

PEAC 2025 Philippine Education Conference

International Large-Scale Assessments and School Reform

What can private schools learn from ILSAs?



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Philippine
Development Plan
2017-2022

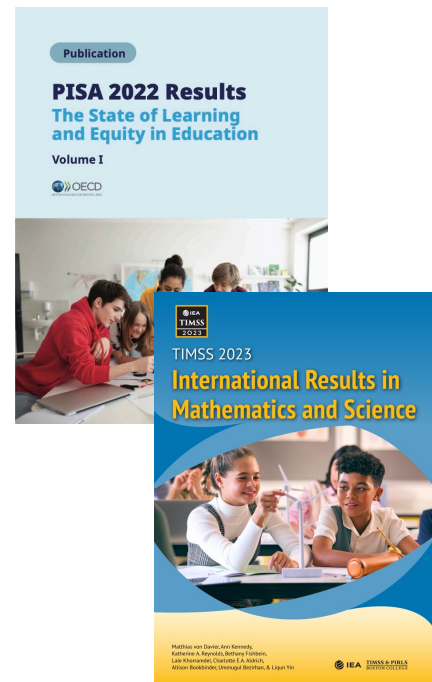
“Participate in international large-scale assessments (ILSAs). The country’s participation in ILSAs such as the Trends in International Mathematics and Science Study, Programme for International Student Assessment, and South-East Asia Primary Learning Metrics will be prioritized to measure learning outcomes vis-à-vis other countries and provide information to evaluate the country’s progress in improving math, science, and literacy and build evidence for policy development and decision-making.”

NEDA (2020, p. 173), *Updated Philippine Development Plan (2017-2022)*

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What ILSAs results say...

- ILSAs assess a country's education system
- ILSA results estimate the overall proficiency of target student population in a country in selected domains
 - Individual students' scores represent proficiency with reference to learning standards
 - Country scores combine individual student scores
 - Country scores are also be ranked in relation to other countries/territories



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Country	Average Scale Score
³ Singapore	625 (3.9) ▲
¹ Hong Kong SAR	602 (3.3) ▲
Korea, Rep. of	600 (2.2) ▲
Chinese Taipei	599 (1.9) ▲
Japan	593 (1.8) ▲
² Russian Federation	587 (3.3) ▲
¹ Northern Ireland	566 (2.7) ▲
² England	559 (3.0) ▲
Ireland	548 (2.5) ▲
² Latvia	546 (2.6) ▲
¹ Norway (S)	543 (2.2) ▲
² Lithuania	542 (2.8) ▲
Austria	539 (2.0) ▲
¹ Netherlands	538 (2.2) ▲
² 1 United States	535 (2.5) ▲
Czech Republic	533 (2.5) ▲
¹ Belgium (Flemish)	532 (1.9) ▲
Cyprus	532 (2.9) ▲
Finland	532 (2.3) ▲
² Portugal	525 (2.6) ▲
¹ Denmark	525 (1.9) ▲
Hungary	523 (2.6) ▲
² Turkey (S)	523 (4.4) ▲
Sweden	521 (2.8) ▲
Germany	521 (2.3) ▲
Poland	520 (2.7) ▲
Australia	516 (2.8) ▲
Azerbaijan	515 (2.7) ▲
Bulgaria	515 (4.3) ▲
Italy	515 (2.4) ▲
² Kazakhstan	512 (2.5) ▲
¹ 2 Canada	512 (1.9) ▲
² Slovak Republic	510 (3.5) ▲
Croatia	509 (2.2) ▲
Malta	509 (1.4) ▲
² Serbia	508 (3.2) ▲
Spain	502 (2.1) ▲
TIMSS Scale Centerpoint	500
Armenia	498 (2.5) ▲
Albania	494 (3.4) ▲
² New Zealand	487 (2.6) ▽
France	485 (3.0) ▽
¹ Georgia	482 (3.7) ▽
United Arab Emirates	481 (3.7) ▽
Bahrain	480 (2.6) ▽
North Macedonia	472 (5.3) ▽
Montenegro	453 (2.0) ▽
Bosnia and Herzegovina	452 (2.4) ▽
Qatar	449 (3.4) ▽
² Kosovo	444 (3.0) ▽
Iran, Islamic Rep. of	443 (3.9) ▽
Chile	441 (2.7) ▽
Oman	431 (3.7) ▽
² Saudi Arabia	398 (3.6) ▽
Morocco	383 (4.3) ▽
Kuwait	383 (4.7) ▽
South Africa (S)	374 (3.6) ▽
² Armenia	360 (3.6) ▽
² Philippines	357 (5.4) ▽

	Mean score in PISA 2022		
	Mathematics	Reading	Science
Bulgaria	417	404	421
Moldova	414	411	417
Qatar	414	419	432
Chile	412	448	444
Uruguay	409	430	435
Malaysia	409	388	416
Montenegro	406	405	403
Mexico	395	415	410
Thailand	394	379	409
Peru	391	408	408
Georgia	390	374	384
Saudi Arabia	389	383	390
North Macedonia	389	359	380
Costa Rica	385	415	411
Colombia	383	409	411
Brazil	379	410	403
Argentina	378	401	406
Jamaica*	377	410	403
Albania	368	358	376
Indonesia	366	359	383
Morocco	365	339	365
Uzbekistan	364	336	355
Jordan	361	342	375
Don't know*	347	307	388
Philippines	355	347	356
Guatemala	344	314	313
El Salvador	343	365	373
Dominican Republic	339	351	360
Paraguay	338	373	368
Cambodia	336	329	347

What ILSAs results say

- Media and popular discussions have tended to focus on **low rank** compared to other countries
- Moving up in the ranks does not mean students are learning better

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What ILSAs results say...

- Focus on scores and attainment of proficiency standards/benchmarks

- TIMSS 2019 : Philippines

Benchmark	Mathematics	Science
Advanced	0%	0%
High	1%	1%
Intermediate	6%	5%
Low	19%	13%

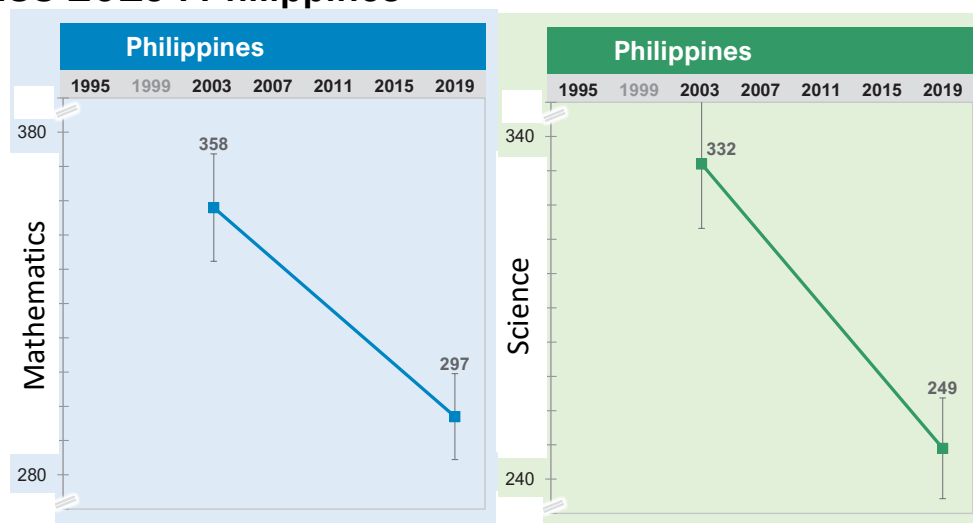
- PISA 2022 : Philippines

Standard	Mathematics	Science	Reading
Level 5 or 6	< 1%	< 1%	< 1%
Level 2 (minimum)	16%	23%	24%

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What ILSAs results say...

- TIMSS 2019 : Philippines



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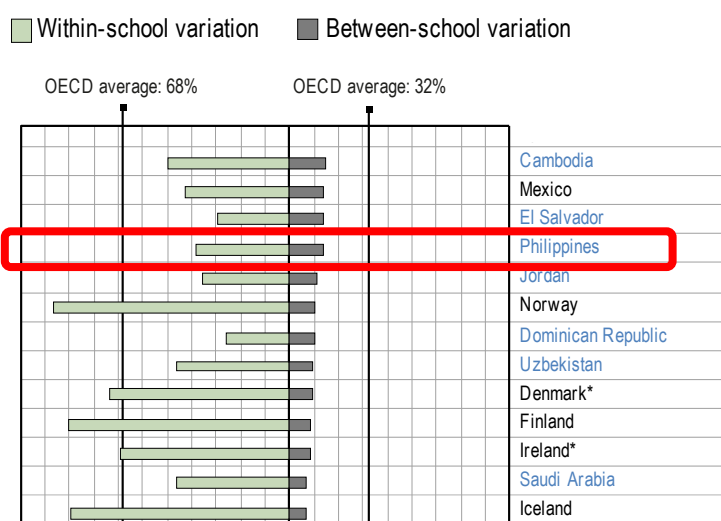
What ILSAs results say...

- Remember: ILSAs assess a country's education system
- ILSAs do NOT say anything about the **students' intelligence or innate abilities**
 - Scores represent what students were able to learn in their schools (in the country)



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What ILSAs results say about Philippine schools...



- There is not much variations within Philippine schools
- There is also not much variation among (or across) Philippine schools
- Relatively speaking, all our schools are performing badly

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What about private schools?



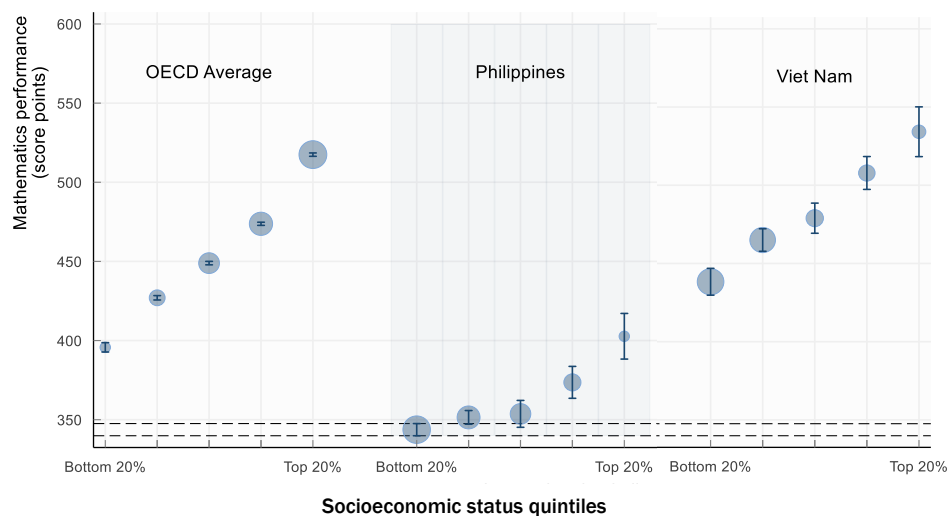
**TABLE 2-B
PERFORMANCE BY SCHOOL TYPE IN PISA 2018-2022**

School Type	2018	2022	2018-2022 (+-)	2022 Difference (Pub vs Prv)
Mathematics				
Public	344	345	1	59 ↑ (Private)
Private	392	404	11	
Science				
Public	348	344	-4	73 ↑ (Private)
Private	397	417	21	
Reading				
Public	329	333	3	83 ↑ (Private)
Private	388	416	29	

Source: OECD PISA 2018 and 2022

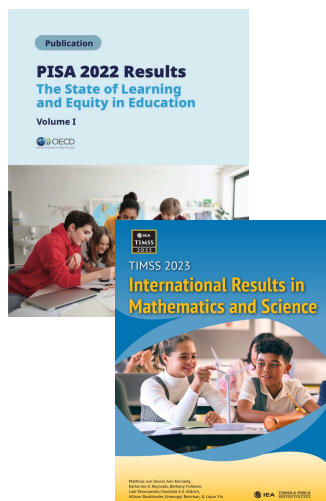
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Low proficiency amid inequity in Philippine education



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How can ILSAs inform school reform?

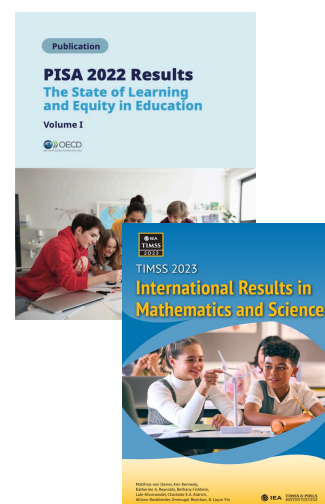


- Remember: ILSAs assess school systems, NOT individual schools
- But ILSAs provide so much information and insights:
 - Detailed frameworks for characterizing competencies in different learning domains
 - Assessment frameworks for these domains
 - Student experiences
 - Student beliefs, attitudes, and perceptions
 - Home environment
 - School and classroom environment

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How can ILSAs inform school reform?

- We need to think beyond the low ranks
- We need to understand the factors that predict the low scores
- Need: careful research
 - Generally, Philippine educators are not really good at this (Sorry 🙏)
 - But a few groups have done some systematic research on ILSAs (PIDS, DLSU, AIM, ADMU)



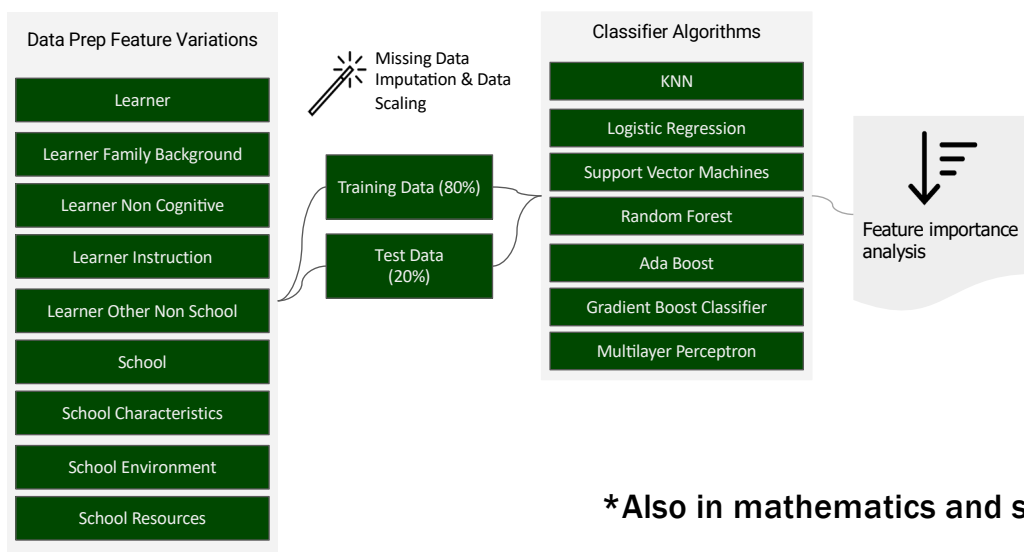
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A few examples of what can be learned from more careful study of ILSAs



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Predicting of poor proficiency in reading in PISA using machine learning approaches



***Also in mathematics and science**

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education sciences

Using Machine Learning Approaches to Explore Variables Influencing Reading Proficiency in Filipino Learners

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Abstract: Filipino students ranked last in reading proficiency in the PISA 2018, with only 19% meeting the minimum. To the range of factors that contribute to low reading proficiency, target of interventions to help students with poor reading skills, specifically binary classification methods (Level 1) and lower vs. higher (Level 2) or better) data from a nationally representative sample of 15-year-old students were used to analyze PISA data from the student questionnaire to test models that best identify the poorest-performing Filipino students. The goal was to explore factors that could help identify the students who are vulnerable to very low achievement in science and that could indicate possible targets for reform in science education in the Philippines. The random forest classifier model was found to be the most accurate and more precise, and Shapley Additive Explanations indicated 15 variables that were most important in identifying the low-proficiency science students. The variables related to metacognitive awareness of reading strategies, social experiences in school, aspirations and pride about achievements, and family/home factors, include parents' characteristics and access to ICT with internet connections. The results of the factors highlight the importance of considering personal and contextual factors beyond the typical instructional and curricular factors that are the foci of science education reform in the Philippines, and some implications for programs and policies for science education reform are suggested.

Keywords: reading proficiency; non-cognitive variables; motivation; growth mindset; reading self-concept; PISA

Humanities & Social Sciences Communications

ARTICLE

Profiling low-proficiency science students in the Philippines using machine learning

Allan B. I. Bernardo¹, Macario O. Cordel II², Marissa Ortiz Calleja³, Jude Michael M. Teves³, Sashmir A. Yap³ and Unisse C. Chua⁴

Abstract: Filipino students performed poorly in the 2018 Programme for International Student Assessment (PISA) mathematics assessment, with more than 50% obtaining scores below the lowest proficiency level. Students from public schools also performed worse compared to their private school counterparts. We used machine learning approaches, specifically binary classification methods, to model the variables that best identified the poor performing students (below Level 1) vs. better performing students (Levels 1 to 6) using the PISA data from a nationally representative sample of 15-year-old Filipino students. We analyzed data from students in private and public schools separately. Several binary classification methods were applied, and the best classification model for both private and public school groups was the Random Forest classifier. The ten variables with the highest impact on the model were identified for the private and public school groups. Five variables were similarly important in the private and public school models. However, there were other distinct variables that relate to students' motivations, family and school experiences that were important in identifying the poor performing students in each school type. The results are discussed in relation to the social and cognitive experiences of students that relate to socioeconomic contexts that differ between public and private schools.

Keywords: mathematics achievement; machine learning; Philippines; public vs. private schools; school type; socioeconomic differences; PISA

ing Profiles of Low-Performing Mathematics Students and Private Schools in the Philippines: Insights from Learning

do^{1,*}, Macario O. Cordel II², Minnie Rose C. Lapinid³, Jude Michael M. Teves³, Sashmir A. Yap³ and Unisse C. Chua⁴

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Abstract: Filipino students performed poorly in the 2018 Programme for International Student Assessment (PISA) mathematics assessment, with more than 50% obtaining scores below the lowest proficiency level. Students from public schools also performed worse compared to their private school counterparts. We used machine learning approaches, specifically binary classification methods, to model the variables that best identified the poor performing students (below Level 1) vs. better performing students (Levels 1 to 6) using the PISA data from a nationally representative sample of 15-year-old Filipino students. We analyzed data from students in private and public schools separately. Several binary classification methods were applied, and the best classification model for both private and public school groups was the Random Forest classifier. The ten variables with the highest impact on the model were identified for the private and public school groups. Five variables were similarly important in the private and public school models. However, there were other distinct variables that relate to students' motivations, family and school experiences that were important in identifying the poor performing students in each school type. The results are discussed in relation to the social and cognitive experiences of students that relate to socioeconomic contexts that differ between public and private schools.

Keywords: mathematics achievement; machine learning; Philippines; public vs. private schools; school type; socioeconomic differences; PISA

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READING VARIABLES

- Negative reading self-concept
- Low metacognitive awareness of reading strategies
- Low enjoyment of reading
- Low reading of fiction for enjoyment

TEACHING VARIABLES

- Frequent teacher feedback
- Asking students their thoughts on the reading material
- Low teacher enthusiasm

ICT VARIABLES

- Low ICT resources at home
- Infrequent use of ICT to learn about a topic
- Infrequent use of ICT to chat
- Frequent use of ICT for reading emails

MOTIVATIONAL VARIABLES

- Low persistence in mastering tasks
- Low mastery learning goals
- Low valuing for schooling
- Low expected occupational status after high school
- Low growth mindset beliefs

SCHOOL ENVIRONMENT VARIABLES

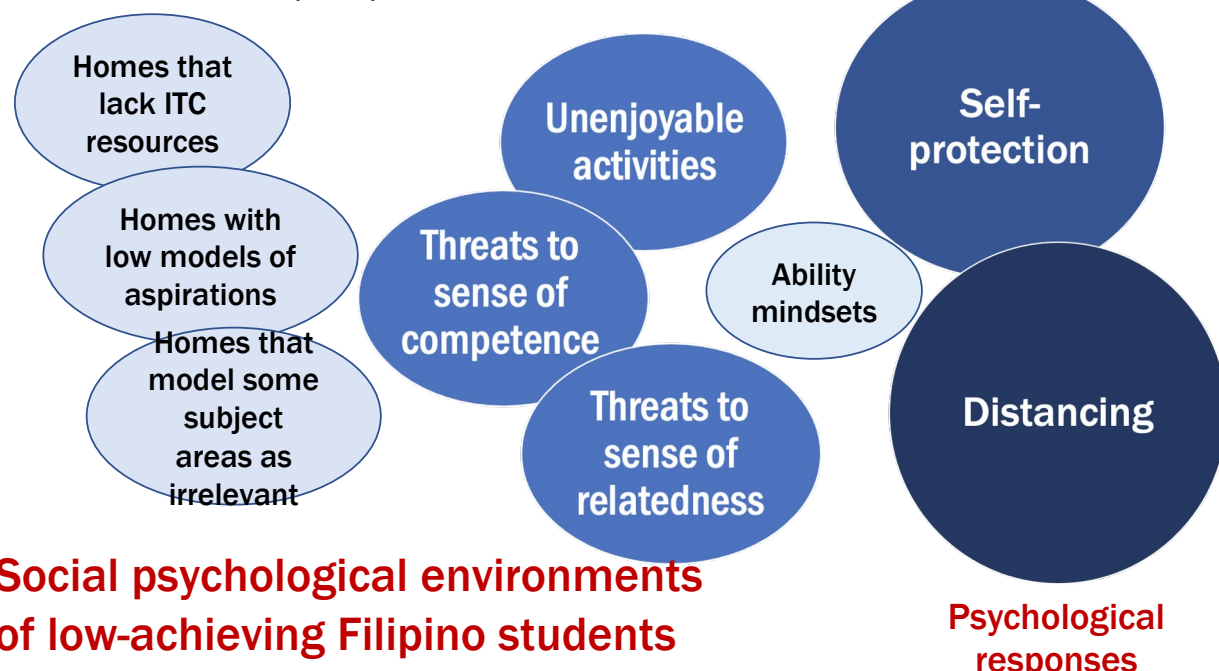
- High exposure to bullying
- Low sense of belonging
- Low perceived cooperation among students

Low Economic, Social, and Cultural (ESC) Status of family

Bernardo, Cordel, et al. (2021)

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Bernardo, Cordel, et al. (2021)



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Needs-supportive teaching and student reading proficiency in PISA

- Learners basic needs : autonomy, competence, relatedness
- Autonomy supportive teaching: offer explanatory rationale, take the students' perspective, and welcome students' ideas to determine their learning.
- Competence supportive teaching: providing structure such as setting clear expectations, giving constructive feedback, adjusting teaching strategies, and offering instrumental help.
- Relatedness supportive teaching: investing their time on students by showing affection, understanding, and enjoyment in interacting with students



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Haw, King, & Trinidad (2021)

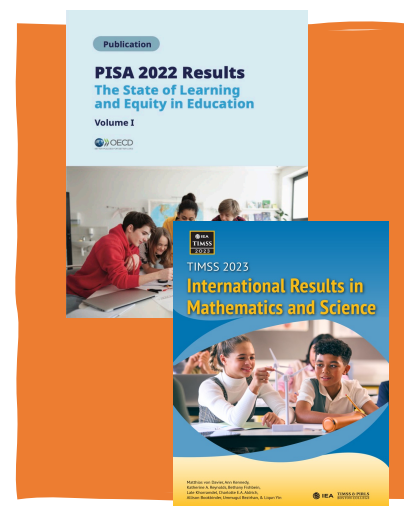


Needs-supportive teaching

- positively predicted Filipino students' reading achievement
 - both public and private schools
 - both urban and rural schools
 - in different socioeconomic community contexts

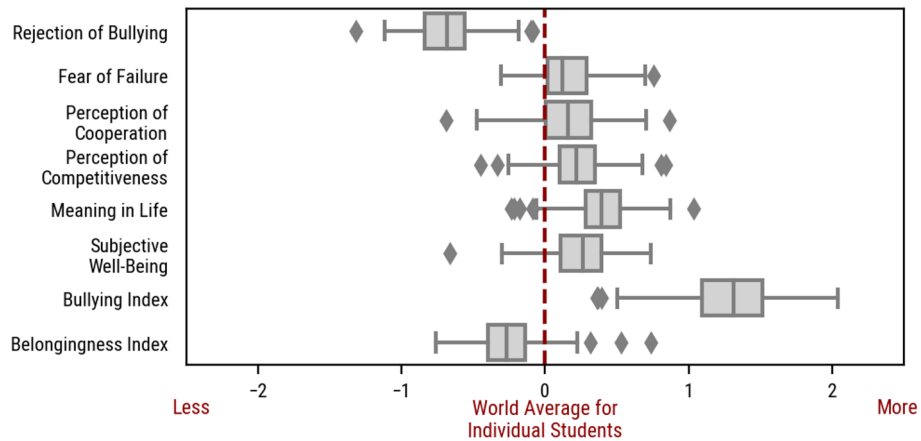
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ILSAs and Filipino students well-being



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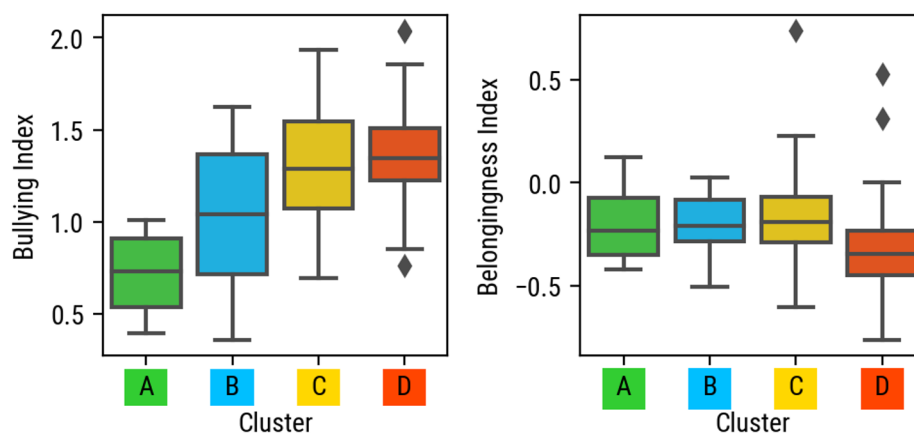
Machine learning cluster analysis of school environments



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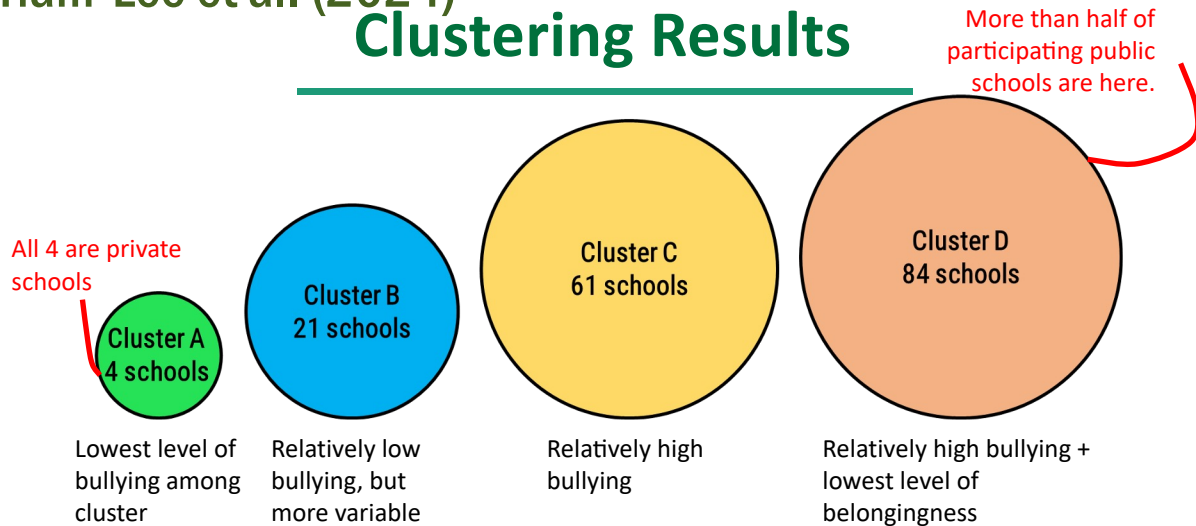
Tiam-Lee et al. (2024)

Clustering Results



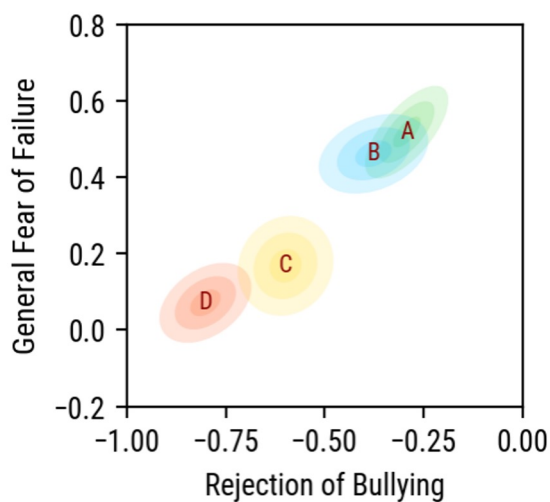
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Tiam-Lee et al. (2024) Clustering Results



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Tiam-Lee et al. (2024) Environment Profiles of Each Cluster



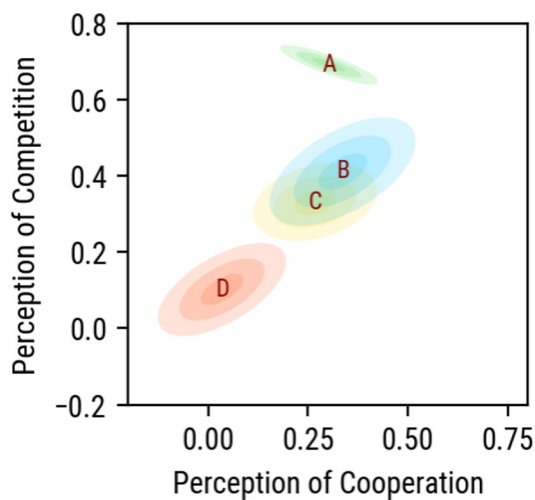
Clusters A and B:
high rejection of bullying
high fear of failure

Clusters C and D:
low rejection of bullying
low fear of failure

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Tiam-Lee et al. (2024)

Environment Profiles of Each Cluster



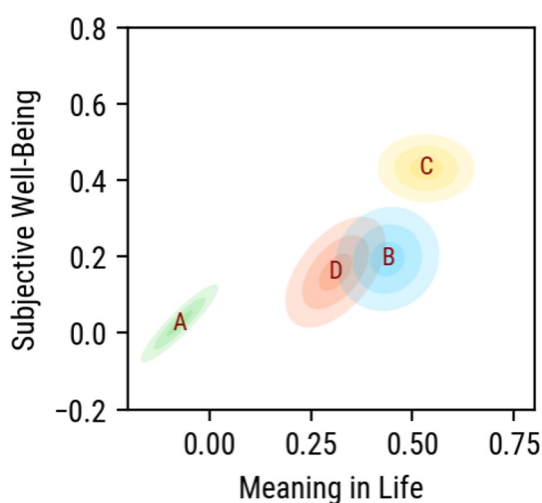
Clusters A, B, and C have similar perception of cooperation, but **Cluster A** has a **significantly higher perception of competition**.

Cluster D has a **significantly lower perception of cooperation** and **significantly lower perception of competition**.

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Tiam-Lee et al. (2024)

Environment Profiles of Each Cluster



Clusters C:

High subjective well-being
High meaning in life

Cluster A:

Surprisingly low meaning in life

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Tiam-Lee et al. (2024)



- **Less-bullied clusters A and B are similar.**
 - High rejection of bullying, high fear of failure
 - Main difference: A has significantly less meaning in life, high sense of competition
- **More bullied clusters C and D are similar:**
 - Low rejection of bullying, low fear of failure
 - Main difference: C has high subjective well-being, while D has low sense of competition, low sense of cooperation, and low sense of belonging.

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Other Philippine research on ILSAs

- Growth mindset and academic proficiency
- Metacognitive strategies for reading
- Science literacy and students' pro-environmental attitudes
- Global citizenship competencies



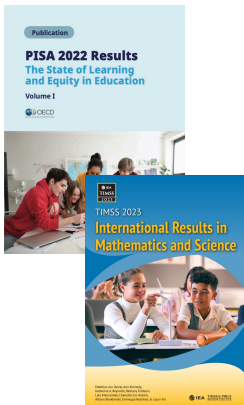
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Asian and global research on ILSAs

- Effects of using formative assessment systems on student achievement
- Implications of ability-based groupings for achievement
- Financial models for schools
- Tracking policy changes on achievement (longitudinal analysis)
- Cultural level beliefs and achievement

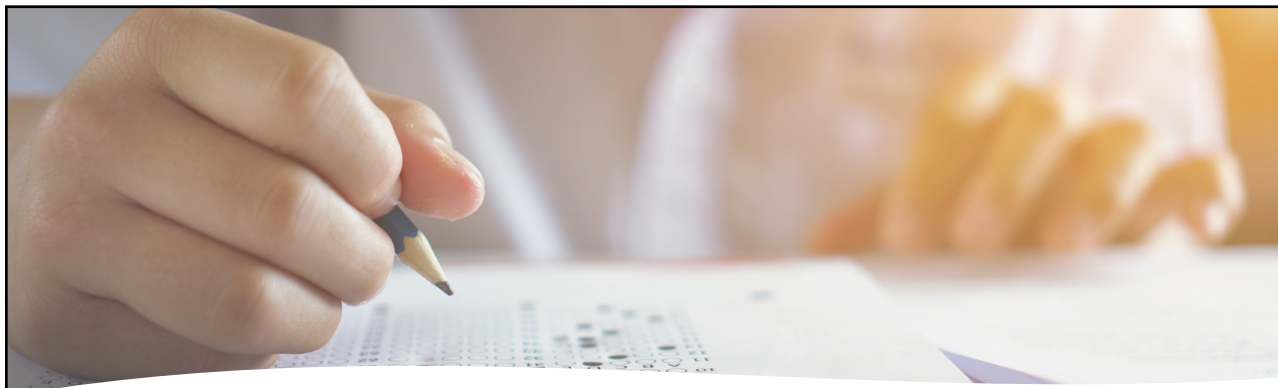
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Summary

- Describe what we know from recent ILSAs (PISA and TIMSS)
- Clarify what information and insights can and cannot be derived from ILSAs
- Clarify how school reform can be guided by ILSA-based research
- Provide some examples of ILSA-based research in the Philippines

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Concluding points

- Large scale assessment data can enrich knowledge about student learning in our schools
- But we cannot just look at ranks and scores
- We need to analyze the data more thoughtfully to extract insights relevant for our schools practices and reforms
- Hope: PEAC and education reformers provide more support for research on Philippine ILSA data

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**THANK YOU VERY MUCH
FOR LISTENING!!!**



Allan B. I. Bernardo
De La Salle University

Here 
for the **future.**

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