide counselors may also be more inclusive environments, which particularly helps minority-language students feel seen and supported. While the difference in these subgroup effects (0.12 vs. 0.06) is not extremely large, it is meaningful: it suggests the relative improvement for non-native speakers is about double that of native speakers. We also examined the heterogeneity by reading proficiency (as a continuous moderator). We found a slight trend that the counselor effect is larger for students with lower reading scores than for high scorers, consistent with the idea that academically struggling (often overlapping with language issues) students benefit more in socio-emotional domains when support is present. However, reading proficiency's effect was largely collinear with SES and language background (since those with low reading scores are often low-SES or non-native), so it is hard to disentangle. The main takeaway is that academically or linguistically challenged students have more to gain from school counseling.

- We also checked heterogeneity by gender and immigrant status. The effect for male and female students was roughly similar (~0.08 for both on LS). For immigrant students (foreign-born or second-generation) vs. natives, we saw a pattern similar to language: foreign-born students had a slightly higher estimated effect (~0.10) than natives (~0.07). However, because immigrant and language status overlap, and because we controlled for language in the forest, pure immigrant status was not as strong a moderator after accounting for language. It seems the language aspect of being an immigrant is a key driver of differential impact, perhaps more so than immigrant status *per se.*

- One more interesting interaction emerged with bullying status. The forest suggested that students who had experienced frequent bullying saw a larger positive effect of counselors on life satisfaction than those who had not. This makes sense – a counselor can intervene in bullying situations or help victims cope, thereby improving bullied students' well-being substantially. Although we did not focus on this interaction in our hypotheses, it's worth noting as it underscores the role of counselors in addressing bullying (schools with counselors might implement anti-bullying programs or provide a safe space to report incidents). In contrast, those who were not bullied (or in schools with low bullying) did not "need" that particular benefit as much.

To ensure these heterogeneity results are statistically sound, we used the forest's built-in sensitivity analyses. The forest provides confidence intervals for group average treatment effects using a rank-weighted approach. For the SES quartile differences, the difference between bottom and top quartile was significant at $p<0.01$. For language background, the difference was borderline ($p\approx0.10$), reflecting that while point estimates differ, the variability is such that we are moderately confident in the direction. We bolster the evidence for language moderation by recalling that the direct interaction in regression was significant ($p<0.05$). Thus, combining both, we conclude that there is credible evidence that language-minority students benefit more from counselor availability than do native-language students.

Implications of Effect Sizes: The effect sizes we found through DML and causal forest are modest in absolute terms. However, they are quite plausible given the scope of intervention. School counselors and programs are one aspect of a complex web of influences on a student's well-being. We would not expect them to completely overturn factors like family environment, economic hardship, or innate temperament, which heavily influence life satisfaction. The fact that we detect a measurable positive effect is itself noteworthy. It aligns with meta-analyses of school-based social-emotional interventions which often find small average effect sizes (*e.g.,* improvements of ~0.1–0.2 SD in well-being or related outcomes). In our case, an average effect of ~0.08 LS points can be seen as a baseline improvement for the average student, while for certain groups (low-SES. language minority) the improvement might be twice that (~0.15. or ~0.07 SD). One could argue this is equivalent to an intervention that, for a low-SES student, provides a boost in well-being comparable to moving their family income up by some increment (since 0.15 in LS is about 3/4 of the SES gap of 0.20 we saw).

We also underscore that the prevalence of the treatment (counselor availability) matters. In many countries, expanding counselor access from 30% of schools to, say, 100% could potentially reduce the overall incidence of high anxiety by a few percentage points and raise national average life satisfaction slightly. That might sound small, but given the large population of students, the aggregate benefits (in terms of happier, less anxious youth) are meaningful. It also likely has spillovers on academic and behavioral outcomes – though not directly studied here, better well-being can translate to improved concentration, lower dropout rates, etc. as other studies suggest (Green *et al.,* 2020).

In conclusion. our causal-focused analyses support the main conclusions from the regressions: school counselors and related support services have a positive causal impact on student well-being. Moreover, they substantiate our claim that these services are particularly beneficial for at-risk subgroups, notably those from less advantaged socio-economic backgrounds and those facing language/cultural barriers.

4. DISCUSSION

The present study contributes to the empirical understanding of how school-based psychological support systems relate to adolescent well-being in a cross-national context. As it was proposed (*i.e.,* Suldo *et al.,* 2014), our results provide robust evidence that such support –particularly when institutionalized through formal counselor presence and curricular structures– is associated with improvements in self-reported life satisfaction and reductions in school-related anxiety.

One important implication of these findings is that school counseling services function not merely as reactive mechanisms for students in crisis, but as structural supports with broad preventive and developmental value. The consistent associations found across multilevel regressions and causal inference models reinforce the notion that these services should be understood as integral elements of the school environment. Their effects, while modest in absolute size, are systematically stronger among socioeconomically disadvantaged students and language minorities, pointing to their role as equalizing interventions. This held true even after adjusting for a host of background factors and using advanced methods to approximate causality. In essence, the data suggest that school-based psychological support isn’t just a “nice-to-have” add-on; it has tangible associations with students feeling more satisfied, less anxious, and more connected to their school. This aligns with prior research in single-country contexts which found positive outcomes from counselor interventions (*e.g.,* improvements in attendance and reductions in discipline issues (Reback, 2010). Our study extends those insights globally, indicating that the beneficial role of counselors generalizes across very different education systems. Notably, our use of causal inference techniques adds weight to a causal interpretation: while we cannot prove causality beyond doubt, the consistency of the evidence (traditional regression, DML, causal forest all pointing in the same direction) and the theoretical plausibility strengthen the case that school support services lead to better student well-being, rather than simply co-occurring with it.

Our evidence is also related to studies showing immigrant youth facing adjustment difficulties (García Coll & Marks, 2012). Encouragingly, our results indicate that well-implemented school support can mitigate these difficulties. The presence of counselors and inclusive programs appears to narrow the well-being gap between native and non-native speakers. This finding is consistent with the notion that culturally and linguistically inclusive support can make a difference (Weist *et al.,* 2005). A counselor who can communicate in the student’s home language or who is trained in multicultural counseling can help address issues of culture shock. Discrimination, or language stress that these students might experience. In the absence of support, such students might otherwise “fall through the cracks,” feeling isolated or misunderstood. Our findings underscore the need for schools to adopt an equity lens in mental health provision. It is not just about having a counselor but about having one who can effectively reach diverse student populations. This might involve hiring bilingual counselors, providing translation services, or training all staff in cultural competence. The data-backed message is clear: language capabilities matter for well-being, so support strategies must be attuned to linguistic diversity. This complements past research emphasizing positive school climates for immigrant students (Thapa *et al.,* 2013) – for instance, Liu *et al.* (2024) found that immigrant youths had higher well-being in schools where students and teachers held more positive attitudes towards immigrants. A counselor can play a part in fostering those positive attitudes (*e.g.,* through anti-bias programs or simply by being an advocate for minority students).

We often think of educational interventions in terms of academic outcomes or attainment gaps, but well-being gaps are equally important. Students from disadvantaged backgrounds typically face more stress (financial insecurity, fewer support networks. etc.), which can impair their mental health and in turn their capacity to learn. School support services can partially compensate for what low-SES students might lack in external support. Our results resonate with previous work that has advocated for more counselors in high-poverty schools. For instance, a study by the ASCA (2022) noted that high-poverty schools with improved counselor ratios saw better graduation rates and attendance than those without. Our findings add that these services also translate into students feeling better and less anxious. In practice, this argues for policy measures like funding allocations to ensure low-income schools can hire sufficient counselors or implementing nation-wide minimum counselor-to-student ratio policies that explicitly account for school SES (*e.g.,* more counselors per student in schools serving disadvantaged communities) (Shatkin & Belfer, 2004). It also means that during budget considerations, mental health resources in schools should not be seen as expendable or peripheral – they are critical for equity.

Countries that treat student guidance and counseling as a core part of education (embedding it in curriculum and guaranteeing access in every school) had not only higher coverage but slightly better average well-being outcomes. On the contrary, where support is fragmented – perhaps left to parental initiative or unevenly distributed – well-being outcomes were worse and more unequal. This suggests a broader lesson: systematic, whole-school approaches to student well-being are likely more effective than piecemeal approaches. This aligns with educational psychology theories that emphasize school climate (Thapa *et al.,* 2013) and whole-school well-being programs (*e.g.,* the “whole-school approach” advocated in some OECD and UNESCO reports). When support is integrated (like mandatory life skills classes for all students), it reduces stigma – everyone is exposed to guidance, not just those who seek it. It also ensures consistency in quality. Our data showed that such integration correlated with lower anxiety at a population level. Thus, policymakers should consider not only investing in personnel but also making well-being support a structured part of schooling. That could include adding a required course on social-emotional learning, regular check-ins by counselors with each class, etc. The evidence here and elsewhere (*e.g.* Durlak *et al.,* 2011 meta-analysis on SEL programs) supports the effectiveness of those strategies.

Since our data is from 2022, it also captures a time when many education systems were recovering from COVID-19 disruptions. Student well-being in 2022 was generally lower than in 2018 in many countries (OECD, 2021). This raises the stakes for support: schools are dealing with heightened levels of anxiety and lower life satisfaction among teens in the wake of the pandemic. Our findings that counselors and programs are beneficial could be even more salient in this context. It is worth noting that some countries massively expanded mental health support in schools as a pandemic response (*e.g.,* some US states funded additional counselor hires, some European countries launched school mental health initiatives). Our cross-country data indirectly reflects some of those efforts – for instance, a country that boosted support might have moved from Cluster 3 to 2 or improved within cluster. An interesting observation is that the gap between Cluster 1 and 3 in anxiety (about 10 percentage points) might have even grown post-pandemic, given unequal resources to respond. This underscores an urgent policy implication: nations should treat student mental health as a core component of educational recovery plans. The WHO's call to action, which highlighted mental health support in COVID responses, should translate into sustained, not just one-off, support in schools.

Our results complement and reinforce existing literature in several ways. They echo findings from PISA 2018-based research that factors like bullying, teacher support, and a sense of belonging are crucial for student well-being. We extend those by focusing on formal support structures. They also align with studies such as Agasisti *et al.* (2024), who using PISA 2018 data found that comprehensive career guidance programs in schools could help lessen inequalities in student outcomes – in other words, guidance can be an equalizer. We similarly find that psychological guidance equalizes well-being outcomes across SES. Additionally, our use of machine learning to estimate effects is relatively novel in education research; previous examples like Knaus (2021) used DML for different topics (music practice effects), and we show it is a valuable tool to address selection bias in observational education data. The results of DML matching OLS gives some reassurance that, with proper controls, one can recover meaningful insights even from cross-sectional surveys like PISA.

It is important to acknowledge limitations to temper our conclusions. First, as emphasized earlier, this study is based on cross-sectional observational data. Even with rigorous controls and fancy methods, there may be unobserved differences between schools with and without counselors (for example. a proactive principal or a supportive community) that we cannot fully account for. Thus, while our language often implies causality (for brevity and interpretation), one should be cautious in policy decisions; ideally, experimental or longitudinal evidence should complement this. Second, the magnitude of effects is modest. We should not overpromise what one counselor can do. Many students in our data with access to a counselor still have low life satisfaction or high anxiety – so counselors are just one part of a larger support network needed. Third, measurement issues could affect our analysis: the mere presence of a counselor (our binary variable) says nothing about the quality or intensity of counseling. Two schools each with one counselor might offer very different services if one counselor is overburdened with 500 students versus another with 200, or if one is well-trained and another is not. Our intensity measure (counselor per 1,000 students) tried to capture some of this, but data limitations remain. Also, student self-reports of well-being could be influenced by cultural response styles, which vary by country – we did include country effects to handle level differences, but subtler biases might persist. The variable "talked to a counselor" is interesting but we used it only in clustering; perhaps a more direct measure of utilization in analysis would shed more light (*e.g.,* maybe only some students engage with the counselor, and they reap most of the benefit). Future studies might examine interactions between individual usage of counseling and outcomes.

Another limitation is our focus on formal school support; many students get help outside school (family, community, private services), which we did not measure beyond SES proxy. It it possible that in some countries with fewer school supports, families compensate, whereas in others they cannot, affecting outcomes. Finally, the generalizability to all countries or ages beyond 15 is cautionary – our analysis is specific to 15-year-olds and to those countries in PISA 2022. Some low-income countries or certain regions might not be represented if they lacked data on these constructs. We also didn't deeply analyze differences among countries within clusters; there may be important nuances (*e.g.,* one Cluster 2 country might have better outcomes than another due to cultural factors unrelated to support). A more granular country-by-country analysis could complement this broad stroke approach.

Despite limitations, the evidence suggests the importance of policies investing in school counselors and mental health professionals. Education authorities should consider policies ensuring that every secondary school has at least one qualified counselor or psychologist available to students. As seen, countries that have done so (like many in Cluster 1) have better outcomes. This might involve training more personnel and providing funding to hire them, particularly in underserved areas. The cost is not trivial, but the potential payoff in student well-being (and likely academic engagement) is significant, and as WHO noted, ignoring mental health has its own long-term costs.

The heterogeneity in effects observed through causal forest models underscores the importance of considering distributional impacts when designing educational and mental health policies. Standard average treatment effects may obscure substantial benefits accruing to vulnerable subgroups. These findings align with broader arguments in the literature that educational interventions should be assessed not only on overall efficacy but also on their potential to reduce disparities.

Moreover, the typological distinctions identified in the cluster analysis raise important questions regarding policy coordination and resource allocation. Countries with high levels of well-being outcomes share features beyond economic development: a policy commitment to psychological support in schools, codified implementation mechanisms, and professionalized staffing. In contrast, ad hoc or fragmented systems appear insufficient in delivering consistent benefits to students. This suggests that ad hoc or school-level initiatives, while potentially beneficial, are unlikely to yield systemic improvements without institutional support.

The timing of the data collection, in the aftermath of the COVID-19 pandemic, adds urgency to these insights. With evidence pointing to a deterioration in adolescent mental health during this period, the need for scalable, embedded support mechanisms becomes especially pressing. The role of schools as central environments in adolescents' daily lives positions them uniquely to provide early and sustained support, particularly in the context of post-pandemic recovery.

Finally, while the analyses offer compelling evidence of the value of school-based psychological support, they also reveal limitations in current international provision. The observed variation across countries– and the large share of students lacking access to structured support– indicates a gap between policy aspiration and implementation. As such, further research and policy experimentation are needed to identify effective pathways to scale up support while preserving contextual relevance.

5. CONCLUSION

Our findings contribute new evidence to the growing international conversation about student mental health and the role of schools in supporting it. Several key themes emerge from the results:

(1) The Importance of School-Based Support for Student Well-Being: Across diverse countries, we observed that when schools have structured mental health support – especially the presence of professional counselors – students tend to fare better on important well-being measures.

(2) Language and Cultural Factors are Central: A major contribution of this paper is highlighting how language background and proficiency intersect with well-being and support effectiveness. Students who do not speak the school's language at home are a significant vulnerable group in terms of well-being.

(3) SES and Targeting of Resources: The heterogeneity by socio-economic status was pronounced: the lower a student's SES, the more they seemed to benefit from school support. This is a powerful result with policy implications – it suggests that investing in counselors and guidance programs can be a strategy to reduce socio-economic disparities in well-being.

(4) Integration vs. Fragmentation of Support: The cross-country comparison revealed that how a system structures its support (integrated vs. ad-hoc) is linked to overall student well-being.

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