Decoding Contextual Factors Differentiating Adolescents' High, Average, and Low Digital Reading Performance Through Machine-Learning Methods

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***Abstract*—The prevalence of information and communication technologies (ICTs) has brought about profound changes in the field of reading, resulting in a large and rapidly growing number of young digital readers. The article intends to identify key contextual factors that synergistically differentiate high and low performers, high and average performers, and low and average performers in digital reading, through the utilization of machine-learning methods, namely, support vector machine (SVM) and SVM recursive feature elimination. In addition, the Shapley additive explanations (SHAP) method was applied to augment the machine-learning models and detect the features impact on the final output. The latest-released Programme for International Student Assessment reading data were analyzed, and the samples included 276 269 15-year-old students from 38 Organization for Economic Cooperation and Development countries. The results show that an optimal feature set of contextual factors at the school, classroom, and student levels in the high–low model, high–average model, and low–average model boast high accuracy. Compared with average-performing students, high-performing students spend more time reading emails and are associated with high-quality teaching that incorporates digital literacy, and low-performing students are characterized by a lack of interest in ICT use and are more susceptible to the abuse of ICT resources, classroom disorder, and discrimination at school. The use of machine-learning algorithms for pairwise comparisons provides new perspectives for personalized digital reading education, and the evaluation of the effect of every factor using SHAP method offers a clear view for educational researchers. This article sheds light on factors that may contribute to the development of students' digital reading literacy and the practice of adopting an individualized approach to digital reading pedagogy for educators and instructors.**

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I. Introduction

In THE age of information and communication technologies (ICTs), the way people read has undergone substantial changes from paper reading toward digital reading [1]. Digital reading often involves accessing reading materials on the internet (e.g., news and posts on social media) and on digital devices (e.g., computers and e-book readers) [2]. Compared with printed text, it is presented in a more interactive and experiential way, e.g., by incorporating dynamic elements (e.g., video clips and pop-up windows) to visually attract readers' interest [3]. In addition, the nonlinearity of digital reading can increase the cognitive load of readers [4]. Readers in the digitalized world should thus acquire digital reading skills to successfully participate in current academic, social, and career contexts [5].

Regarding the novelty of digital reading, researchers started to analyze the factors that may distinguish students with different digital reading performance, achieving fruitful results. Most of the studies concentrated on students at high- and low-performance levels. For low-performing readers, a series of predictors were identified as crucial (e.g., socioeconomic constraints, motivations, metacognition, ICT skills, and student–teacher interactions) [6]. Recently, researchers distinguished high- and low-performing students based on their digital reading scores in Progress in International Reading Literacy Study (PIRLS). These two cohorts of students differ greatly in their reading motivation, home literacy environment, and perceived teacher fairness and instruction [7], [8]. However, there is a paucity of research on average performers in digital reading into consideration for a more comprehensive analysis of adolescents' digital reading profiles.

Conducted by the Organization for Economic Cooperation and Development (OECD), the Programme for International Student Assessment (PISA) is a triennial assessment that measures 15-year-old students' literacy in reading, mathematics, and science. The latest round of PISA incorporated digital reading into its assessment framework. Students' reading outcomes were classified into proficiency levels ranging from Level 1b to Level

6 based on the cutoff points, and the low performers, average performers, and top performers in digital reading were identified accordingly [9]. Students' interests in reading, as well as other demographic and contextual features, varied across proficiency levels. In this regard, the current article intends to leverage a machine-learning algorithm to identify factors that can distinguish high and low performers, high and average performers, and low and average performers, respectively, in PISA 2018, to provide a detailed analysis of the learning profiles of students at various levels.

The rest of this article is organized as follows. Section II provides the review of the related works dealing with factors of students' digital reading performance, along with the research scope and research questions (RQs) of the present article. In Section III, the research materials and methods are presented to show how the prediction models are built, validated, and explained. This process is composed of five phases, namely, data extraction, data cleaning, model building, model evaluation, and model interpretation. Section IV shows the results of the experiment, including the performance and validation of the machine-learning models, the ranking of the important features, and the influencing direction of these features on the final prediction. In Section V, the results are discussed to answer the RQs in this article. Finally, Section VI concludes this article.

II. Related Work

A. Student-Level Factors and Digital Reading Performance

At the student level, some demographic factors, such as socioeconomic status (SES) [8] and home resources [10], especially cultural capital [11] have a significant positive relationship with digital reading performance. Gender is a factor that received increasing attention in previous education studies. To align with the male/female binary question in PISA questionnaire [12] and the results descriptions [5], the differences between girls and boys are elucidated here. Although a small number of researchers found no decisive gender effects on students' academic digital reading performances [13], others identified significant differences between males and females in digital reading. Previous articles found that male college students excel their female counterparts in the digital reading assessment [14], and the 15-year-old female students outperform male students in other circumstances [15]. In addition, males and females differ significantly in selective reading and sustained attention [16]. Yet, the impact of gender should not be simply examined individually because it reacts with other contextual factors [17]. It is also noted that although some of the previous assessments and studies only centered on the binary gender classification [13], [14], [15], [16], [17], [18], [19], it cannot accurately capture the identity of an individual. Future article should consider increasing the number of gender options to better reflect the gender diversity for a more comprehensive analysis, and to ensure that the respondents feel engaged and respected [20].

Students' reading knowledge and skills (e.g., prior knowledge sources, inferential reasoning strategies, and self-regulated reading processes) [21] and affective factors (e.g., reading self-concept and reading self-efficacy) [22] contribute to successful e-reading. In addition, students in a positive mood do faster in online text processing compared with students in a negative mood [23], which indicates the importance of students' emotions in the online reading process. The impacts of reading attitudes vary across the diverse purposes of digital reading. Attitudes toward academic digital reading are positively associated with reading achievements, while attitudes toward recreational digital reading are negatively associated with reading achievements [13], [24], [25], [26]. This might be due to the different frequencies of use: social reading activities can help build familiarity for digital devices, but once students transcend the optimum threshold, their competence decreases [27].

Regarding the ICT-related student-level factors, researchers identified the positive effects of self-confidence, interest, and autonomy in ICT tasks on students' traditional reading performance [26], [27], [28], and digital reading performance [17]; however, students' enjoyment of social interaction related to ICT negatively correlates with their reading performance [8]. Computer game playing, as an exception, contributes to the higher performance of boys in digital reading tests [11]. Although students who hold positive views toward ICT perform better in digital reading, their performances are influenced by the ICT opinions of their peers at the same school [29]. In addition, necessary skills for web surfing (e.g., metacognitive strategies, navigation skills, and self-regulation) are positively related to digital reading literacy [6], [26], [30], [31]. Specifically, knowledge of metacognitive strategies positively mediates the relationship between ICT use and digital reading literacy [32].

B. Classroom-Level Factors and Digital Reading Performance

Previous articles have identified the importance of teachers' role in promoting students' academic performance, but the findings are mixed across subjects and learning environments [33]. General instructional support is found insignificant in predicting digital reading performance [10], while previous articles highlighted the importance of teachers' specific teaching strategies during class [33]. Instructional behaviors, such as objective-focused fast extensive reading [34] and situated experimental exploration into the literature [35], could help develop components of students' digital reading capability, such as reading fluency and vocabulary.

The necessity of incorporating digital texts into instruction in teaching was also emphasized [36]. Overall, studies suggest that teachers should properly utilize the ICT resources and adequately assign digital reading tasks during class to improve students' digital reading literacy. Some researchers pointed out that the use of video games to train attentional control during class improves reading efficiency [37]. Researchers also identified digital storytelling as an effective tool to enhance students' digital reading performance [38]. This result further proves the importance of the introduction, coordination, and innovation of digital resources in reading. In addition, teachers' professional development of ICT use was also a significant predictor of students' digital reading skills [39]. However, compared with factors at other levels, the classroom-level factors of digital reading are less examined, awaiting further exploration.

C. School-Level Factors and Digital Reading Performance

School type and the equity dimension are generally reported as important predictors of students' digital reading performances [11]. Recent research found that school SES also plays an indispensable role. The performance of students in high-SES schools is more susceptible to student-level factors (e.g., metacognitive strategies and achievement motivation), but the performance of students in low-SES schools is more sensitive to the country-level socioeconomic indicators (e.g., GDP) [40]. Other significant school-level factors include school disciplinary climate [41], the provision of reading-related activities [17], student–teacher rapport [6], and schools' partnership with parents [33].

The influence of the availability of ICT resources at school was widely reported in previous articles, showing mixed results. Studies revealed that an abundance of e-resources at school (e.g., the availability of laptops, mobile phones, and the Internet) can promote students' digital reading performance, and male students are more susceptible to the negative effects of ICT resources than female students [14]. Others, however, argued that neither the possession of online mobile devices nor the availability of digital resources at the school level is a significant predictor of students' digital reading performance [10], [13], which might be explained by the inappropriate use of digital equipment. Researchers further indicates the importance of incorporating digital reading activities into the school curriculum [36]. Overall, studies suggested that schools and teachers should properly utilize ICT resources and adequately assign digital reading tasks during class to improve students' digital reading literacy.

D. Present Study

To date, there is a series of problems unresolved concerning the factors that influence adolescents' digital reading performance. First, although some articles have investigated the affective and contextual factors that influence students' digital reading performance, questions remain unanswered regarding the impacts of individual and environmental factors that might jointly function to generate an achievement gap in students' digital reading performance [10]. Second, while some articles have targeted the factors that can distinguish high performers from low performers in reading [8], [32], the subtle differences between students from different achievement spectra should be further explored by including average performers [42]. Research on top-, average-, and low-performing students might thus help explain the mixed findings of impacts identified in previous articles. The current research project aims to conduct secondary analyses of the large-scale PISA reading dataset to identify the key features that boast high accuracy and efficiency in classifying and predicting the performances of the three cohorts of students in digital reading while simultaneously examining the synergistic and specific effects of these features at various levels.

The following RQs are thoroughly discussed in this analysis.

1) What are the key factors that synergistically distinguish high performers from low performers in digital reading?
2) What are the digital reading profiles of high, average, and low performers, respectively?
3) How can we help readers of different achievement spectra improve?

III. Materials and Methods

A. Research Context and Samples

Data were extracted from the latest-released PISA reading dataset.[1] Students from the OECD countries that participated in the digital reading test were examined, that is, a total of 276 269 participants from 38 countries and regions with balanced proportions of females (50.2%) and males (49.8%). The classification is based on the OECD's definition of high, low, and average performers, with reading scores at Levels 5 and 6 (i.e., at or above 625.61 score points), at Levels 1a and 1b (less than 407.47 score points) and in between, respectively. In the PISA, 10 plausible values (PVs) are used to represent the participants' reading performances; however, there are no significant differences between using one PV or five PVs due to the large number of the samples [43]. Therefore, the first PV 1 in Reading was randomly selected to represent each student's reading score [8], [44]. A total of 150 independent factors/variables were collected from the student questionnaire, school questionnaire, and ICT familiarity questionnaire. In addition, the country-level factor, i.e., GDP per capita, collected from the World Bank dataset[2] was also taken into consideration. Detailed descriptions of the 150 factors used in this analysis are provided in Supplementary Material 1 for ease of reference. This article was approved by the Research Ethics Board of the Department of Psychology and Behavioral Sciences of the Zhejiang University.

B. Research Model

The application of machine learning for reading assessment has gained momentum in recent years, including but not limited to the monitoring of digital reading speed [45], the prediction of students' reading comprehension [46], and the identification of influencing factors of digital reading [7]. Compared with conventional methods (e.g., linear regressions and hierarchical linear models), machine-learning algorithms can avoid multicollinearity and clarify the complex interactions between variables in high-dimensional and multimodal reading database, thus gaining much favor from researchers [47].

Support vector machine (SVM) is a pattern recognition classifier created using the extended portrait method [48]. As one of the most robust machine-learning algorithms, SVM has been used for pattern recognition, regression analysis, and binary classification. This is accomplished by creating the most "tolerant" multidimensional hyperplane and mapping input data to a feature space with kernel functions [49], optimally dividing the data into two categories of descriptors. Basically, the hyperplane in the sample space can be described as $wx + b = 0$, where w represents the weight vector that decides the direction of the hyperplane and b represents the bias that decides the distance between the hyperplane and the origin. The hyperplane can thus be marked as (w, b). The distance between a random dot x in the

[1][Online]. Available: http://www.oecd.org/pisa/data/2018database/
[2][Online]. Available: https://data.worldbank.org/

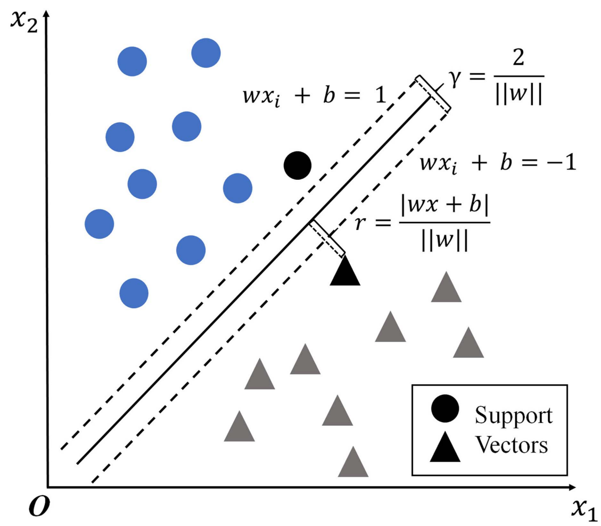

Fig. 1. Mechanism of the SVM.

sample space and (w, b) is

$$r = \frac{|wx + b|}{\|w\|}. \tag{1}$$

Supposing the hyperplane (w, b) can classify the samples correctly. Given $(x_i,\ y\_i) \in D$, if $y_i = +1$, then we have $wx_i + b > 0$; if $y_i = -1$, then we have $wx_i + b < 0$. Let

$$\begin{cases} wx_i + b \geq +1, \ y_i = +1 \\ wx_i + b \geq -1, \ y_i = -1. \end{cases} \tag{2}$$

Accordingly, training sample dots closest to the hyperplane (w, b), which are called as "support vectors," meet (2).

Thus, the distance between the two heterogeneous support vectors and (w, b) is called "margin," which is given as

$$\gamma = \frac{2}{\|w\|}. \tag{3}$$

To find the partition hyperplane with maximum margin involves finding the parameters w and b that can satisfy the constraints in (2) which produce the largest γ, namely

$$\max_{w,b} \frac{2}{\|w\|}$$
$$\text{s.t.} y_i\left(wx_i + b\right) \geq 1, \ i = 1,\ 2, \ldots,\ m. \tag{4}$$

Evidently, to maximize the margin involves maximizing $||w||^{-1}$, which equals to minimizing $||w||^2$, so (4) can be rewritten as

$$\min_{w,b} \frac{\|w\|^2}{2}$$
$$\text{s.t.} y_i\left(wx_i + b\right) \geq 1, \ i = 1,\ 2, \ldots,\ m. \tag{5}$$

This problem can be transformed to a dual problem through the Lagrange function, and the calculation of the parameter can be easily achieved. The components of SVM are shown in Fig. 1.

Considering that the SVM algorithm cannot evaluate the importance of predictors, researchers designed SVM recursive feature elimination (SVM-RFE) to identify the most relevant variables [50]. SVM-RFE operates by deleting the feature with the least weight at each iteration, continuing until all factors have been eliminated [51]. In addition, to examine the ability to generalize a model to an independent dataset, the SVM-RFE cross-validation (CV) can be used to find the best hyperparameters. Given a dataset $D = \{(x_1, y_1), (x_2, y_2), \ldots,\ (x_n, y_n)\}$, in k-fold CV, D is divided into k mutually exclusive subsets. Each time, the union of the $k-1$ subset is used as the training set, and the remaining subset is used as the test set so that the k-group training set can be obtained. Finally, the mean value of the k time results is calculated. Together with the SVM-RFE, CV can provide insights into the optimal number of features to select in the SVM model [52].

C. Instrument Used and Their Evaluation

The performance of the machine-learning model can be measured by a series of indicators, namely, an accuracy score (ACC), a sensitivity score (SEN), a precision score, an $F1$-score, and an area under curve (AUC) score. The ACC refers to the number of successfully predicted high performer plus the number of successfully predicted low performers, versus the total number of students. The SEN indicates the proportion of students that were correctly identified by the ML classifier as high performers, versus the total number of actual high-performing students. The precision is the proportion of students who were actually high performers among all those that the ML algorithm predicted to be such [49]. The $F1$-score is a comprehensive indicator of precision and recall, which allows for comparisons between different algorithms. The AUC is the area under the receiver operating characteristic (ROC) that represents the probability that the ML classifier decides the scores of high performers are higher than those of the low performers [8]. These matrices are developed using a confusion matrix composed of true positive (TP), false positive, true negative, and false negative (FN). TP indicates the positive cases that are correctly predicted by the machine-learning methods, and so forth [53]. These five indicators can be obtained as follows:

$$\text{ACC} = \frac{\text{TN} + \text{TP}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}} \tag{6}$$

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}} \tag{7}$$

$$\text{SEN} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{8}$$

$$F1 - \text{score} = \frac{2\text{T}\left((\text{TP}/\text{TP} + \text{FP}) \times \text{SEN}\right)}{(\text{TP}/\text{TP} + \text{FP} + \text{SEN})} \tag{9}$$

$$\text{AUC} = \int_0^1 \text{ROC}\,(t)\, dt. \tag{10}$$

In addition, a novel visual and intuitive technique, namely, the Shapley additive explanations (SHAP) method is used here to help detect the assign credit for the machine-learning models to each factor and visualize the feature attributions. SHAP method is well recognized in the enhancement of machine-learning interpretability, which has recently been widely used in a series of studies predicting students' educational performance [54],

[55]. The SHAP values originated from game theory jargon, namely, Shapley values. They are composed of two parts: a game and players. "Game" refers to the results of the predictive model, while "players" indicate the features in the model [56]. The Shapley value for a function i out of n total features can be calculated as

$$\phi_i\left(p\right) \sum_{S \subseteq \setminus \{i\}} \frac{|S|!\left(n-|S|-1\right)!}{n!} = \left[p\left(S \cup \{i\}\right) - p\left(S\right)\right] \tag{11}$$

where S is a subset of n, n is the set of all features, $p(S \cup \{i\})$ is a model trained with the subset features, and $p(S)$ is a model trained without the features [56].

D. Data Analysis

In data preprocessing, samples with more than 30% missing data were first removed. The remaining school-level missing data were imputed with information from the same school, and the student-level missing data were imputed with the nearest-neighbor mean value [44]. After that, the nominal and ordinal variables were converted into dummy variables, and the interval variables were normalized through min/max scaling. The preprocessed data were then analyzed with Python 3.7.0. The dataset with 150 factors was examined by the SVM classifier to determine whether the model was able to differentiate these three cohorts of students. The SVM-RFE was then performed to reorder the 150 factors according to their classification weights. Finally, a 10-fold CV was adopted, with nine sections randomly acting as the training data and the remaining section being evaluated to yield the optimal model [57], [58]. The Python code used in this article were uploaded on Github,[3] and the data and descriptions of the samples have been uploaded on IEEE Dataport.[4]

IV. Results

A. Algorithmic Tuning and Classification Performance of the SVM Models

Before training the SVM models, hyperparameter tuning was performed to ensure the efficient model performance. The penalty parameter (c) in the linear SVM model is used to control the tradeoff between the decision boundary [49]. A large c indicates a high penalty, where the SVM model intends to minimize the number of misclassified examples, resulting in a decision boundary with a small margin. In this article, the GridSearchCV function in the Scikit-learn package was applied to identify the optimal value for the penalty parameter [59], [60]. The hyperparameter tuning process of the three models throughout the 10-fold CV is provided in Fig. 2 for ease of reference. The ACC was used as the evaluation metric to determine the "best parameter(s)" [58]. The ACC of the model increased before the best parameter reached a plateau around it and decreased when c exceeded the optimal value. The optimal c for the HL model and LA model is 0.1, and for the HA model, it is 0.01, achieving the highest accuracy. The predictive modeling of student performance was thus performed with the best parameter, showing robust results.

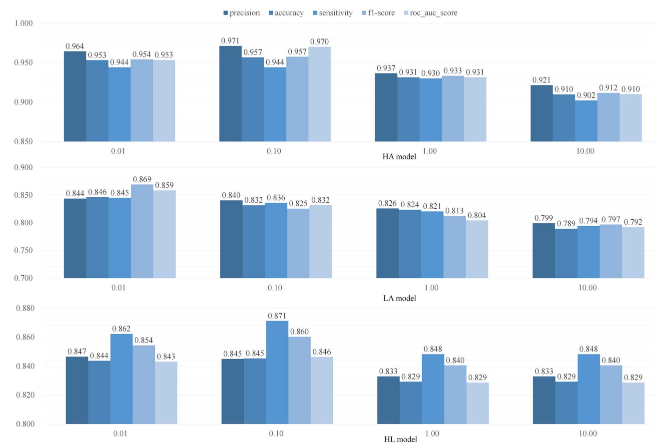

Fig. 2. Parameter tuning process for three SVM models.

TABLE I
PREDICTIVE PERFORMANCE OF THE SIX SVM MODELS

Classification	Number	ACC	AUC	F1	SEN	Precision
high-low	150	0.957	0.970	0.957	0.944	0.971
	20	0.940	0.939	0.927	0.941	0.929
high-average	150	0.846	0.859	0.869	0.845	0.844
	20	0.833	0.827	0.830	0.821	0.819
low-average	150	0.845	0.846	0.860	0.871	0.845
	20	0.831	0.832	0.821	0.828	0.793

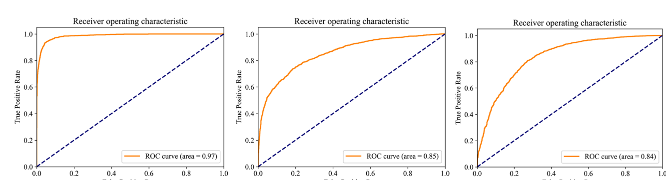

Fig. 3. ROC curves and AUC scores of the SVM models for HL, HA, and LA.

The predictive performance of the three SVM models is presented in Table I. Specifically, the effectiveness of the ROC curve is presented in Fig. 3 along with the AUC straightforwardly. The three SVM models composed of 150 factors all exhibit excellent performances in the binary classification, with all indicators all around 0.80. The high–low (HL) model of the selected features shows the highest ACC at 0.957 in classifying the two cohorts of students, followed by the high–average (HA) model at 0.846 and the low–average (LA) model at 0.845. This indicates that the three cohorts of students can be classified with high accuracies with these features, with the gap between high performers and low performers being the largest. Previous articles found that the minimum number of factors in the optimal factor set that shows robust nonparametric estimates on the statistical relevance of data features for the SVM model was generally between 20 and 30 [44]. In this analysis, we witnessed an upward trend of the ACC score with an increase in the number of factors

[3][Online]. Available: https://github.com/Eve-Peng/Data-and-Code-For-Decoding-Contextual-Factors-

[4][Online]. Available: https://ieee-dataport.org/documents/original-and-imputed-data-decoding-contextual-factors-differentiating-adolescents%E2%80%99-high

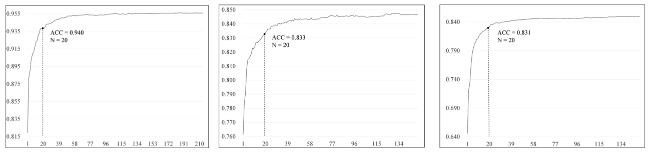

Fig. 4. Accuracy scores of various sets of variables with 10-fold CV for the three pairwise distinctions.

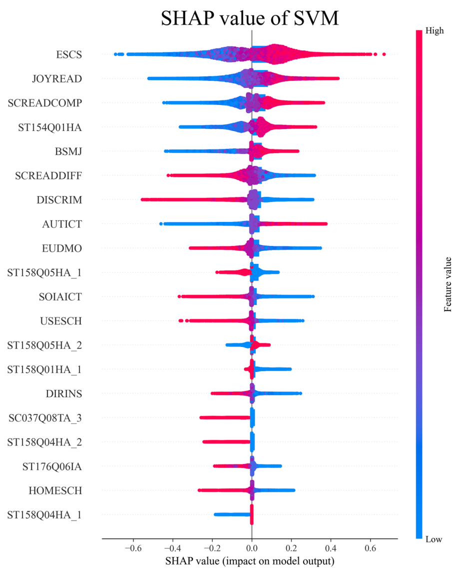

Fig. 5. SHAP values and influencing directions for features in the HL model.

selected. When the number of features selected reaches 20, the performances of the HL model, HA model, and LA model level out at 0.940, 0.833, and 0.831, respectively (see Fig. 4)

B. Ranking and Descriptions of the 20 Key Factors for the Three Pairwise Distinctions

The ranking and descriptions of the 20 key factors for the HL model, HA model, and LA model are elaborated in Tables II and III, respectively. The results show that a variety of contextual factors from the student, classroom, and school levels synergistically contribute to the three pairwise distinctions of digital readers with high accuracy and efficiency. Some of the factors of importance overlap (e.g., ESCS, JOYREAD, EUDMO, SCREADDIFF, and BSMJ), while others indicate noteworthy differences, e.g., INTICT was significant only in the LA model, and DISCLIMA was only identified as important in the LA model. In addition, the different rankings of some variables that are commonly identified as influential in the three models also need to be given special attention. The main thrust of the discussion delves into the most important features that distinguish high performers and low performers in digital reading, comparing the HA and LA models for the reading profiles of high-, average-, and low-performing students.

TABLE II
DESCRIPTIVE STATISTICS OF THE KEY FACTORS IN THE THREE MODELS

Variables	Descriptions	Overall Mean (SD)	Mean (SD) for High Performers	Mean (SD) for Average Performers	Mean (SD) for Low Performers
ESCS	Index of economic, social and cultural status	-0.027 (1.027)	0.628 (0.752)	0.051 (0.961)	-0.546 (1.104)
BSMJ	Students expected occupational status	67.092 (17.805)	74.084 (12.230)	68.248 (16.923)	60.483 (20.433)
JOYREAD	Like reading	-0.025 (1.109)	0.735 (1.082)	-0.018 (1.118)	-0.350 (0.921)
SCREADCOMP	Perception of reading competence	-0.002 (0.979)	0.717 (0.909)	0.034 (0.938)	-0.408 (0.948)
SCREADDIFF	Perception of reading difficulty	0.001 (0.978)	-0.512 (0.844)	-0.039 (0.945)	0.336 (1.020)
EUDMO	Eudaemonia	0.075 (0.906)	-0.111 (0.905)	0.060 (0.906)	0.200 (0.886)
SOIAICT	ICT as a topic in social interaction	-0.003 (0.809)	-0.184 (0.773)	-0.001 (0.810)	0.061 (0.806)
AUTICT	Perceived autonomy related to ICT use	0.019 (0.815)	0.152 (0.799)	0.037 (0.806)	-0.093 (0.838)
INTICT	Interest in ICT	0.014 (0.847)	0.095 (0.683)	0.052 (0.818)	-0.145 (0.973)
HOMESCH	Use of ICT outside of school (for school work activities)	-0.002 (0.841)	-0.106 (0.560)	-0.024 (0.809)	0.115 (1.009)
GFOFAIL	General fear of failure	0.010 (0.952)	0.214 (0.951)	0.014 (0.955)	-0.085 (0.928)
WORKMAST	Work mastery	0.043 (0.966)	0.180 (0.900)	0.082 (0.944)	-0.141 (1.039)
ST176Q01IA	Reading emails	3.080 (1.052)	3.370 (1.003)	3.090 (1.024)	2.900 (1.131)
ST176Q02IA	Chatting online	4.570 (0.908)	4.630 (0.803)	4.630 (0.822)	4.330 (1.148)
ST176Q05IA:	Searching information online to learn about a topic	3.830 (0.976)	4.050 (0.797)	3.870 (0.926)	3.570 (1.143)
ST176Q06IA	Taking part in online group discussions or forums	2.570 (1.160)	2.500 (1.013)	2.550 (1.143)	2.640 (1.264)
ST158Q01HA	Teaching to use keywords when using a search engine	1.448 (0.497)	1.485 (0.500)	1.471 (0.499)	1.355 (0.479)
ST158Q04HA	Teaching to understand the consequences of making information publicly available online	1.227 (0.419)	1.157 (0.3641)	1.211 (0.416)	1.293 (0.455)
ST158Q05HA	Teaching to use the short description below the links in the list of results of a search	0.533 (0.499)	1.676 (0.468)	1.548 (0.498)	1.430 (0.495)
ST158Q06HA	Teaching to detect whether the information is subjective or biased	1.443 (0.497)	1.355 (0.479)	1.459 (0.498)	1.425 (0.494)
ST154Q01HA	The length of reading text in class	3.690 (1.473)	4.330 (1.245)	3.770 (1.451)	3.200 (1.486)
SC037Q08TA	Teacher mentoring	2.120 (0.641)	2.050 (0.595)	2.120 (0.636)	2.120 (0.673)
SC061Q01TA	Student truancy	2.300 (0.810)	2.110 (0.771)	2.260 (0.799)	2.520 (0.821)
ADAPTIVITY	Adaptation of instruction	0.002 (0.999)	0.168 (0.967)	0.013 (0.990)	-0.099 (1.030)
DIRINS	Teacher-directed instruction	-0.012 (0.956)	-0.133 (0.824)	-0.038 (0.925)	0.124 (.1.086)
USESCH	Use of ICT at school	0.017 (0.822)	-0.074 (0.644)	-0.020 (0.798)	0.178 (0.937)
PROAT5AM	Teachers: ISCED LEVEL 5A Master	0.380 (0.330)	0.421 (0.338)	0.385 (0.332)	0.347 (0.318)
DISCLIMA	Disciplinary climate in class	0.013 (1.062)	-0.306 (0.514)	0.059 (1.041)	-0.225 (1.110)
DISCRIM	Discriminating school climate	-0.100 (0.722)	0.227 (1.020)	-0.152 (0.687)	0.155 (0.833)

Note. The data were retrieved from the PISA 2018 database. M refers to the mean score, and SD refers to the standard deviation.

C. Direction of Effects for Each Feature in the Models

The directions of the effects of each feature on students' digital reading performance produced by the SHAP methods are provided in Figs. 5, 6, and 7. Each dot in the figure is the SHAP value of a feature of a case, with the vertical axis

TABLE III
RANKING OF THE 20 KEY FACTORS FOR THE THREE PAIRWISE DISTINCTIONS

MODEL	HIGH-LOW		HIGH-AVERAGE		LOW-AVERAGE	
	RANK	FEATURE	RANK	FEATURE	RANK	FEATURE
STUDENT-LEVEL FACTORS	1	ESCS	1	ESCS	1	ESCS
	2	JOYREAD	2	JOYREAD	2	ST154Q01HA
	3	SCREADCOMP	3	SCREADCOMP	3	BSMJ
	5	BSMJ	7	EUDMO	4	SCREADDIFF
	6	SCREADDIFF	8	AUTICT	8	EUDMO
	8	AUTICT	9	SOIAICT	9	SCREADCOMP
	9	EUDMO	10	BSMJ	13	JOYREAD
	11	SOIAICT	11	ST176Q01IA	14	ST176Q05IA
	18	ST176Q06IA	13	SCREADDIFF	17	ST176Q02IA
	19	HOMESCH	15	HOMESCH	18	INTICT
			18	GFOFAIL	19	WORKMAST
					20	ST176Q06IA
SCHOOL-LEVEL AND CLASSROOM-LEVEL FACTORS	4	ST154Q01HA	4	ST158Q05HA_1	5	DISCRM
	7	DISCRIM	5	ST154Q01HA	6	ST158Q05HA_1
	10	ST158Q05HA_1	6	ST158Q06HA_2	7	ST158Q01HA_2
	12	USESCH	12	DISCRIM	10	DISCLIMA
	13	ST158Q05HA_2	14	DIRINS	11	SC061Q01TA
	14	ST158Q01HA_1	16	ADAPTIVITY	12	USESCH
	15	DIRINS	17	SC037Q08TA_3	15	ST158Q04HA_2
	16	SC037Q08TA_3	19	PROAT5AM	16	DIRINS
	17	ST158Q04HA_1	20	ST158Q05HA_2		
	20	ST158Q04HA_2				

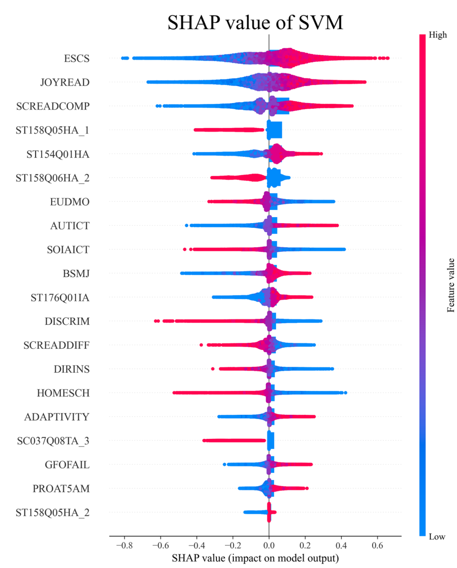

Fig. 6. SHAP values and influencing directions for features in the HA model.

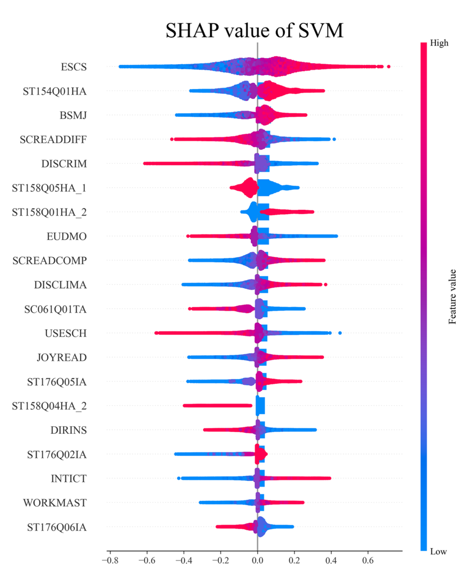

Fig. 7. SHAP values and influencing directions for features in the LA model.

indicating the feature value, the horizontal axis indicating the SHAP value, the red dots representing high feature values, and blue dots representing low feature values. For instance, for the ESCS, its SHAP value corresponding to the red dot is positive, which means that the high feature value of ESCS contributes to students' reading performance from the average of all samples.

Common features identified as important in the three models show similar influencing directions. The positive effects of ESCS, JOYREAD, SCREADCOPM, BSMJ, and AUTICT, and the negative impacts of SCREADDIFF, DISCRIM, SOIAICT, EUDMO, and DRINS are highlighted. For the student-level ICT-related factors, the frequency of taking part in online group discussions or forums (ST176Q06IA) is negatively related to digital reading performance in the HL and LA model, the frequency of reading emails (ST176Q01IA) is positively related to digital reading performance in the HA model, the frequency of searching information online to learn about a particular topic (ST176Q05IA) is positively related to digital reading performance in the LA model, while the frequency of chatting online (ST176Q02IA) is limitedly positively related to digital reading performance in the LA model. For the classroom-level and school-level factors, the length of the reading materials (ST154Q01HA) used in class is a significantly positive factor that distinguishes the high performers from the low performers, and the high performers from the average performers, showing grand importance. The different ICT skills taught at school are all positively correlated with students' digital reading performance, though their importance varies across pairwise distinctions. For instance, teaching how to detect whether information is subjective or biased (ST158Q06HA) is positively related to students' digital reading performance only in the LA model.

V. DISCUSSION

A. Response to RQ (1): Key Factors That Synergistically Distinguish High Performers From Low Performers in Digital Reading

The current article contributed to the ongoing discussion on the contextual factors that influence students' digital reading performances through the utilization of a machine-learning algorithm and the analysis of cross-national reading sources. The results indicate that a variety of contextual factors synergistically shape the digital reading performances of high and low performers.

Ten of the twenty key features are student-level factors, with students' family social, economic, and cultural status (ESCS) ranking first, exerting the strongest effects on the classification results. This finding reinforced the strong effect of students' family economic background on digital performance [6]. It is noted that students' expected occupational statuses (BSMJ) are indispensable in fostering high-performing digital readers [61]. The PISA 2018 results indicate that students who would like to work as ICT professionals in the future were more in touch with the digital environment and read books or the news more often on digital devices than other students [62]. However, since the impacts vary with the dimensions of occupational expectations, future article should disentangle the impact of the various dimensions of this factor.

Four of the student-level factors are motivational components of reading and ICT. Whether students like reading (JOYREAD) was found to be a strong predictor of the performance of digital readers, echoing the findings of many previous articles [63], [64]. In terms of self-efficacy, perception of competence (SCREADCOMP) and difficulty (SCREADDIFF) of reading were also found to be significant positive and negative predictors, respectively. Positive attitudes toward reading can help improve students' memorization, elaboration, and control strategies serving as an important mediator between contextual factors and students' digital reading performance, and vice versa [41]. Regarding ICT-related student-level factors, students' perceived autonomy related to ICT use (AUTICT) is positively related to their digital reading performance, while students' ICT use for social interaction (SOIAICT), frequency of taking part in online group discussions or forums (ST176Q06IA), and ICT use outside of school for school work activities (HOMESCH) were found to be negatively associated with their performance. The results echo with previous findings about the promoting effects of ICT because the autonomy of ICT use is closely and positively related to the self-regulatory process during digital reading [29]. However, ICT use for social interaction and taking part in online discussions could be detrimental for students' digital reading performance because these activities may decrease time available for academic purposes [65]. In addition, the large amount of time spent on ICT use outside of school for school work activities may indicate low efficiency for completing school work, and abuse of ICT without the supervision of parents and teachers.

Regarding classroom-level factors, the length of the reading material used in class (ST154Q01HA) is identified as a strong predictor. Longer reading materials increase the difficulty of reading, thus cultivating students' abilities to cope with complex contents and logic in reading materials [66]. Students' use of ICT at school (USESCH) is a noteworthy negative predictor of their HL performance classification, while teachers' instructional behaviors related to the use of ICT can positively predict students' digital reading performance. Teachers showing students how to use the short description below the links in the list of results of a search (ST158Q05HA) and helping students understand the consequences of making information publicly available online on social platforms (ST158Q04HA) are found to be important positive predictors in this analysis. The results confirm previous findings and further highlight the importance of cultivating digital literacy to improve digital reading performance [67]. Contrary to previous findings, teacher-directed instruction (DIRINS) is found to be negatively associated with students' digital reading performance. This result does not mean that teacher-directed instructions can inhibit students' digital reading performances. In large-scale educational assessments, this derived variable cannot fully capture the various qualities, circumstances, and forms of instruction, thus having only general impacts. A series of researchers have examined the effects of instruction, concluding that factors such as teachers' pedagogical content beliefs [68], teaching strategies [69], and professional development [70] affect the quality of instruction. In addition, the current article identifies teacher mentoring (SC037Q08TA) as an important factor that positively affects students' digital learning, further emphasizing the importance of the quality and capability of teachers in promoting high-performing digital readers.

B. Response to RQ (2): Digital Reading Profiles of Students of Different Achievement Spectra

The HA model and LA model identified through the SVM provide insights into the nuanced differences between students of different achievement spectra that were not revealed by the HL model. Through comparisons of high and average performers, and of low performers and average performers, the specific learning features of the average performers are identified.

On the one hand, compared with high performers, average-performing digital readers read emails less frequently (ST176Q01IA), which was an interesting finding in our analysis. Most previous articles examined email-reading activities along with other online social activities, providing mixed findings about their impacts on digital reading performance [24], [65]. Our analysis further highlights the nuanced differences between reading emails and other online social activities and its significant role in distinguishing high performers from average performers. Different from other online social activities, receiving and sending emails is a more "formal" mode of dialog journaling that involves careful dictation, rich content, and sometimes file attachments [71]. More importantly, this asynchronous collaborative digital learning environment allows for more in-depth consideration and critical reflection about the topic discussed.

Another noteworthy finding is that compared with average performers, highly skilled readers are strongly associated with higher teacher qualifications (PROAT5AM). Teachers with higher qualifications generally have more professional knowledge and practices, providing individualized instruction for various students [70]. In addition, the HA model also highlights the importance of teachers teaching average-performing students to detect whether information online is subjective or biased (ST158Q06HA). Previous article has found that perceived credibility of an online article and recall are both strong predictors of knowledge gain during digital reading [3], [72]. Considering that students can feel overwhelmed by a deluge of messages, teachers should assist students in being cautious and prudent in judging multiple sources online [73], which could thus further improve their digital reading comprehension and engagement.

On the other hand, the LA model indicates that low-performing digital readers are characterized by a lack of interest in ICT (INTICT) compared with average performers. Previous articles show that students with more positive attitudes toward computers take part in computer-related activities more frequently and thus develop more advanced computer knowledge and skills [17]. Different from print reading, motivational components related to ICT use are thus an important part of promoting low-performing students' digital reading literacy [74]. Our results contribute to the ongoing discussion of the role of interests affecting low-performing digital readers, which helps answer the question of whether digital reading and print reading share the same motivational process.

The use of ICT at school (USESCH) is a feature that boasts higher importance ranking in the LA distinction than in the other two distinctions. Low-performing students generally use more computer devices at school than average performers and high performers in digital reading. Specifically, they take part in online group discussions or forums (ST176Q06IA) more frequently, while they search for information online to learn about a particular topic (ST176Q05IA) less frequently, which further confirms the findings of previous article [63]. Our analysis also finds that this phenomenon is more common in students with low digital reading proficiencies and low work mastery (WORKMAST). Due to a lack of self-regulation and basic skills, these students are more prone to the excessive use of ICT and addiction to online social activities, highlighting the significance of the school's role in the planned application of ICT in digital reading education.

The LA model also indicates that low digital reading performers are more susceptible to truancy (SC061Q01TA) and are more likely to be in an out-of-order classroom disciplinary climate (DISCLIMA) than average performers. These two factors are found to be less effective in the HA model. Informed by the general learning theory that students' learning is influenced by their surroundings, an orderly classroom and school environment has been considered an important variable for student learning. It is also notable that discriminating school climate (DISCRIM) ranks second in the LA model, indicating that low-performing students may suffer more from discrimination from either peers or teachers. Experiences with discrimination and prejudice in school environments can worsen students' academic performances [75]. If students perceive that teachers are unfair or biased, they may double down on deviant exploits [76]. This article identifies the importance of a supportive, disciplined, inclusive, and welcoming school and classroom climate, which could contribute to better digital reading achievement, especially for low-skilled digital readers. Only in schools that are equal and classrooms that are strictly managed can students explore their potential to the greatest extent.

C. Response to RQ (3): Providing Tailored Instruction and Guidance for Digital Readers in an Innovative way

Different from conventional statistical methods, the machine-learning algorithms used in this article could help reveal the complex associations among variables through the three pairwise comparisons between students of different achievement levels. Previous investigations have utilized a series of machine-learning algorithms to predict students' academic performance. Supervised classifiers are widely adopted, and their performance has been validated and compared across learning contexts and disciplines in studies using PISA database [8]. Regarding students' mathematics performance, previous articles have compared logistic regression, Fisher's discriminant analysis, and SVM algorithms, showing that SVM algorithms outperform the former two, and the optimal feature set is mainly composed of student-level factors [44]. For reading, researchers used data from PISA 2015 and compared three machine-learning methods for variable selection, concluding that they could produce comparable results and students' reading performance is significantly positively related to their academic anxiety [77]. Another study used logistic regression, SVM, decision tree, and extreme gradient boosting simultaneously to predict high- and low-performing readers in PIRLS, showing students' affective variables related to reading, rather than teachers' instructional practices, to be the most significant factors [58]. This article confirmed these findings by using SVM to identify more student-level affective variables than the school-level factors in the HL model and HA model with high efficiency, and innovatively identified the significant teacher-related features in the LA model, which has not been determined by previous article. This indicated that teacher instruction is essential for low-performing students because these students with low self-regulation ability and learning capability usually lack autonomy in learning.

The factors identified in the three machine-learning models not only help distinguish high and low digital reading performers with high accuracy but also innovatively provide information on their specific reading profiles, according to which tailored instruction for gradual improvement could be devised, and the flexibility of educational offerings should be considered to provide broader knowledge base for digital reading literacy [78]. The HL distinction of this article leads us to consider the importance of the cooperation and coordination of various parties (i.e., students, parents, teachers, and principals) to achieve high digital reading proficiency. Students should equip themselves with interests in reading and ICT use as well as the corresponding skills and should develop strong self-disciplinary habits to avoid the overuse of ICT resources. To enhance students' digital reading competence, it is essential for parents and teachers to prioritize information-seeking activities rather than recreational activities at both home and school for students, which resonates with the findings of previous articles [8]. Instructional behaviors for ICT use in the classroom should not be dismissed. Educators and instructors should adaptively guide students' ICT use in reading class, with an emphasis on various aspects according to the levels of the specific digital readers. The instructors should also be fully qualified and prepared to function in digital education settings [79]. More importantly, they should further reflect upon how ICT resources can facilitate specific pedagogical strategies [80]. In reading class, multimodal online reading materials with appropriate length should be designed and provided, accompanied by effective instructions, tailored feedback, and appropriate supervision to provide a productive and enjoyable learning environment.

For students with an average or high level of digital reading proficiency, instructors should further foster their autonomy in both ICT use and reading. In addition, instructors should help them develop morally sound values and outlooks on the digital world so that they can have a more accurate positioning and grasp of the information contained in reading materials. For low-skilled digital readers, however, attention should be given to the cultivation of interests in ICT and basic ICT skills. Teachers should incorporate ICT resources into teaching and mobilize ICT resources at school to help them create a cognitive engagement and a sense of affinity to the digital environment, psychologically accept digital reading, and become interested in it to improve their digital reading self-efficacy. For instance, flipped classrooms are found to largely improve low-performing students' learning motivation and learning strategy [81]. In addition, computer-aided learning, which deals with basic knowledge of reading (e.g., phonological and orthographic syllables), should be considered for the low-performing readers [82]. Due to a lack of self-regulated learning strategies, low-level digital readers often abuse social media for recreational purposes at school. To fully exploit the potential of ICT-related instruction, school principals and teachers should thus try to create a well-disciplined school and classroom climate and supervise the use of ICT resources.

VI. Conclusion and Limitations

Through the utilization of SVM and the SHAP method, this article explored the effects of multilevel factors on students' digital reading performances based on the PISA 2018. Compared with previous articles in this field, this article not only involves a detailed comparison of students of different achievement spectra through three dichotomous machine-learning classifications but also supplements the results with the SHAP method to increase their interpretability. The invitation of machine-learning methods into the field of reading research helps ascertain the important determinants from the large-scale dataset with high efficiency. The factors newly found via different machine-learning models can shed light on the existing reading education theories from a different perspective, and the three pairwise distinctions can reveal nuanced differences between students, underlying students' unique reading profiles and help the instructors provide tailored pedagogical support. The SHAP method can help to quantify feature importance at the observation level for the machine learning algorithm and show the dynamic effects of the factors. It increases the interpretability of the opaque machine-learning algorithm in a straightforward and intuitive way. Researchers can further use this powerful method to identify the optimal threshold for the quantity of a factor, contributing to the development of students' sustainable habits and the optimization of system design for a supporting learning environment. It is thus an effective tool that should be incorporated within the student reading performance prediction framework for a more comprehensive and in-depth analysis [55].

The collective impacts of the optimal feature set composed of the 20 most important predictors of the three levels were systematically measured. In addition, the article revealed the unique rules of the influencing pattern of digital readers of different achievement spectra through the development of two other models, namely, an HA model and an LA model. This article provides important insights into individualized pedagogy and instruction, the coordination of ICT resources, and concerns about students' overall and sustainable reading literacy development in the digital era.

A few limitations in this article can be addressed in future investigations. First, the SVM used in this article could examine only the collective impacts of the optimal feature set. However, the detailed associations between these key factors should be analyzed with the help of techniques, such as mediation analysis (e.g., how students' interests in ICT and ICT self-efficacy might mediate the relationship between ICT resources at home and school and digital reading performances). Second, as a cross-sectional assessment, the PISA cannot measure students' changes in reading literacy over a long period of time. Future analysis should focus on the collection of longitudinal data for an overall investigation of the development of students' digital reading literacy. Third, considering that the utilization of different machine-learning methods may yield different optimal features and show divergent efficiencies, future article should compare the performance of these powerful approaches in various contexts for a more comprehensive analysis of the determinants of students' digital reading performance.

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