11-2021

Using Machine Learning Approaches to Explore Non-Cognitive Variables Influencing Reading Proficiency in English Among Filipino Learners FINAL REPORT

Rochelle I. Lucas

Macario O. Cordell II

Jude Michael M. Teves

Sashmir A. Yap

Unisse C. Chua

See next page for additional authors

Authors

Rochelle I. Lucas, Macario O. Cordell II, Jude Michael M. Teves, Sashmir A. Yap, Unisse C. Chua, and Allan I. Bernardo

Using Machine Learning Approaches to Explore Non-Cognitive Variables Influencing Reading Proficiency in English Among Filipino Learners
FINAL REPORT

DLSU-AKI Working Paper Series 2021-11-075

By: Rochelle I. Lucas
Macario O. Cordel II
Jude Michael M. Teves
Sashmir A. Yap
Unisse C. Chua
Allan B. I. Bernardo
De La Salle University

This final report was derived from the published article below.

Bernardo, A. B. I., Cordel, M. II, Lucas, R.I., Teves, J. M. M., Yap, S. A., & Chua, U. C. (2021). Using machine learning approaches to explore non-cognitive variables influencing reading proficiency in English among Filipino learners. *Education Sciences, 11*, Article 628. https://DOI.org/10.3390/educsci11100628

Using Machine Learning Approaches to Explore Non-Cognitive Variables Influencing Reading Proficiency in English among Filipino Learners

Final Report

Rochelle I. Lucas [1]

Macario O. Cordel II [2]

Jude Michael M. Teves [3]

Sashmir A. Yap [4]

Unisse C. Chua [5]

Allan B. I. Bernardo [6]

[1] Department of English and Applied Linguistics, De La Salle University; rochelle.lucas@dlsu.edu.ph

[2] Dr. Andrew L. Tan Data Science Institute, De La Salle University; macario.cordel@dlsu.edu.ph

[3] Dr. Andrew L. Tan Data Science Institute, De La Salle University; jude.teves@dlsu.edu.ph

[4] Dr. Andrew L. Tan Data Science Institute, De La Salle University; sashmir.yap@dlsu.edu.ph

[5] Dr. Andrew L. Tan Data Science Institute, De La Salle University; unisse.chua@dlsu.edu.ph

[6] Department of Psychology, De La Salle University; allan.bernardo@dlsu.edu.ph

Using Machine Learning Approaches to Explore Non-Cognitive Variables Influencing Reading Proficiency in English Among Filipino Learners

Abstract

Filipino students ranked last in reading proficiency among all countries/territories in the PISA 2018, with only 19% meeting the minimum (Level 2) standard. It is imperative to understand the range of factors contributing to low reading proficiency, specifically variables that can be the target of interventions to help the students with poor reading proficiency. We used machine learning approaches, specifically binary classification methods, to identify the variables that best predict low (Level 1b and lower) vs. higher (Level 1a or better) reading proficiency using the Philippine PISA data from a nationally representative sample of 15-year-old students. Several binary classification methods were applied, and the best classification model was derived using support vector machines (SVM), with 81.2% average test accuracy. The 20 variables with the highest impact in the model were identified and interpreted using the socioecological perspective of development and learning. These variables included students' home-related resources and socioeconomic constraints, learning motivation and mindsets, reading classroom experiences with teachers, reading self-beliefs, attitudes and experiences, and social experiences in the school environment. The results were discussed with reference to the need for a system perspective to address poor proficiency that requires interconnected interventions that go beyond the students' reading classroom.

Keywords: reading proficiency; non-cognitive variables; machine learning; support vector machines; motivation; growth mindset; reading self-concept; bullying; school connectedness; PISA

Reading literacy is an essential competency for academic learning; high levels of reading proficiency are especially important for higher learning, where students are required to access and to process information in texts in different domains of learning in school (Kern & Friedman, 2009; Smith et al., 2000; Wharton-McDonald & Swiger, 2009) and in other aspects of adult life (Coulombe et al., 2004; Duke, 2004). This is partly why international assessments of education have focused on reading as one of the testing domains. For example, the Programme for International Student Assessment (PISA) regularly assesses 15-year-old students' reading proficiency together with their science and mathematics proficiency. In the PISA 2018, the Philippines ranked last among 79 countries in reading (Organisation for Economic Co-operation and Development [OECD], 2019a). Around 80% of Filipino students who participated did not reach a minimum level of proficiency in reading (Level 2); this is one of the largest shares of low performers amongst all PISA-participating countries. The PISA 2018 provides extensive data on a wide range of factors that can be explored to understand students' proficiency in the various domains, and in previous studies on the performance of Filipino students have inquired into the alignment of the Philippine reading curriculum with the PISA reading assessment framework (Romero & Papango, 2020) on school resource and school climate (Trinidad, 2020), socioeconomic status and students' beliefs (Bernardo, 2020). In this study, we use machine learning approaches to explore a wide range of non-cognitive factors that may account for the poor reading proficiency of Filipino learners. The aim was to provide models that can distinguish between Filipino students with low reading proficiency and those with better reading proficiency using different machine learning classification approaches to analyze various non-cognitive factors related to Filipino students' home backgrounds, learning beliefs and motivations, classroom and school experiences, among others.

The PISA 2018 Reading Assessment and Philippine Results

The PISA 2018 framework for reading proficiency features a "typology of cognitive processes involved in purposeful reading activities as they unfold in single or multiple text environments" (Organisation for Economic Co-operation and Development, 2019a, p. 88). More specifically, three broad categories of cognitive processes are assessed with more specific cognitive processes specified in each category: (a) locating information (accessing and retrieving information within a text, searching for and selecting relevant text), (b) understanding (representing literal meaning, integrating, and generating differences), and (c) evaluating and reflecting (assessing quality and credibility, reflecting on content and form, detecting, and handling conflict).

Proficiency levels were provided to guide the assessment of reading, with Level 2 considered as the minimum proficiency standard. Only 19% of Filipino students attained Level 2 proficiency or better. Among the Filipino students who did not reach the minimum, 15.8% were classified in the lowest reading proficiency level (Level 1c or lower). According to the PISA 2018 report, students who were grouped at Level 1c: "… can understand and affirm the meaning of short, syntactically simple sentences on a literal level, and read for a clear and simple purpose within a limited amount of time. Tasks at this level involve simple vocabulary and syntactic structures" (Organisation for Economic Co-operation and Development, 2019a , p. 88). In the case of Filipino students, these reading proficiencies refer to reading in English. The Filipino students grouped into this level can perform only the most basic reading tasks after at least five years of formal instruction in reading in English.

In addition to assessing specific cognitive skills in the domain of reading, the PISA 2018 also underscored the importance of several non-cognitive factors in reading, including the readers' motivations, strategies, practices in different situations, as well as the readers' perceptions regarding their teachers' practices, classroom support, and resources for learning at home and in school (OECD, 2019b). The PISA 2018 also had questionnaires for school heads and parents that inquired into the environment, resources, and various forms of support for students' learning. The Philippines opted not to answer the parent questionnaire but had school heads answer the school questionnaire. Overall, the PISA 2018 assessment provides a wide range of factors related to the students and their home and school backgrounds and experiences that could be explored to understand the important factors that predict reading proficiency.

Predictors of Reading Proficiency

As is true in most domains of learning, reading proficiency is shaped by the synergistic effects of various personal, instructional, and contextual factors (Tse & Xiao, 2014). Although there is a strong focus on teaching methods and activities in the reading classroom (Cheung et al., 2009; Okkinga et al., 2018), these instructional factors are likely to interact with a student's specific dispositions. There has been attention given to the learners' general and specific cognitive abilities and intellectual aptitudes, which may constrain their ability to benefit from specific forms of reading instruction (Burns et al., 2018; Ghabanchi & Rastegar, 2014). However, there are non-cognitive factors like dispositions and experiences related to reading that also shape reading proficiency. For example, enjoyment of reading (Beglar et al., 2011), range of personal reading activities (Wilhelm & Smith, 2016), intrinsic motivation to read (Hebbecker et al., 2019), reading self-concept (Ma et al., 2021), awareness of reading strategies (Friesen & Haigh, 2018), including metacognitive (Zhang et al., 2014), and self-regulation strategies (Vidal-Abarca et al., 2010) of the reader are all important predictors of acquiring good reading proficiency. However, other factors that are not specifically related to students' reading experiences are also known to be related to reading proficiency. These factors are typically collectively referred to as motivational factors, such as mastery or learning goals (Toste et al., 2020), task engagement (Whitney & Bergin, 2018), and task persistence (Cho et al., 2019), but also include factors such as academic emotions (Goetz et al., 2007) and other beliefs like students' mindsets (Bernardo et al., 2021).

Aside from student-related factors, research has also identified contextual factors that influence students reading proficiency. The contextual factors typically provide resources and support for learning and development processes associated with the acquisition of higher proficiency in reading and other domains of learning. The most pertinent social contexts for the student are the home and school environments, with each context involving different actors, social interactions, and resources (Chen et al., 2019).

Regarding the home environment, several studies point to parents' educational attainment, work status, and home assets as variables that directly affect the student's achievement (Cabrera & La Nasa, 2000; Ngorosho, 2010). These home assets include cultural and learning resources such as books, artworks, and music (Xiao & Hu, 2019). These different factors tend to support students' efforts and motivations to learn reading and other domains and are thus positively associated with reading proficiency. There is a more complex relationship between the availability of ICT resources at home, with some studies suggesting that the purposes of ICT use at home might be a moderating factor (Hu et al., 2018). As should be apparent, these factors in the home environment tend to be associated with the families' socioeconomic status (Hu et al., 2018), a factor that is strongly correlated with achievement in the PISA studies (OECD, 2019a).

Regarding the school environment, we could distinguish between factors in the immediate learning environment in the classroom where students are learning to read and the broader school environment (Chen et al., 2019). Within the reading classroom, the students interact with their teacher and classmates, and the factors that can influence their reading proficiency include the specific pedagogical approaches and learning activities used by the teacher (Xiao & Hu, 2019), how the teacher provides feedback and support for the students

(Ma et al., 2021; Chen et al., 2019], and even the teachers' effort, motivations, and enthusiasm for teaching the subject (Shin et al., 2017). The social aspects of the classroom climate are also important factors that influence student learning (Alivernini & Manganelli, 2015), such as whether the classroom fosters either a collaborative or competitive learning environment and nurtures a mastery learning motivation among the students (Poon et al., 2016).

Beyond the classroom, there are also important factors in the school environment that are known to play a role in supporting student learning and achievement. For example, the resources that school has for learning, like information technology (Hu et al., 2018) and reading materials (Shin et al., 2017), and also extracurricular activities to advance students' related skills (Broh, 2002) are shown to be important supports for student achievement in some contexts. Such factors tend to be related to the source of funds and the general levels of resources that schools have, which refer to the basic infrastructure, materials, and teacher resources (Trinidad, 2020; Shin et al., 2017), which are often constrained in developing countries like the Philippines. Although not related to resources, there are other factors in the school environment that seem to be important as they relate to the social and interpersonal experiences of the student. For example, the school climate (Alivernini & Manganelli, 2015), the students' social connectedness (Gerra, 2020), and exposure to bullying (Turunen et al., 2019) are also found to be significant predictors of achievement in some contexts.

The preceding brief review of some predictors of reading achievement of students is not intended to be a comprehensive summary of all the relevant predictors of reading achievement. Instead, the brief review is intended to provide a sense of the range of factors within the student and arising from the students' interactions in relevant social environments, consistent with socioecological (Bronfenbrenner, 2009) and sociocultural (Bernardo & Liem, 2013) models of human development and learning. We also note that most educational research undertakings typically focus on a select number of factors on testing specific hypotheses or theoretical models of their relationships with student reading achievement.

The Current Study

The PISA 2018 database provides information on a very wide range of factors that were assessed as possible predictors of students' proficiency in reading, mathematics, and science. Because the 2018 assessment focused specifically on reading, the survey included numerous items and factors that specifically pertained to students' experiences, beliefs, and attitudes related to reading (OECD, 2019b). A few studies have explored predictors of Filipino students' reading proficiency, and these studies focused on a subset of factors considered to be of interest (Trinidad, 2020; Bernardo et al., 2021; Prudencio, 2020). In this study, we utilize machine learning approaches to explore a wide range of candidate variables in the PISA 2018 database to predict the reading proficiency of Filipino students.

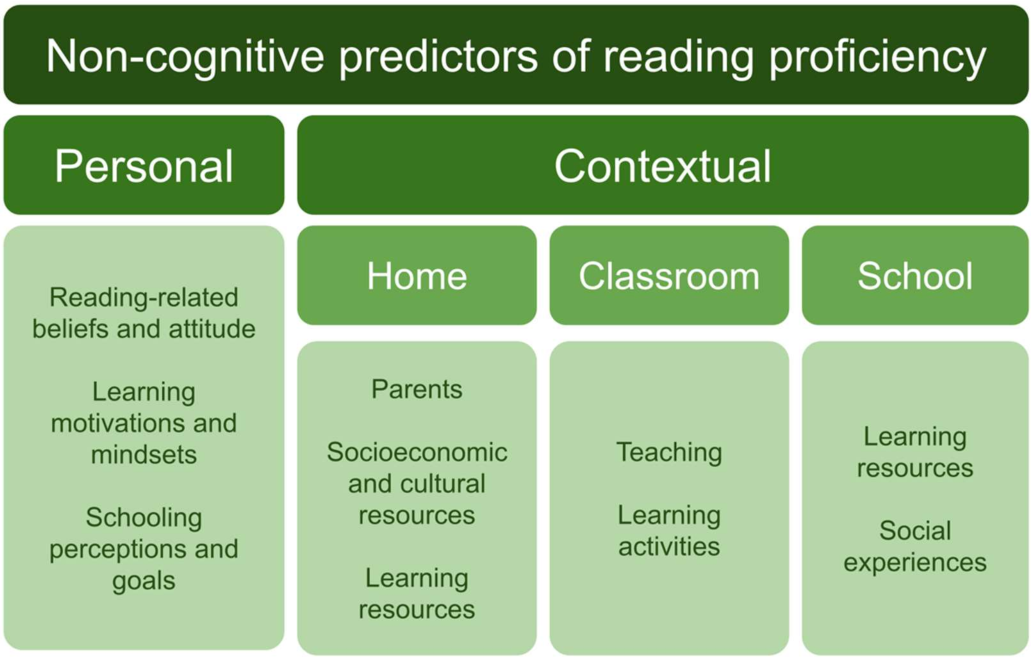
The specific objective of the study was to identify the key variables from an overall set of 122 variables that could best distinguish the lowest proficiency Filipino students from those that performed around or above the standard. Our primary focus was to distinguish the students who performed significantly below standard according to the PISA reading levels (i.e., Levels 1b, 1c, and below), as these very poor readers are likely to be the ones who will be unable to progress in education and who need to be the focus on educational interventions. Thus, the aim was to identify the variables that best distinguish these poor readers from the rest of the Filipino students, based on the assumption that these variables will point to vulnerabilities in the poor readers that could be the target of interventions.

For this aim, different machine learning classification approaches, particularly binary classification models, were compared to determine the optimal classifier for distinguishing low and better-performing students. A binary classification model, during the training phase, uses input data to iteratively tweak the model parameters by minimizing the difference between the model's prediction and the input ground truth label. The stopping condition for the training iterations is typically one of the following: a pre-determined maximum number of iterations is reached, the validation performance is not improving, or the validation performance worsens. These machine learning classification models are evaluated using cross-validation to measure the generalizability of the model and accuracy metric to measure the prediction performance. As opposed to the regression model, which finds the best fit curve that predicts the continuous-valued reading performance, a binary classification model searches for a discrete function that maps the input variables to two discrete categories. Previous efforts that used regression models for analyzing PISA reading performance capture only the linear (Trinidad, 2020; Bernardo, 2020; Torres et al., 2021) and quadratic (Gubbels et al., 2020) relationships of input variables and the target variable, ignoring their more complex interrelation. Our work utilizes binary classification models, which consider the underlying higher-order relationships between the input variables and the reading level classification of students.

The plan for analysis was guided by previous empirical studies in literacy development and reading education, which indicated the types of candidate variables to be used in the analysis. The variables considered for the analysis could be conceptually organized into two broad categories: personal and contextual variables, with the contextual category further organized into three subcategories: home, classroom, and school variables (see Figure 1). The personal variables refer to beliefs, attitudes, experiences related to reading, and motivational variables that apply to learning in general. Home contextual variables refer to characteristics of the parents, socioeconomic status-related variables, and resources for learning at the students' homes. Classroom contextual variables refer to teacher-related variables, including instructional approaches and activities and perceived characteristics of language and reading classrooms. Finally, school contextual variables refer to resource-related variables of the school, other organizational characteristics, and the students' social experiences in their schools.

Figure 1

Schematic Representation of Conceptual Framework of Variables in the Study



Materials and Analytic Methods

The Dataset

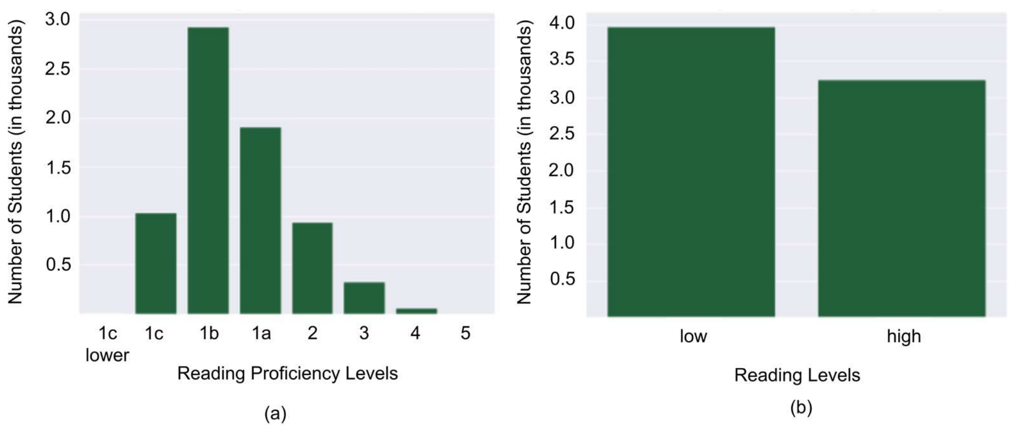
The data from the Philippine sample in the OECD PISA 2018 database was used in the study. The data are publicly accessible at https://www.oecd.org/pisa/data/2018database/. The complete nationally representative sample comprised 7,233 15-year-old Filipino students, selected using a two-stage stratified random selection system. Stratified sampling was used to select 187 schools from the country's 17 regions, and then students were randomly sampled from each school (Besa, 2019). Note, however, that as is typical in machine learning classification and regression tasks, the variables are treated as flat rather than hierarchical sets, and as such, stratification and information on primary sampling units are not incorporated into the machine learning model.[1]

For machine learning modeling purposes, the students were grouped into the low and high reading proficiency groups. Low proficiency students are those with poor proficiency at reading levels 1b and below; high proficiency students are those with better reading levels 1a and better (although their proficiency levels are not actually considered high with reference to the PISA levels). Note that because the PISA 2018 was designed to assess the learning of a population, the assessment framework was focused on reducing errors in making inferences about the population and less on reducing errors at the individual level. As such, the PISA 2018 assessment does not provide actual reading achievement scores for each student; instead, it provides an estimate of an individual student's proficiency in each domain by mathematically computing distributions around the reported values and then assigning random values for each student from the posterior distributions. Thus, instead of directly estimating a student's proficiency, the PISA 2018 provided 10 plausible values that represent 10 random values drawn from the posterior distribution of the student's possible scores for reading (OECD, 2019a). For the students' proficiency levels, we referred to the Plausible Value 1 for the reading domain in the PISA dataset. We used the first plausible for the overall reading proficiency like previous studies on the PISA dataset have used only one plausible value (Trinidad, 2020; Bernardo, 2020; Dewaele & Li, 2021) based on the assumption that one plausible value is said to provide unbiased estimates of population parameters. The distribution of students based on their reading level and group is summarized in Figure 2, which also shows that 55% and 45% of the students belonged to the low and high-performing groups, respectively.

For the analysis, 122 variables were considered; 41 variables are derived variables or indexes, and the rest were single item responses. Some students had variables with missing values tagged as "M" or "N"—these tags were changed into null values in Python to facilitate data imputation, and for some variables, data were not collected for the Philippine survey. The range of values of each variable was rescaled to 0 to 1. The variables with 100% missing values were dropped from modeling and analysis, and those with a few missing data points were imputed using k-nearest neighbors (kNN). The optimal value for k in kNN was empirically determined by comparing the distribution of the original variable and imputed variable, using Mann-Whitney U Test. The *k* value that provides the most number of features with the same distribution was chosen; in this case, $k = 7$. After imputation, 90% of the variables followed the same distribution compared to the original.

Figure 2

Distribution of Reading Levels of Students (a) and the Distribution of Students Using High-Low Groupings (b)



Note: For machine learning, a comparable distribution of each group, that is, low and high, is preferable to remove bias in model training.

Machine Learning Modeling

Benchmarking the machine learning (ML) models was then conducted by optimizing the parameters during training. The dataset was randomly split so that 80% of the samples were used for training the ML models while the remaining samples were used for testing. The ML models considered were support vector machines (or SVM), logistic regression, multilayer perceptron, gradient boosting classifier, random forest, AdaBoost, and kNN. Recent work involving the 2018 PISA database (Cabrera & La Nasa, 2000; Sheikh et al., 2019) used SVM-based machine learning approaches to identify high-performing students. The models of these studies achieved an average accuracy of at most 0.78. Their works are insightful, but we argue that the decision model should be optimal for the feature selection to be more valid.

Table 1

The Machine Learning Models Considered for This Work (First Column), the Hyperparameters Tweaked for Model Optimization (Second Column), and the Final Values for These Hyperparameters (Third Column)

Machine Learning Models	Tweaked hyperparameters	Optimized value for the hyperparameters
SVM	Kernel = polynomial, radial basis function c = 0.1, 1, 10	Kernel = radial basis function, c = 1.0
Logistic Regression	c = 0.001, 0.01, 0.1, 10, 100, 1000	c = 0.01
Multilayer Perceptron	Hidden layers = (32, 32), (32, 32, 16), (32, 32, 32) Activation function = sigmoid, tanh, relu Learning rate = 0.01, 0.001, 0.0001	Hidden layers = (32, 32, 32) Activation function = sigmoid Learning rate = 0.0001
Gradient Boosting Classifier	n_estimators = 6, 8, 10, 12, 14, 16, 18, 20	n_estimators = 20
Random Forest	n_estimators = 6, 8, 10, 12, 14, 16, 18, 20	n_estimators = 20
Ada Boost	n_estimators = 6, 8, 10, 12, 14, 16, 18, 20	n_estimators = 20
kNN	k = 3, 5, 6	k = 7

The best value for the hyperparameters of each ML model, summarized in Table 1, was chosen through a *grid search* approach comparing the accuracy of the model (and not any other metric that compares individual models to each other).[2] The hyperparameters tweaked and the values considered are summarized in Table 1. Then, the best performing configuration of the best performing model is used as the final ML model. The summary of the training performance of these models is provided in Figure 3, and the summary of the testing performance is summarized in Figure 4, with SVM as the best-performing classifier. We note that the accuracy of SVM is higher than comparable models available in the extant literature (Chen et al., 2019; Dong & Hu, 2019).

Figure 3

Five-Fold Cross-Validation Training Performance of Classifiers for Different Hyperparameter Values

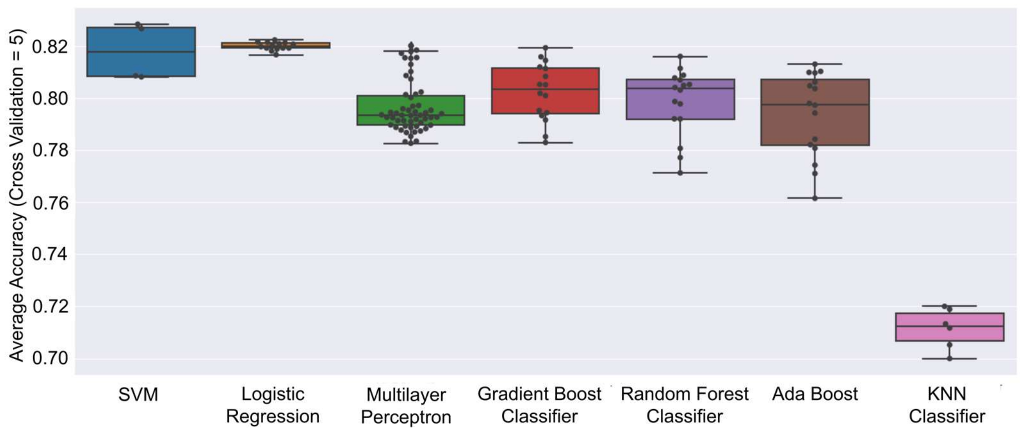


Figure 4

Summary of the Test Accuracies of the Classifiers and the Confusion Matrix for Classifying the Low (Negative) and High (Positive) Reading Performances Using SVM

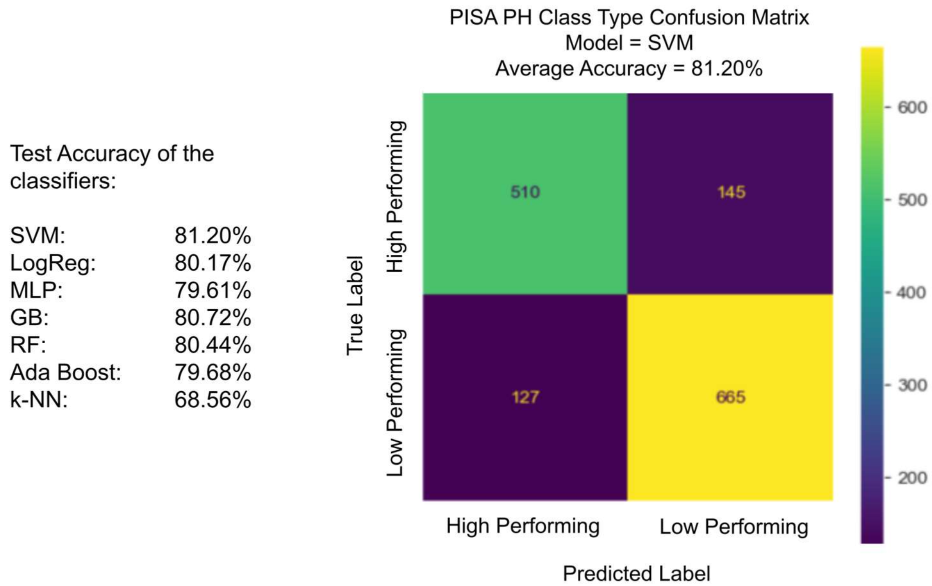
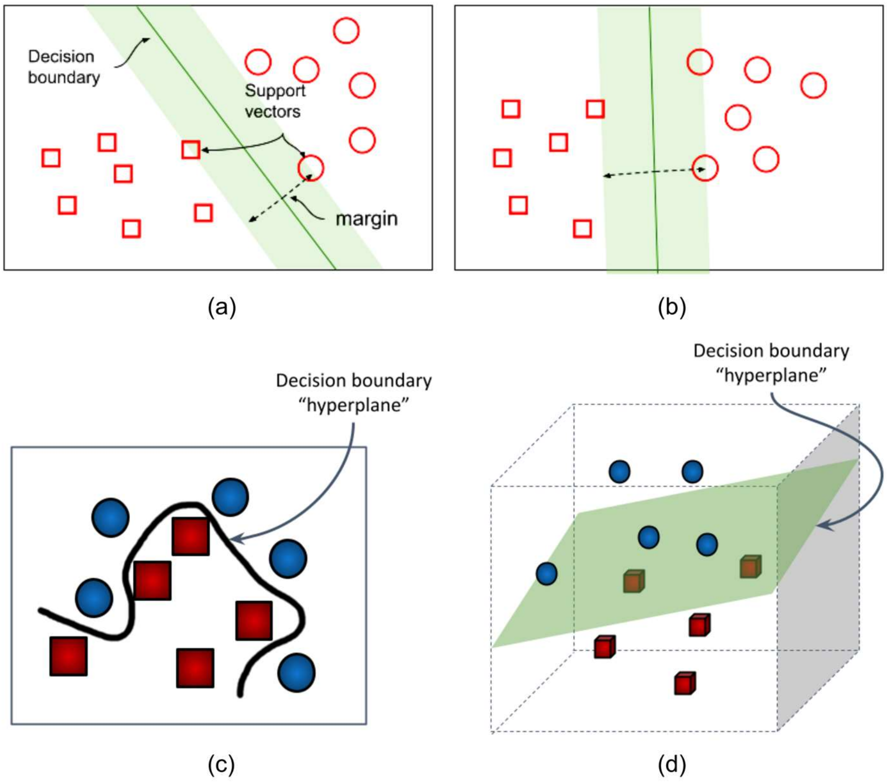


Figure 5

(a) The SVM Decision Boundary for a Two-Feature (i.e., x-position and y-position), Classification (□ or ○) Task Showing the Decision Boundary, the Maximized Margin Between the Two Classes of Samples, and the Support Vectors That Define the Decision Boundary. (b) A Decision Boundary Showing That the Feature x Position is More Important Than the Feature y Position in Determining the Classification of a Sample. For a More Complex Classification Task, the Input Space (c) Needs to be Transformed Into a Feature Space (d) Via a Kernel Where it is Easier to Find a Linear Model for a Decision Boundary



SVM, as the best ML model for this work based on the test performance, is a machine learning method that finds a particular linear model by maximizing the space between the decision boundary or hyperplane $z = \mathbf{w}^T\mathbf{x} + b$ and the data points, $\mathbf{x}$, where $\mathbf{w}$ and b are the SVM parameters, $\mathbf{w}$ is the normal vector to the hyperplane, such that the hyperplane margin equals $2/||\mathbf{w}||$ and the offset of the hyperplane from the origin along $\mathbf{w}$ equals $b/||\mathbf{w}||$. By maximizing the space, the SVM increases the total confidence in the prediction. The closest training points to the decision boundary are the support vectors used to specify the decision boundary between the classes. Please refer to Figure 5 (a) and (b) for the illustration of the SVM classification on data with two features. For this work, with 114-dimensional data, a radial basis function kernel $k(\mathbf{x}_1, \mathbf{x}_2) = \exp(-\gamma||\mathbf{x}_1 - \mathbf{x}_2||^2)$ is used, with $c = 1.0$ and $\gamma = 1/(N\sigma)$ where $N = 114$ and σ is the variance of $\mathbf{x}$, to transform the input space into a feature space, such that a hyperplane decision boundary can be found, as illustrated in Figure 5 (c) and (d).

Results

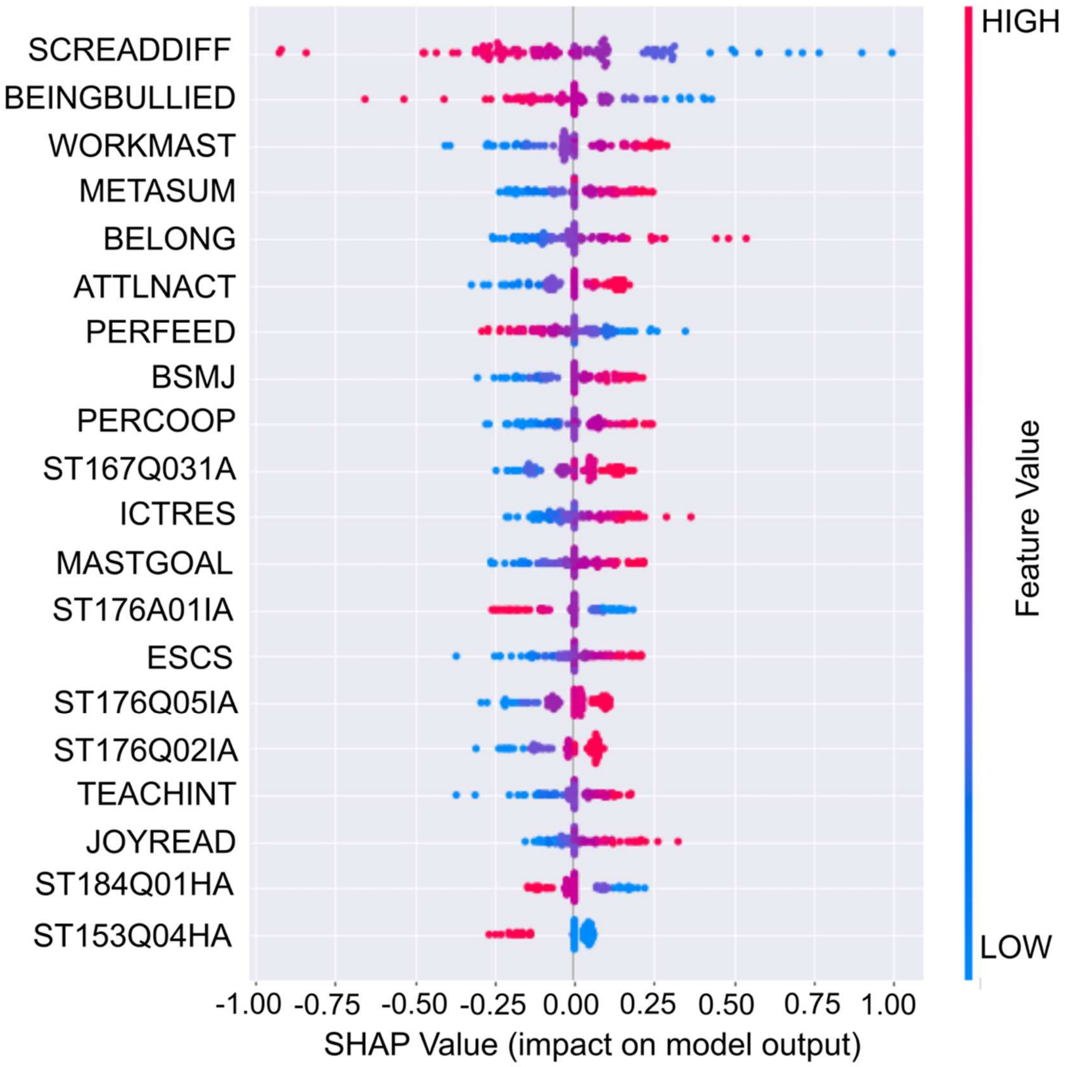
Most Important Variables

The best way to make sense of the SVM model is to take a closer look at the key variables that determine the classification of students' performance into low and high categories. For this purpose, we used the SHapley Additive exPlanations (SHAP), summarized in Figure 6 (Lundberg & Lee, 2017). SHAP assigns each variable an importance value (y-axis) according to their mean absolute SHAP values. The color bar in each row provides more details regarding how each variable affects the reading performance (PV1READ), that is, positive or negative impact (x-axis). Red (blue) dots mean higher (lower) values for a variable.

As illustrated in Figure 6, the top important variable related to the classification of students into low and better-performing students in reading is SCREADDIFF (i.e., students' self-concept of having perceived difficulty in reading). A high value of SCREADDIFF has a negative impact on the prediction, and a low value of the SCREADDIFF has a positive impact on the prediction. In other words, SCREADDIFF is negatively correlated with the target variable, PV1READ. Similarly, BEINGBULLIED, the next most important variable, is negatively correlated with the target variable, and WORKMAST is positively correlated with the target variable. In summary, of the top 20 variables that are impactful to the prediction of student reading performance, six variables are negatively correlated with the target variable PV1READ, and the rest are positively correlated. Most of the 20 are indexes computed to measure theoretical factors, but five variables are single items that were included as part of some other index, and one variable was a single-item measure of a factor (*fixed mindset*). We discuss these variables in more detail and organize them into meaningful conceptual clusters below.

Figure 6

Visualization Showing the Top 20 Important Variables in Descending Order



Note: The *x*-axis shows whether the influence of that variable value is linked with higher or lower prediction. Each dot represents a variable value of one training data. A dot nearer the red color means a high variable value and a dot nearer the blue color means a low variable value.

Reading-Related Beliefs and Enjoyment

Four of the top 20 variables are non-cognitive personal variables related to reading. SCREADDIFF is an index computed to measure students' perceived difficulty in reading, and the poor readers tended to report higher levels of difficulty. In contrast, the poor readers tended to report lower scores for the other three variables: METASUM is an index for the students' metacognitive awareness of strategies for summarizing texts, JOYREAD is an index of students' reading enjoyment, and ST167Q031A is the item indicating that students read fiction because they want to. These four variables indicate that poor readers differ from the better readers in that they have a lower intrinsic interest in reading, weaker metacognitive awareness of reading strategies, and more perceived difficulties in reading; these results are consistent with the literature on the role of reading self-concept (Ma et al., 2021), intrinsic enjoyment of reading (Wilhelm & Smith, 2016; Hebbecker et al., 2019), and metacognitive awareness of strategies in reading (Mohseni et al., 2020; Sheikh et al., 2019) in students' reading achievement.

Teacher-Related/Instructional Variables

There were three teacher-related variables among the top 20 variables, two of which might be associated with the reading-related variables above. PERFEED is the index on teacher feedback that indicates how often the reading teacher in English tells the student about areas of improvement. ST153Q04HA is a specific item that refers to a yes-no question about whether their reading teacher in English asks the students to "give your personal thoughts about the book or chapter." In both variables, students in the poor reading proficiency group tended to have more positive values, which indicates that their teachers were reported as doing these activities more. These activities are known to be positively associated with students' reading proficiency (Ma et al., 2021). However, the result suggests that these might have a negative association with the reading proficiency of Filipino students, and we consider possible explanations in the discussion below.

The third teacher-related variable is TEACHINT, which is an index of perceived teacher enthusiasm. Students in the poor reading proficiency group tended to report lower values, suggesting that they were more likely to perceive their reading teachers as having low enthusiasm in the classroom. Research suggests that teacher enthusiasm is indirectly related to student achievement in language classes, with teacher enthusiasm directly influencing students' learning engagement in the classroom (Dewaele & Li, 2021).

ICT Resources and Use

ICT-related variables were also important predictors in the SVM categorization model. ICTRES was an index computed to measure the availability of ICT resources in the students' homes, and students in the poor proficiency group were more likely to have low values on this index. However, lack of access to ICT at home is not the only concern, as poor reading proficiency group also reported low values on being involved in two ICT related activities: ST176Q05IA ("searching information online to learn about a particular topic") and ST176Q021A ("chat online"). Unlike their counterparts who had better reading proficiency, the poor proficiency students were less likely to use ICT for these purposes, which requires reading of texts and presumably supports learning activities of high school students. These two activities are more active and interactive compared to the other important ICT-related activity, ST176Q01IA ("reading emails). Poor reading proficiency students were more likely to report higher values on this item. Thus, these students not only have less access to ICT resources at home, but they are also less likely to be involved in using activities that use ICT interactively to support their learning activities. If they use ICT, it is for more passive activities like reading an email. This pattern of results is consistent with earlier research (Gumus & Atalmis, 2011; Moran et al., 2008).

Student Beliefs, Motivations, and Aspirations

Consistent with extensive research on the role of motivational factors in students' reading proficiency (Toste et al., 2020; Whitney & Bergin, 2018; Cho et al., 2019) , five motivation-related indexes were found to be high impact predictors of the SVM model. In four of these variables, students in the poor reading proficiency group reported lower values: WORKMAST, MASTGOAL, ATTLNACT, and BSMJ. WORKMAST is the index computed to represent the motivation and persistence to master given learning tasks, whereas

MASTGOAL is the index computer to assess the students' goal of mastery learning. Both indexes emphasize mastery learning as elements of learning motivation across the learning domain, and poor reading proficiency students have low values on both indexes.

ATTLNACT is the index measuring the value of schooling and was measured with items related to the importance of trying hard at school to get a good job or into a good college. Poor proficiency students reported lower values on this index, and relatedly also on the BSMJ index that reports the students' expected occupational status after high school. In a sense, the poor proficiency students have lower pragmatic value for schooling, perhaps because they already set low expectations about the kind of jobs they think they will get after school.

The other motivational variable is a mindset or belief associated with the malleability of their intelligence. ST184Q01HA is a single item that measures agreement with a statement on fixed intelligence; the reverse score of the item is assumed to indicate a measure of the growth mindset. Thus, poor reading proficiency students are more likely to have high values on the idea that their level of intelligence cannot be changed even with effort.

Social Experiences in School

Also consistent with previous studies (Dong & Hu, 2019; Gomez & Suarez, 2020), three important predictors in the SVM model relate to the students' perceptions regarding their social experiences in school. BEINGBULLIED is the index that measures the students' exposure to bullying, and the poor reading proficiency students report higher values on this index. However, they report lower values on two other indexes: BELONG is the index measuring the students' sense of belonging in their schools, and PERCOOP represents the students' perception that cooperation is encouraged in their school.

Economic, Social, and Cultural Status

ESCS is the index computed in the PISA to measure the students' socioeconomic status. The measure is derived from student reports on the availability of household items and other possessions and their parents' education and occupational status. The importance of socioeconomic status as a predictor of achievement was observed across almost all countries/territories in PISA 2018 (OECD, 2019a), including the Philippines (Bernardo, 2020; Besa, 2019). The poor reading proficiency students tended to have low values in ESCS. We can also discern that many of the other important variables are also associated with socioeconomic statuses, such as the availability of ICT at home, students' learning motivations, and expected occupational status. In the next section, we discuss how socioeconomic status might undergird the most important variables distinguishing low and higher reading proficiency students using socioecological and sociocultural perspectives.

Discussion

We used several binary classification models to identify the best model to categorize Filipino students as either low or high in reading proficiency and determined that the SVM provided the best model. The top 20 variables (indexes and items) that had the highest impact on the SVM model were identified. These non-cognitive variables characterize the beliefs, motivations, experiences, and resources that distinguish the Filipino readers with the lowest proficiency in reading from the rest of the students. Using socioecological (Bronfenbrenner, 2009) and sociocultural (Bernardo & Liem, 2013) theoretical approaches on human development and learning, we can make sense of how the top 20 variables converge in a coherent profile of the poor reading proficiency students in their social environments.

Ecological systems theory of human development (Bronfenbrenner, 2009) assumes that social interaction processes within a child's social and cultural environments shape all aspects of their development, including their cognitive, emotional, and social cognitive development. These environments range from the most proximal with interactions with parents, siblings, and other family members to increasing distal environments like the classroom and school with interactions with teachers, classmates, and other adults in school.

The child's development is even influenced by interactions in more distal environments like their community and the broader society and its institutions, political and economic systems, social media, and others. As regards the development of children's educational and learning-related beliefs, attitudes, motivations, and other psychological functions, we could also see them as being shaped by their interactions in the home, school, and other relevant social environments (Leventhal & Brooks-Gunn, 2000; Mok et al., 2020). Even actual educational achievement can be viewed as being distally shaped by these environmental systems (Engelhardt et al., 2019). Below we discuss three interrelated contexts that seem to strongly impact low reading achievement: (a) the low socioeconomic context of family/home, (b) the reading classroom context, and (c) the school's social context.

The Home of Low Socioeconomic Status Families

Among the 20 variables with the strongest impact on the SVM model, ESCS (the index of socioeconomic and culture status) is possibly the best variable that underscores specific characteristics of the social environment that undergird many of the other variables with a strong impact. Low socioeconomic status (SES) of the student's family is clearly associated with access to ICTRES (availability of ICT at home), which thus limits involvement in interactive IT activities (ST176Q05IA & ST176Q02IA) that are helpful in learning. SES has also been shown to be associated with Filipino high school students' motivations. An earlier study on Filipino high school students indicated SES differences were associated with differences in achievement motivation (including mastery goals), valuing for schooling, and a sense of purpose (Bernardo et al., 2015). In that study, students from lower SES environments had lower motivation scores than their counterparts from higher SES environments. This finding echoes the pattern of results found among poor reading proficiency students' values on the motivational variables: WORKMAST, MASTGOAL, ATTLNACT, and BSMJ. More recent research also indicates how the association between fixed/growth mindset (c.f., ST184Q01HA) and achievement was observed only among higher SES students (Bernardo, 2020). Thus, the disadvantaged socioeconomic environment of the Filipino student may be associated with several of the highest impact predictors of reading proficiency.

Education researchers have long documented moderate to strong SES-related achievement gaps (Sirin, 2005; Chmielewski, 2019) and the results of our study among Filipino students provide further evidence on the importance of this factor, but also more specific insights into how SES might be constraining important proximal predictors of student achievement in reading such as their motivations and effective use of ICT for learning. Thus, socioeconomic status does not only constrain resources for learning; it also seems to have an effect of shaping education-related motivations and aspirations. As we will discuss later, however, these motivational dimensions of learning could still be shaped by experiences in the school with appropriate interventions so that deprivations in the family home can be remediated by actions of the teacher and other actors in the school and the immediate community.

The Reading Classroom Context

Many other factors seem to implicate the important role of experiences in the classroom and in the school that relate to the Filipino students' sense of self as a learner. Specific experiences with teachers could be meaningfully associated with specific reading-related student attributes. For example, the teachers' manner of providing feedback (PERFEED) might be aggravating the students' self-concept in reading (SCREADDIFF). Consistent with previous research (Ma et al., 2021), the teachers' lack of enthusiasm (TEACHINT) might be reinforcing the students' own lack of intrinsic interest in reading as an activity (JOYREAD, ST167Q031A). The teachers' manner of engaging students in the reading task (ST153Q04HA) could be a factor for students' lack of metacognitive awareness of reading strategies (METASUM). Applying the socioecological perspective, these students are also the ones who come from resource-deprived homes and who have weaker education-related motivations and aspirations. With this in mind, we can see how the teachers' actions might serve to further weaken the students' motivations. Teacher feedback that "affirms" the students' self-concept of having difficulties in reading and fixed intelligence and teachers' lack of enthusiasm that aligns with the students' own lack of intrinsic enjoyment of reading might exacerbate the students' low mastery learning orientation, task persistence, and value of schooling.

The School Social Environment

The students' school as a social environment also gives rise to specific experiences that seem to negatively relate to students' reading proficiency. Two of these factors were actually included in the PISA 2018 survey as part of the assessment of student well-being (BELONG and BEINGBULLIED). However, our results show that these aspects of the students' well-being are also associated with their reading proficiency. Collectively, the three variables related to students' school experiences (the third is PERCOOP) characterize the poor reading proficiency students as being socially disconnected from the school; they have a low sense of belonging, perceive their fellow students not to value cooperation, and have frequently been exposed to bullying, a finding consistent with previous research (Yu & Zhao, 2021).

Feeling socially disconnected in school is most likely going to limit the influence of the school as a social environment for socializing and developing important cognitive, affective, and social goals for these students (Arslan, 2019; Bond et al., 2007), which might explain why these variables have a strong impact on the model predicting reading proficiency. Drawing from the socioecological perspective again, for the students with this low reading proficiency, their feeling of social disconnectedness is going to bolster their low sense of value for schooling and their low mastery learning goals, among other non-cognitive variables that interact to influence their reading proficiency. It seems that the interrelated contexts of the Filipino students' learning and development could constrain the learning of reading in sustained ways.

The Insight From Machine Learning Approach

Although many of the variables identified in the SVM model and discussed in this section have been identified as important predictors of reading proficiency and academic achievement in previous studies, there is added insight from the use of the machine learning binary classification models. It revealed a set of variables that have higher-order relationships and reading proficiency. These higher-order relationships should not be seen as mere mathematical relationships but as representing meaningfully interacting variables that can be understood with reference to models that assume how students' learning and development are shaped by social interaction in different levels of social ecologies (Bronfenbrenner, 2009). In the foregoing discussion, we highlighted how specific variables seem to arise from the social ecologies of the home, the reading classroom, and the school. However, it is also very likely that there also meaningful relationships across these environments. For example, the students' SES is sometimes characterized as an important factor in understanding social disconnectedness in school (Sampasa-Kanyinga & Hamilton, 2016), although these feelings of disconnectedness might contribute to lower motivations and values for schooling (Korpershoek et al., 2004). The machine learning approach and the socioecological perspective of development help us understand that these variables work as a system to characterize the attributes and experiences of Filipino students who are reading at very low levels of proficiency.

Towards a System Perspective and Approach to Intervention

By implication, attempts to also understand how to help Filipino students achieve higher proficiency levels should also adopt a systems perspective. Helping students with poor reading proficiency cannot simply involve improving curriculum and pedagogy. Instead, it requires multiple interventions and approaches that try to target different variables within the students' various interlinked social environments.

Addressing Poverty as a Context.

The salient role of the students' families' SES in relation to reading proficiency and other important variables such as IT resource access and utilization, student motivations, learning-related beliefs, and aspirations shows that the problem of low reading proficiency is also, to a significant extent, a problem of poverty. As such, educational improvement efforts need to be embedded in broader efforts to improve the economic condition of families and communities. However, as a more practical point, these findings point to students who are most at risk of poor reading proficiency from lower SES families. The results of the study also point to other markers of those at risk of low proficiency, and as such, provide useful guides for targeted interventions in schools.

School-Based Interventions.

The education and psychology literatures point to numerous viable classroom-based or school-based interventions to improve students' mastery-oriented motivations (Hulleman & Barron, 2016; Law, 2011), beliefs, and mindsets (O'Mara et al., 2006; Yeager et al., 2019). Some such interventions even seem to moderate the SES-related achievement gaps (Destin et al., 2019) and gaps related to students' educational aspirations (Castleman & Goodman, 2018; Chiapa et al., 2012).

As the results also suggest a higher-order relationship among specific teaching characteristics, students' reading-related beliefs and strategies, and reading achievement, the specific focus could be given to the teaching of reading and the motivation of teachers of reading directed at developing better pedagogical and assessment approaches that will nurture better intrinsic enjoyment of reading and appreciation of effective strategies of reading (Merisuo-Storm & Soininen, 2014; Ramírez-Leyva, 2015). Indeed, the educational and psychological literature presents a range of options for teachers who wish to modify their instructional and assessment approaches to strengthen students' motivations, mindsets, and values related to education. There are also interventions that can be implemented outside the classroom, like those in homeroom classes, extracurricular activities, and other out-of-school experiences. Filipino educators need to contextualize these interventions to the experiences of the students in their own schools and communities to make more direct connections to the challenges that students experience. This starts with teachers and other stakeholders understanding and appreciating how important these non-cognitive variables are to support students' efforts to learn reading.

Social Connectedness in Schools.

As regards the social experiences of students with poor reading proficiency, the research literature points to different school-based programs to address bullying (Gaffney et al., 2019; Wachs et al., 2019) and to improve social connectedness and cooperation to foster more positive school climates (Darling-Hammond & Cook-Harvey, 2018; Noble-Carr et al., 2014). As these approaches suggested in the research literature were developed and studied in other counties, they will need to be contextualized in the Philippine educational communities. Further, sustaining the preceding point regarding the students who are known to be at risk and their teachers should be prioritized in such intervention programs.

As we emphasize the need for a system perspective on understanding and addressing the learning problems of our students, we wish to note that there was an opportunity to gather even richer information from the optional questionnaires available in the PISA 2018 that were supposed to be answered by parents and teachers. Concurrent with the PISA 2018, the Teaching and Learning International Survey (TALIS) was also administered, which also aimed to gather more detailed information from teachers. More information from the students' parents and teachers could have presented more variables that could have characterized the home and classroom environments of the students and perhaps strengthened some of the inferences presented in the current study.

Localization of Interventions and Actions

A strong implication of the preceding discussion is that the interventions to help Filipino students with poor reading proficiency need to be localized and contextualized. The interventions need to be situated within the immediate contexts of the students' learning experiences. In more concrete terms, if the goal is to help improve students' reading proficiency, we also need to make students feel more socially connected to the community within their school, to have them develop more positive self-beliefs, stronger motivations, and higher aspirations, and to have teachers and resources who will support these social cognitive, affective, and motivational sets. And the actions that will help students will need to be emergent and realized in their social ecologies.

This assertion does not claim that interventions to reform the curriculum and to improve the qualifications and competencies of reading teachers are not important. Indeed, those reforms that are decided at the national level might have an important long-term impact on improving reading even among those who are already meeting the reading standards. However, even the manner in which those reforms are implemented eventually will still need to be contextualized within the social ecologies and around the individual classrooms and schools.

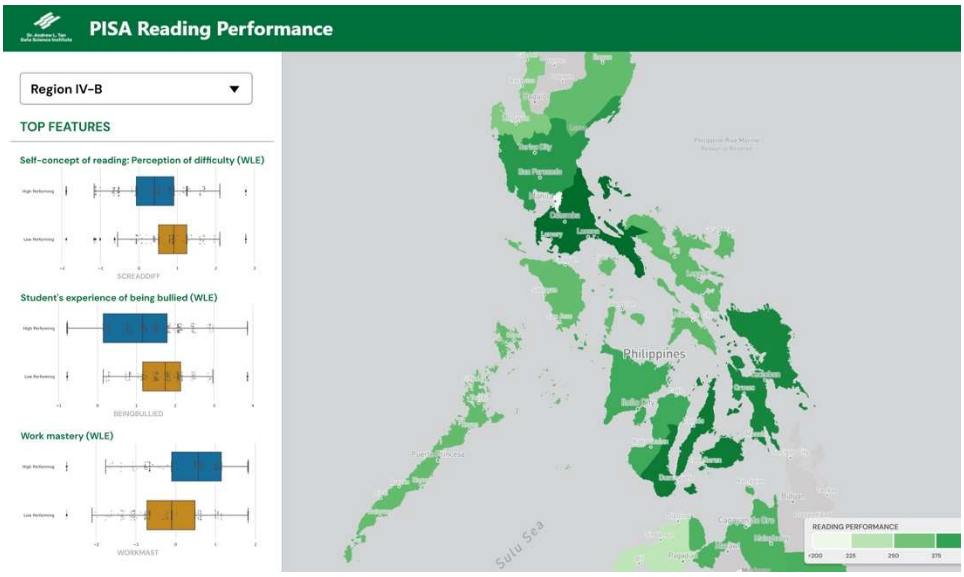
Our proposed localized and contextualized actions are made more urgent as a consequence of the closure of schools during the COVID-19 pandemic, which has very likely further intensified students' sense of disconnectedness with their schools. The lack of direct contact with teachers and the students' difficulties with the modular approach or online learning approaches might also have further deleterious effects on students' self-beliefs and motivations related to learning. Indeed, the lack of ITC resources in many families has called attention to how socioeconomic inequalities mark students' experiences and achievement. Thus, the interventions to address the system of variables identified in our study will need to be further contextualized in the new problems that arose from the pandemic.

Data Analytic Tools

To help contextualize the specific results, we developed an interactive web PISA Key Variable Visualization Tool (PISA-KVVT) application showing the variables found to influence the English reading proficiency of Filipino learners, as shown in Figure 7. Using NuxtJS, the PISA-KVVT was developed based on the top features of the model combined with regional information. To display the geospatial component, Mapbox GL JS was used. The PISA-KVVT can also be applied to visualize and analyze variables-related risks from a regional perspective. In other words, the visualization tool can be used to explore the specific scores related to the high impact variables across the different regions of the country. The visualization will be made available to the public upon paper acceptance.

Figure 7

The PISA Key Variables Visualization Tool



Note: The PISA Key Variables Visualization Tool provides an overview of the performance of a region in the Philippines through the interactive choropleth map. Upon selection of a specific region (upper left), additional details on the student and school information are presented on the side panel in charts and figures. It has provisions for choosing to view the distribution of the variables across the country in the choropleth map to further investigate how each variable contributes to the reading performance. The web application was developed using Vue.js and Nuxt.js.

Conclusion

In conclusion, the study was undertaken to take a broader exploration of a wider range of non-cognitive variables that might help characterize the experiences and attributes of Filipino students who were assessed to have poor reading proficiency. Using binary classification machine learning approaches, an SVM model was found to have the best prediction accuracy. The 20 variables with the strongest impact in the model were meaningfully interpreted as reflecting students’ experiences in the home, classroom, and school environment. The results point not only to targets for interventions to help these students improve their reading proficiency but also highlight the need for a systemic view of the students’ vulnerabilities and a systemic approach to addressing these students' interconnected concerns. We further propose that this systemic approach be applied in developing interventions that will be localized and contextualized to fully realize how the students’ social environments are shaping their learning experiences and achievement in reading.

Notes on Analysis

1 Typically in machine learning classification and regression tasks, and in this work, the variables are treated as flat, rather than hierarchical sets, without any explicit structure, that is, primary sampling units that would relate the variables to each other. This can be seen in the initialization of the weight vectors and update function (discussed in the following paragraphs). Thus, stratification and information on primary sampling units are not incorporated into the machine learning model.

There are different weight configurations for different machine learning models. For our work, we use a Support Vector Machine model, which looks for a decision boundary that will be the basis for classifying the input data or survey samples. The decision boundary is defined by a set of weight vectors that are perpendicular to the sample (input data) space. For a specific decision boundary, only a set of input samples that are in the "gutter" of the decision boundary margins have relevant weight vectors.

The weight vectors are typically initialized using very small, normally distributed random numbers or, sometimes, a zero vector. These are updated every training iteration by minimizing the cost function (2). If the derivative of the cost function is zero, then we are guaranteed that the cost/penalty for the model predictions is minimum. Searching for the global minimum is part of the evaluation. The cost function is dependent on the weight vectors and their corresponding target variables and input variables (2) such that as you update the weight vectors (3), the cost function should decrease.

$$y_i(\mathbf{w}^T x + b) \geq 1 \tag{1}$$

$$J(\mathbf{w}) = \frac{1}{2}||\mathbf{w}||^2 + C[\frac{1}{N}\sum \max(0, 1 - y_i(\mathbf{w}^T x_i + b)] \tag{2}$$

$$\nabla J(\mathbf{w}) = \frac{1}{N}\sum_i^n \begin{cases} \mathbf{w} & \text{if } \max(0, 1 - y_i(\mathbf{w}^T x_i) = 0) \\ \mathbf{w} - C y_i x_i & \text{otherwise} \end{cases} \tag{3}$$

$$k(\mathbf{x}_1, \mathbf{x}_2) = e^{(-\lambda||\mathbf{x}_1 - \mathbf{x}_2||^2)} \tag{4}$$

SVM is a linear model (1), but when a kernel (4) is used to transform the input into a nonlinear dimension, SVM can model nonlinear relationships. For linear, lower-dimensional SVM models, for example, binary classification with 3-dimensional variables or 2-dimensional variables inputs, identifying the important variables is trivial just by looking at the weights. For higher-dimensional, nonlinear models (SVM with kernels), such as in this work, we needed SHAP to explain the variable importance.

2 The main metric to determine the best classification model for a task depends on the application. For example, in identifying whether a sample has a disease or not, preference is on the false negative rate metric rather than the accuracy. For a dataset with highly unbalanced samples, such as in anomaly detection, F1-score is checked rather than accuracy. For determining the features that are salient in classifying student performance, the best metric is accuracy.

For this work, two factors were considered in the choice of the machine learning model for variable or feature analysis: (a) interpretability and (b) average classification accuracy. Because both SVM and logistic regression models are interpretable models, we chose the model with the highest testing accuracy. We did not check other metrics that will support the choice of SVM over logistic regression; instead, we assume that the model should be optimal, that is, it should provide the best accuracy for the analysis to be more valid.

References

Alivernini, F., & Manganelli, S. (2015). Country, school and students factors associated with extreme levels of science literacy across 25 countries. *International Journal of Science Education, 37*(12), 1992–2012.

Arslan, G. (2019). School belonging in adolescents: Exploring the associations with school achievement and internalising and externalising problems. *Child Educational Psychology*, *36*(4)*,* 22–33. doi:10.1007/978-3-030-64537-3_21

Beglar, D., Hunt, A., & Kite, Y. (2011). The effect of pleasure reading on Japanese university EFL learners' reading rates. *Language Learning Journal, 62*(3)*,* 665–703. https://doi.org/10.1111/j.1467-9922.2011.00651.x

Bernardo, A. B. I., Cai, Y., & King, R. B. (2021). Society level social axiom moderates the association between growth mindset and achievement across cultures. *British Journal of Educational Psychol*ogy: Advance online publication. https://doi.org/10.1111/bjep.12411

Bernardo, A. B. I. (2020). Socioeconomic status moderates the relationship between growth mindset and learning in mathematics and science: Evidence from PISA 2018 Philippine data. *International Journal of School and Educational Psychology, 9*(2), 208–222. https://doi:10.1080/21683603.2020.18326354

Bernardo, A. B. I., Ganotice, F. A., & King, R. B. (2015). Motivation gap and achievement gap between public and private high schools in the Philippines. The *Asia-Pacific Education Researcher, 24*, 657–667. https://doi.org/10.1007/s40299-014-0213-2

Bernardo, A. B. I., & Liem, G. A. D. (2013). Mapping the spaces of cross-cultural educational psychology. In G. A. D. Liem & A. B. I. Bernardo (Eds.), *Advancing cross-cultural perspectives on educational psychology* (pp. 345–357). Information Age Publications.

Besa, F. (2019). *Philippines country note. Programme for International Student Assessment (PISA). Results from PISA 2018*. OECD Publishing. http://www.oecd.org/pisa/publications/PISA2018_CN_PHL.pdf

Bond, L., Butler, H., Thomas, L., Carlin, J., Glover, S., Bowes, G., & Patton, G. (2007). Social and school connectedness in early secondary school as predictors of late teenage substance use, mental health, and academic outcomes. *Journal of Adolescent Health*, *40*(4), e9–e18. https://doi.org/1016/j.jadohealth.2006.10.103

Broh, B. A. (2002). Linking extracurricular programming to academic achievement: Who benefits and why? *Sociology of Education, 75*(1), 69–95. https://doi.org/10.2307/3090254

Bronfenbrenner, U. (2009). *The ecology of human development: Experiments by nature and design*. Harvard University Press.

Burns, M. K., Davidson, K., Zaslofsky, A. F., Parker, D. C., & Maki, K. E. (2018). The relationship between acquisition rate for words and working memory, short-term memory, and reading skills: Aptitude-by-treatment or skill-by-treatment interaction? *Assessment for Effective Intervention,43*(5)*,* 182–192. https://doi.org/10.1177/1534508417730822

Cabrera, A. F., & La Nasa, S. M. (2000). Three critical tasks America's disadvantaged face on their path to college. *New Directions for Institutional Research, 107,* 23–29, https://doi.org/10.1002/ir.10702

Castleman, B., & Goodman, J. (2018). Intensive college counseling and the enrollment and persistence of low-income students. *Education Finance and Policy*, *13,* 19–41. https://doi.org/10.1162/edfp_a_00204

Chiapa, C., Garrido, J., & Prina, S. (2012). The effect of social programs and exposure to professionals on the educational aspirations of the po*or. Economics of Education Review, 31*(5)*,* 778–798, https://doi.org/10.1016/j.econedurev.2012.05.006

Coulombe, S., Tremblay, J.-F., & Marchand, S. (2004). *Literacy scores, human capital and growth across fourteen OECD countries*. Statistics Canada.

Chen, J., Zhang, Y., Wei, Y., & Hu, J. (2019). Discrimination of the contextual features of top performers in scientific literacy using a machine learning approach. *Research in Science Education, 51(1),* 129-158, https://doi.org/10.1007/s11165-019-9835-y

Chmielewski, A. K. (2019). The global increase in the socioeconomic achievement gap, 1964 to 2015. *American Sociological Review*, *84*(3)*,* 517–544. https://doi.org/10.1177/0003122419847165

Cho, E., Toste, J. R., Lee, M., & Ju, U. (2019). Motivational predictors of struggling readers' reading comprehension: The effects of mindset, achievement goals, and engagement. *Reading and Writing 32,* 1219–1242. https://doi.org/10.1007/S11145-018-9908-8

Cheung, W., Tse, S., Lam, J., & Loh, K. (2009). Progress in international reading literacy study 2006 (PIRLS): Pedagogical correlates of fourth-grade students in Hong Kong. *Journal of Research in Reading*, *32*(3)*,* 293–308. https://doi.org/10.1111/j.1467-9817.2009.01395.

Darling-Hammond, L., & Cook-Harvey, C. M. (2018). *Educating the whole child: Improving school climate to support student success.* Learning Policy Institute.

Destin, M., Hanselman, P., Buontempo, J., Tipton, E., & Yeager, D. S. (2019). Do student mindsets differ by socioeconomic status and explain disparities in academic achievement in the United States? *AERA Open*, *5*(3),1-12. https://doi.org/10.1177/2332858419857706

Dewaele, J. M., & Li, C. (2021). Teacher enthusiasm and students' social-behavioral learning engagement: The mediating role of student enjoyment and boredom in Chinese EFL classes. *Language Teaching. Research*, *25(*6), 922-945 . https://doi.org/10.1177/13621688211014538

Dong, X., & Hu, J. (2019). An exploration of impact factors influencing students' reading literacy in Singapore with machine learning approaches. *International Journal of English Linguist*ics, *9(5*), 52–65. doi:10.371/journal.pone.0251545

Duke, N. K. (2004). The case for informational text. *Educational Leadership, 61*(*6)*, 40–44.

Engelhardt, L. E., Church, J. A., Paige Harden, K., & Tucker-Drob, E. M. (2019). Accounting for the shared environment in cognitive abilities and academic achievement with measured socioecological contexts. *Developmental Science*, *22.* https://doi.org/10.1111/desc.12699

Friesen, D., & Haigh, C. (2018). How and why strategy instruction can improve second language reading comprehension: A review. *The Reading Matrix*, *18*, 1–18.

Gaffney, H., Farrington, D. P., & Ttofi, M. M. (2019). Examining the effectiveness of school-bullying intervention programs globally: A meta-analysis. *International Journal of Bullying Prev*ention, *1*, 14–31. doi:10.1007/s42381-019-007-4

Gerra, G., Benedetti, E., Resce, G., Potente, R., Cutilli, A., & Molinaro, S. (2020). Socioeconomic status, parental education, school connectedness and individual socio-cultural resources in vulnerability for drug use among students. *International Journal of Environmental Research and Public Health*, *17*(4). https://doi.org/10.3390/ijerph17041306

Ghabanchi, Z., & Rastegar, R. E. (2014). The correlation of IQ and emotional intelligence with reading comprehension. *Reading, 14*(2), 135–144.

Goetz, T., Frenzel, A. C., Pekrun, R., Hall, N. C., & Lüdtke, O. (2007). Between-and within-domain relations of students' academic emotions. *Journal of Educational Psychology,99,* 715–733. doi:10.1037/0022-0063.99.4.715

Gomez, R., & Suarez, A. M. (2020). Do inquiry-based teaching and school climate influence science achievement and critical thinking? Evidence from PISA 2015. *International Journal of STEM Education, 7.* https://doi.org/10.1186/s40594-020-00240-5

Gubbels, J., Swart, N. M., & Groen, M. A. (2020). Everything in moderation: ICT and reading performance of Dutch 15-year-olds. *Large-scale Assessments in Education,8,* https://doi.org/10.1186/s40536-020-0079-0

Gumus, S., & Atalmis, E. (2011). Exploring the relationship between purpose of computer usage and reading skills of Turkish students: Evidence from PISA 2006. *Turk*ish *Online Journal of Educational Technology*, *10*(3), 129–140.

Hebbecker, K., Förster, N., & Souvignier, E. (2019). Reciprocal effects between reading achievement and intrinsic and extrinsic reading motivation. *Scientific Studies of Reading, 23*(5), 419–436, doi:10.1080/10888438.2019.1598413

Hu, X., Gong, Y., Lai, C., & Leung, F. K. (2018). The relationship between ICT and student literacy in mathematics, reading, and science across 44 countries: A multilevel analysis. *Computers and Education, 125*, 1–13. https://doi.org/10.1016/j.compedu.2018.05.021

Hulleman, C. S., & Barron, K. E. (2016). Motivation interventions in education: Bridging theory, research, and practice. In L. Corno & E. Anderman (Eds.), *Handbook of educational psychology* (pp. 160–171). Routledge.

Kern, M. L., & Friedman, H. S. (2009). Early educational milestones as predictors of lifelong academic achievement, midlife adjustment, and longevity. *Journal of Appl*ied *Develomental Psychology*, *30*(4), 419–430. doi:10.1016/j.app.dev.208.12.025

Korpershoek, H., Canrinus, E. T., Fokkens-Bruinsma, M., & de Boer, H. (2020). The relationships between school belonging and students' motivational, social-emotional, behavioural, and academic outcomes in secondary education: A meta-analytic review. *Research Papers in Educ*ation, *35*(6)*,* 641–680. doi:10.1080/02671522.2019.1615116

Romero, A. D. & Papango. M. C. (2020). PISA reading literacy vis-à-vis K to12 English curriculum. In M. U. Balagtas & M. C. Montealegre (Eds.), *Challenges of PISA: The PNU report (*pp. 33-56). Philippine Normal University and Rex Institute for Student Excellence, Inc.

Law, Y. K. (2011). The effects of cooperative learning on enhancing Hong Kong fifth graders' achievement goals, autonomous motivation and reading proficiency. *Journal of Research in Read*ing, *34*(4)*,* 402–425. doi:10.1111/j.1467-9817.2020.01445x

Leventhal T., & Brooks-Gunn, J. (2000). The neighborhoods they live in: The effects of neighborhood residence on child and adolescent outcomes. *Psychological Bulletin Journal,*, *126*(2)*,* 309–337. doi:10.1037/0033-290.9.126.2.309

Lundberg, S., & Lee, S. (2017). A unified approach to interpreting model predictions. In 31st Conference on Neural Information Processing System (NIPS), Long Beach, CA, USA.

Ma, L., Luo, H., & Xiao, L. (2021). Perceived teacher support, self-concept, enjoyment and achievement in reading: A multilevel mediation model based on PISA 2018. *Learning and Indivual Differences,85.* doi:10.1016/j.lindif.2020.101947

Merisuo-Storm, T., & Soininen, M. (2014). Interesting reading materials and exercises encourage also reluctant boys to read. *Procedia Social Behavioral and Sci*ences,*116*, 2583–2588, doi:10.1016/j.sbspro.2014.01.615

Mohseni, F., Seifoori, Z., Ahangari, S., & Khajavi, Y. (2020). The impact of metacognitive strategy training and critical thinking awareness-raising on reading comprehension. *Cogent Education*, *7.* https://doi.org/10.1080/2331186X.2020.1720946

Mok, S. Y., Bakaç, C., & Froehlich, L. (2020). 'My family's goals are also my goals': The relationship between collectivism, distal utility value, and learning and career goals of international university students in Germany. *International Journal for Educational and Vocational Guidance*, *21,* 355-378. https://doi.org/10.1007/s10775-020-09447-y

Moran, J., Ferdig, R. E., Pearson, P. D., Wardrop, J., & Blomeyer, R. L. (2008). Technology and reading performance in the middle-school grades: A meta-analysis with recommendations for policy and practice. *Journal of Literacy Research, 40*, 6–58, https://doi.org/10.1080/10862960802070483

Ngorosho, D. (2010). Reading and writing ability in relation to home environment: A study in primary education in rural Tanzania. *Child Indicators. Research*, *4,* 369–388. https://doi.org/10.1007/s12187-010-9089-8

Noble-Carr, D., Barker, J., McArthur, M., & Woodman, E. (2014). Improving practice: The importance of connections in establishing positive identity and meaning in the lives of vulnerable young people. *Child and Youth Services Review*, *47*(3), 389–396. doi:10.1016/j.child.youth.2014.10.017

Okkinga, M., van Steensel, R., van Gelderen, A. J. S., van Schooten, E., Sleegers, P. J. C., & Arends, L. R. (2018). Effectiveness of reading-strategy interventions in whole classrooms: A meta-analysis. *Educational Psychology Review*, *30,* 1215–1239. doi:10.1007/s10648-018.9445-7

O'Mara, A. J., Marsh, H. W., Craven, R. G., & Debus, R. L. (2006). Do self-concept interventions make a difference? A synergistic blend of construct validation and meta-analysis. *Education Psychology 41*(3), 181–206. doi:10.1207/215326985ep4103_4

Organisation for Economic Co-operation and Development. (2019a). *PISA 2018 results (Vol I): What students know and can do.* OECD Publishing. https://doi.org/10.1787/5f07c754-en

Organisation for Economic Co-operation and Development. (2019b). *PISA 2018. Assessment and analytic framework.* OECD Publishing. https://doi.org/10.1787/b25efab8-en

Poon, C. L., Lam, K. W., Chan, M., Chng, M., Kwek, D., & Tan, S. (2016). Preparing students for the twenty-first century: A snapshot of Singapore's approach. In A. Editor, B. Editor, C. Editor & D. Editor (Eds.), *Educating for the 21st century* (pp. 225–241). Publisher. https://doi.org/10.1007/978-981-10-1673-8_12

Prudencio, M. C. (2020). The effect of parental characteristics and home resources on reading performance of 15-year old students in the Philippines. *The New Educational Review*, *62*. doi:10.15804/tner.2020.62.6.06

Ramírez-Leyva, E. M. (2015). Encouraging reading for pleasure and the comprehensive training for readers. *Investigacion Bibliotecologica 30*(69),93–116. doi:10.1016/j.ibbai.2016.04.014

Sampasa-Kanyinga, H., & Hamilton, H. A. (2016). Does socioeconomic status moderate the relationships between school connectedness with psychological distress, suicidal ideation and attempts in adolescents? *Preventive Medicine*, *87*, 11–17. https://doi.org/10.1016/j.ypmed.2016.02.010

Sheikh, I., Soomro, K., Kamal, A., & Hussain, N. (2019). Metacognitive awareness of reading strategies, reading practices and academic attainments of university students. *International Jounral of Educational Development 6,* 126–137. doi:10.22555/joeed.v6i.2749

Shin, S., Slater, C. L., & Ortiz, S. (2017). Leader perceptions and student achievement. *International Journal of Educational Managemen*t, *31*(7)*,* 1103–1118. https://doi.org/10.1108/IJEM-03-2016-0054

Smith, M. C., Mikulecky, L., Kibby, M. W., Dreher, M. J., & Dole, J. A. (2000). What will be the demands of literacy in the workplace in the next millennium? *Reading Research Quarterly*, *35*(3), 378–383. https://doi.org/10.1598/RRQ.35.3.3

Sirin, S. R. (2005). Socioeconomic status and academic achievement: A meta-analytic review of research. *Review of Educational Research, 75*(3)*,* 417–453. https://doi.org/10.3102/00346543075003417

Torres, L. R., Ordóñez, G., & Calvo, K. (2021). Teacher and student practices associated with performance in the PISA reading literacy evaluation. *Frontiers in Educ*ation, *6*. https://doi.org/10.3389/feduc.2021.658973

Toste, J. R., Didion, L., Peng, P., Filderman, M. J., & McClelland, A. M. (2020). A meta-analytic review of the relations between motivation and reading achievement for K–12 students. *Review of Educational Res*earch, *90*(3), 420–456. https://doi.org/10.3102/0034654320919352

Trinidad, J. E. (2020). Material resources, school climate, and achievement variations in the Philippines: Insights from PISA 2018. *International Journal of Educational Development*, *75*.https://doi.org/10.1016/j.ijedudev.2020.102174

Tse, S., & Xiao, X. (2014). Differential influences of affective factors and contextual factors on high-proficiency readers and low-proficiency readers: A multilevel analysis of PIRLS data from Hong Kong. *Large-scale Assessments in Education, 2*. https://doi.org/10.1186/s40536-014-0006-3.T

Turunen, T., Kiuru, N., Poskiparta, E., Niemi, P., & Nurmi, J. E. (2019). Word reading skills and externalizing and internalizing problems from Grade 1 to Grade 2—Developmental trajectories and bullying involvement in Grade 3. *Scientific Studies of Reading*, *23*(2)*,* 161–177. https://doi.org/10.1080/10888438.2018.1497036

Vidal-Abarca, E., Mañá, A., & Gil, L. (2010). Individual differences for self-regulating task-oriented reading activities. *Journal of Educational Psycho*logy, *102*(4)*,* 817–826. https://doi.org/10.1037/a0020062

Wachs, S., Bilz, L., Niproschke, S., & Schubarth, W. (2019). Bullying intervention in schools: A multilevel analysis of teachers' success in handling bullying from the students' perspective. *Journal of Early Adolescence*, *39*(5), 642–668. doi:10.1177/027243618780423

Whitney, S. D., & Bergin, D. A. (2018). Students' motivation and engagement predict reading achievement differently by ethnic group. *Journal of Genetic Psycho*logy, *179*(6), 357–370. doi:10.1080100221325.2018.1527754

Wharton-McDonald, R., & Swiger, S. (2009). Developing higher order comprehension in the middle grades. In S. E. Israel & G. G. Duffy (Eds.), *Handbook of research on reading comprehension* (pp. 510–530). Routledge.

Wilhelm, J. D., & Smith, M. W. (2016). The power of pleasure reading: What we can learn from the secret reading lives of teens. *English Journal*, *105*(6), 25–30.

Xiao, Y., & Hu, J. (2019). The moderation examination of ICT use on the association between Chinese Mainland students' socioeconomic status and reading achievement. *International Journal of Emerging Technologies in Learning, 14*(5), 107–120. https://doi.org/10.3991/ijet.v14i15.10494

Yeager, D. S., Hanselman, P., Walton, G. M., Murray, J. S., Crosnoe, R., Muller, C., et al. (2019). A national experiment reveals where a growth mindset improves achievement. *Nature*, *573,* 364–369. https://doi.org/10.1038/s41586-019-1466-y

Yu, S., & Zhao, X. (2021). The negative impact of bullying victimization on academic literacy and social integration: Evidence from 51 countries in PISA. *Social Science & Humanities Open, 4*. https://doi.org/10.1016/j.ssaho.2021.100151

Zhang, L., Goh, C. C. M., & Kunnan, A. J. (2014). Analysis of test takers' metacognitive and cognitive strategy use and EFL reading test performance: A multi-sample SEM approach. *Language Assessment Q*uarterly, *11,* 76–102. https://doi.org/10.1080/15434303.2013.853770