TURJE
www.turje.org

2025
Volume: 14 Issue: 1

Turkish Journal of Education

https://doi.org/10.19128/turje.1431545
Research Article

Received 04.02.2024
Accepted 15.11.2024

Predictors of reading performance of fourth-grade Turkish students

Kıvanç Bozkuş
Artvin Çoruh University, Department of Educational Sciences, Artvin, Türkiye, kbozkus@artvin.edu.tr

ABSTRACT Using machine learning, this research aimed to examine the crucial factors that predict the reading performance of fourth-grade students from Türkiye who participated in PIRLS 2021. When trained with the data of 3589 fourth-grade students and their 405 independent variables, the support vector machine (SVM) algorithm properly distinguished between high- and low-performing students based on 16 key contextual factors at the school, teacher, and family levels. The main factors were at the school level and were related to placing a major emphasis on instruction and the ability of students to borrow books. The teacher-level factors were the assessment strategy, helping students develop reading comprehension skills or strategies, and motivation. The only family-level factor was the parental commitment to ensure that students are ready to learn. Compared to the results of the whole PIRLS 2021 data, the findings of this research revealed a big difference in the key factors predicting the reading performance of fourth graders from Türkiye. Possible reasons were discussed, and new educational policies, interventions, and research practices were suggested. At the policy level, an approach that systemically addresses school, teacher, and family factors may yield more meaningful improvements in reading performance. In terms of interventions, the findings suggest a focus on interactive teaching and assessment strategies that involve students actively interacting with text. As for research practices, this study highlighted the potential of machine learning as a valuable tool to understand the complex, multi-dimensional nature of student performance.

Keywords: *Machine learning, PIRLS, Reading performance, SVM, Türkiye*

Dördüncü sınıf Türk öğrencilerinin okuma performansının yordayıcıları

ÖZ Makine öğrenimini kullanan bu araştırma, PIRLS 2021'e katılan Türkiye'den dördüncü sınıf öğrencilerinin okuma performansını yordayan önemli faktörleri ortaya çıkarmak amacıyla yapılmıştır. Destek vektörleri makine (SVM) algoritması, 3589 dördüncü sınıf öğrencisine ait 405 bağımsız değişkeninin verileriyle eğitildiğinde, okul, öğretmen ve aile düzeyindeki 16 temel bağlamsal faktöre dayanarak yüksek ve düşük performans gösteren öğrencileri doğru bir şekilde ayırmıştır. Ana faktörler okul düzeyindedir ve bunlar öğretime ve öğrencilerin kitap ödünç alma becerisine büyük önem verilmesiyle ilgilidir. Öğretmen düzeyindeki faktörler ise değerlendirme stratejisi, öğrencilerin okuduğunu anlama becerilerini veya stratejilerini geliştirmelerine yardımcı olma ve motivasyondur. Aile düzeyindeki tek faktör, ebeveynlerin öğrencilerin öğrenmeye hazır olmalarını sağlama konusundaki kararlılığıdır. PIRLS 2021 verilerinin tamamıyla karşılaştırıldığında bu araştırmanın bulguları, Türkiye'deki dördüncü sınıf öğrencilerinin okuma performansını öngören temel faktörlerde büyük bir fark olduğunu ortaya çıkarmıştır. Olası nedenler tartışılmış ve yeni eğitim politikaları, müdahaleler ve araştırma uygulamaları önerilmiştir. Politika düzeyinde, okul, öğretmen ve aile faktörlerini sistemli bir şekilde ele alan bir yaklaşımın, okuma performansında daha anlamlı iyileştirmelere yol açabileceği belirtilmiştir. Müdahaleler açısından, bulgular, öğrencilerin metinle aktif olarak etkileşime girdiği etkileşimli öğretim ve değerlendirme stratejilerine odaklanmanın gerekliliğini öne sürmektedir. Araştırma uygulamaları açısından, bu çalışma, öğrenci performansının karmaşık, çok boyutlu doğasını anlamak için makine öğreniminin önemli bir araç olarak potansiyelini vurgulamaktadır.

Anahtar Sözcükler: *Makine öğrenmesi, Okuma performansı, PIRLS, SVM, Türkiye*

Citation: Bozkuş, K. (2025). Predictors of reading performance of fourth-grade Turkish students. *Turkish Journal of Education, 14*(1), 1-18. https://doi.org/10.19128/turje.1431545

INTRODUCTION

The educational system worldwide is a diverse arena, teeming with numerous intrinsic and extrinsic factors that contribute to students' academic achievement. Student performance is the product of an intricate blend of contextual factors at the school, teacher, and family levels, which together construct the scaffolding for academic success. Understanding these dynamics is pivotal to developing effective pedagogical strategies and educational policies. This study focuses specifically on the reading performance of fourth-grade students in Türkiye who participated in the Progress in International Reading Literacy Study (PIRLS) 2021.

Reading performance, a crucial aspect of academic progress, is indicative of future success because it serves as the foundation for all other learning activities. The PIRLS provides a global platform for measuring fourth-grade kids' reading comprehension skills, providing researchers with useful data for understanding global trends and country-specifics. When it comes to a detailed investigation of the elements affecting reading performance, particularly in the context of a country such as Türkiye, the literature is still lacking.

This work intends to close this gap by employing a sophisticated machine learning algorithm to examine the PIRLS 2021 data of 3,581 Turkish fourth students. This research gives a thorough examination of the elements that influence student reading performance by focusing on 405 independent variables. Using the support vector machine (SVM) model, the study aims to differentiate between high- and low-performing students, revealing the complex interaction between school, teacher, and family factors that collectively influence a student's reading performance.

This study aims not only to identify the key factors, but also to permit a comparative analysis with the overall results of PIRLS 2021, shedding light on the unique characteristics of the Turkish setting. By unveiling these differences, the research paves the way for an in-depth discussion of possible reasons and implications, ultimately proposing new educational policies, interventions, and research practices.

The findings of this study offer deep insights that have the potential to influence the educational landscape by informing policy and instructional design. Such an approach will enable educators, policymakers, and stakeholders to craft strategies that cater specifically to the unique needs of the Turkish context, ultimately aiming to enhance the reading performance of students.

Review of the Literature

The exploration of students' academic success is a prevalent focus in contemporary pedagogical discourse, with reading proficiency frequently subjected to scrutiny. It is integral to recognize that reading capabilities and comprehension are cornerstones for students' academic victories, an understanding fundamental to crafting effective educational methodologies (Lim et al., 2015). Reading transcends the status of a rudimentary skill for basic literacy. Instead, it serves as a foundational element for understanding and assimilating various forms of textual information that students encounter throughout their educational journey. The ability to accurately decode and interpret written content fosters an enhanced understanding of diverse topics, thereby propelling academic success (Savolainen et al., 2008).

However, the role of reading extends beyond simple comprehension of the curriculum. It functions as a conduit for the enhancement of other vital competencies such as critical thinking, analytical prowess, and cogent communication (Kettler, 2014). For instance, students who regularly engage with a broad array of reading materials have the potential to fortify their cognitive abilities more holistically (Frijters et al., 2018). Skilled readers are typically more motivated to take an active role in classroom activities, collaborate with peers, and approach assignments with enthusiasm, all of which contribute favorably to their academic progression (Kikas et al., 2018).

The landscape of academic success is governed by myriad factors, with reading proficiency occupying a central position. As an essential skill for students, reading underpins the acquisition of knowledge across disciplines (Lin & Powell, 2022). To fully grasp the context-specific factors, it becomes imperative to consider the unique circumstances and settings that each learner navigates beyond their immediate academic environment (Dong & Hu, 2019). A significant body of literature has been dedicated to the exploration of factors that influence student academic performance. These factors can be broadly grouped into three categories: school, teacher, and family. Each level contributes to the multifaceted picture of student achievement in its unique way.

At the school level, prior studies (Wang & Degol, 2016; Wolniak & Engberg, 2010) have recognized the pivotal role that school resources play in shaping student performance. Facilities like libraries and access to instructional resources have been positively linked with increased student achievement (Archibald, 2006). Schools equipped with operational and richly furnished libraries provide students with expanded access to a wide array of books and varied reading resources. This interaction with a plethora of genres, styles, and themes not only enhances their literary landscape but also bolsters their reading abilities (Ameyaw & Anto, 2018). The state of classrooms and auxiliary learning spaces, inclusive of designated reading nooks, is of significant relevance. Students demonstrate a heightened propensity to engage in reading activities within environments that are brightly lit, comfortable, and inviting. It is evident that the quantity of reading undertaken is a crucial determinant in the advancement of reading proficiency (Allington & McGill-Franzen, 2021). However, it is worth noting that in the Turkish context, the role of school resources, specifically the availability of books for students, has received less consideration in the literature.

Teacher-level factors, such as teaching strategies and assessment policies, have also been identified as key contributors to student achievement. For instance, research conducted by Eker (2014) found that effective teaching strategies significantly influence students' reading skills. Meanwhile, other studies have focused on the teacher's role in motivating students (Law, 2011) and fostering a positive learning environment (Bannister et al., 2015), underscoring the impact of these variables on student achievement.

At the family level, the role of parental commitment has been explored extensively in the literature. Numerous studies (Hill & Tyson, 2009; Jeynes, 2007) have shown that strong parental involvement correlates positively with enhanced academic performance. Nonetheless, within the Turkish context, the exploration of family-level factors has been relatively limited, primarily focusing on socio-economic status, with less emphasis on parental commitment to the learning readiness of students.

Integration of machine learning with educational research has emerged as a new field in recent years. In the field of education, machine learning techniques such as SVM have been employed to predict student performance (Chen et al., 2022; Hu et al., 2022), but their application in the context of reading performance, notably in Türkiye, is noticeably lacking.

While these studies provide valuable insights into student academic performance, a critical gap remains in terms of a comprehensive, data-driven exploration of factors affecting reading performance, particularly in specific cultural contexts like Türkiye. This study aims to address this gap by leveraging machine learning to analyze a rich dataset from PIRLS 2021, taking into account a vast array of independent variables at the school, teacher, and family levels.

Problem Situation

Reading comprehension is a cornerstone of education. It forms a foundational basis for learning across all academic disciplines and is a potent determinant of an individual's future academic and professional trajectory (Leahy & Fitzpatrick, 2017). Despite its importance, accurate prediction of reading performance, particularly in large and diverse student populations, remains a formidable challenge. The complexity is further compounded by the need to consider the plethora of interrelated factors that influence reading performance (Dong & Hu, 2019). There is a gap in the literature on the factors that can separate high-performing readers from those who perform poorly (Chen et al., 2022; Hu et al., 2022). The lack of a firm grasp of these factors hinders the creation of comprehensive educational policy and tailored intervention strategies (Lee & Shute, 2010; Swain-Bradway et al., 2015). In a world moving rapidly towards digitization and information abundance, equipping students with competent reading skills is not just desirable but an absolute necessity.

The most substantial challenge lies in understanding and dissecting the role of various school, teacher, and family factors in shaping a student's reading performance. It is not uncommon for educational stakeholders to face a conundrum while designing effective interventions, given the intertwined nature of these factors. While previous studies have contributed to this field by identifying and understanding some general predictors of reading performance (Chen et al., 2022; Hu et al., 2022), a more comprehensive, in-depth, and nuanced analysis specific to a particular cultural and educational context, such as Türkiye, is missing in the literature.

Moreover, traditional statistical approaches used in prior research often lack the sophistication required to handle the vast array of independent variables that may influence student performance. Machine learning models, such as the Support Vector Machine (SVM), promise to overcome this limitation by efficiently processing large datasets and illuminating intricate patterns within them.

In this light, this study aims to address the problem of understanding the complex interplay of factors that predict the reading performance of fourth-grade students in Türkiye. By applying the SVM model to the extensive PIRLS 2021 dataset, this research aims to navigate the intricate mesh of school, teacher, and family-level variables and unravel their respective impacts on reading performance. Furthermore, this study intends to compare these findings with the overarching results of PIRLS 2021, identifying and elucidating the unique factors at play in the Turkish context.

The successful resolution of this problem will provide key stakeholders with the much-needed insights to formulate and implement data-informed educational policies and interventions, with the potential to significantly improve the reading performance of students in Türkiye. Therefore, this research aims to answer these questions:
1) Can contextual factors distinguish fourth-graders of PIRLS 2021 who perform well in reading from those who perform poorly?
2) If so, what factors are of the greatest importance to the classification?
3) If these factors are ranked in order, what differences exist compared to the whole PIRLS 2021 data of 65 countries?

METHOD

This research employed ex post facto design and used machine learning to reveal the key factors predicting the reading performance of fourth-graders from Türkiye who participated in PIRLS 2021. To analyze large data sets using machine learning, some steps should be followed in order (Lewis, 2017; Pallathadka et al., 2022). These steps are obtaining the data set, understanding the data, data pre-processing, feature selection, splitting the data, choice of a machine learning model, training of the model, evaluation of the model, and interpretation of the results. In the following headings, these steps are explained in detail.

Data

The data for this research were procured from the openly accessible dataset of PIRLS 2021 (pirls2021.org/data). Distinguished from its predecessors, PIRLS 2021, successfully conducted in 57 countries and eight benchmarking entities, showcases unique features. A key distinction is the concerted efforts poured into converting PIRLS 2021 into an advanced digital assessment, presenting students with

23 dynamic and immersive texts through an innovative group adaptive approach. Another notable characteristic was the unforeseen COVID-19 pandemic, which transpired amidst the biennial PIRLS 2021 data-gathering phase. Despite numerous disruptions in data collection within schools, most nations managed to meet the standards for high-quality data acquisition. Consequently, PIRLS 2021 now stands as the sole international comparative source for fourth-grade achievement data compiled during the pandemic (Mullis et al., 2023). Participation in PIRLS 2021 saw over 4,000 students from approximately 150 to 200 schools in each participating nation. The data encompass information from roughly 400,000 children, 380,000 parents, 20,000 teachers, and 13,000 schools. An in-depth assessment of the sampling procedure validated that almost all countries adhered to all sampling specifications (Mullis et al., 2023). The vast majority of the 57 participating countries and 8 benchmarking bodies satisfied the population coverage requirements, and a significant portion also met the criteria for minimal exclusion rates (under 5 percent). In summary, the PIRLS 2021 data can be regarded as of high quality (Mullis et al., 2023).

Data gleaned from student, teacher, home, and school questionnaires were assembled, and these files were coalesced into a singular file utilizing a program scripted in R by the author. The consolidated raw file comprised data from 6032 students. This raw data underwent a three-phase pre-processing sequence: purification, imputation, and normalization, as practiced by Hu et al. (2022). Initially, instances containing over 20% absent data were purged. Following the purification phase, the sample count decreased to 5538. Subsequently, the extant missing data points were imputed via the k-nearest neighbor mean value function, which replaces all void values by taking into account the k closest counterparts of each case with missing data. It leverages these proximate values and calculates a weighted mean (based on the distance to the case) to replace the missing values. The k-value was set to 10. Ultimately, the data underwent normalization using centering and variance scaling principles.

At the inception of the data pre-processing, the consolidated raw file incorporated 545 variables. Given that machine learning necessitates substantial computational resources, only those variables with potential implications on student success were retained. Hence, the author manually scrutinized each variable, discarding irrelevant variables from the dataset. Consequently, the final dataset incorporated 405 independent variables.

The dependent variable in this research is the students' reading test scores in PIRLS 2021. In order to forecast the factors influencing student reading performance, an initial step involves creating an identifier variable to differentiate high-performing students. For this purpose, the benchmark score (ASRIBM01) of the first plausible value was arbitrarily chosen to represent the student's reading scores, a method corroborated by prior studies (Chen et al., 2019; Gorostiaga & Rojo-Alvarez, 2016; Hu et al., 2022). The benchmark score encapsulated five categories: 1) below 400 (n= 623), 2) at or above 400 but below 475 (n= 1176), 3) at or above 475 but below 550 (n= 1949), 4) at or above 550 but below 625 (n= 1425), 5) at or above 625 (n= 365). This score was recoded into a fresh variable, serving as the identifier variable utilized in machine learning for model training. The identifier variable is required to signal whether each student is successful. Therefore, the initial two categories of the benchmark score (1) below 400, 2) at or above 400 but below 475) were deemed unsuccessful, while the final two categories (4) at or above 550 but below 625, 5) at or above 625) were classified as successful. The reconstituted identifier variable comprised two categories: 1) low performance (n= 1799), 2) high performance (n= 1790). Consequently, the ultimate dataset incorporated 3589 students and 406 variables.

It is important to clarify the rationale behind this methodological decision and explain why reverting to the original multi-category classification would be detrimental to the study's objectives. This research aims to identify a concise set of factors that can effectively distinguish between high- and low-performing students, ultimately informing targeted interventions. While preserving the full spectrum of reading achievement is important in some contexts, this research specifically focuses on identifying key predictors of success versus struggle. Using the original five-category benchmark score resulted in a complex model with 60 predictive factors and an accuracy of only 0.68. This complexity hinders interpretability and practical application. Conversely, the binary classification, while simplifying the outcome variable, yielded a parsimonious model with 16 factors and a significantly higher accuracy of 0.95. This streamlined model offers greater clarity and actionable insights for educators and policymakers. Furthermore, the binary classification aligns with the research question, which seeks to understand the factors that differentiate students who are likely to succeed from those who are likely to struggle. The selected cut-off point for the binary variable was carefully chosen based on the distribution of scores and reflects a meaningful distinction in performance levels relevant to the research question. The simplification to a binary classification was not arbitrary but a reasoned decision to achieve the specific objectives. This approach, while acknowledging its inherent limitations, yielded a more interpretable and impactful model with significantly higher accuracy compared to utilizing the full five-category scale.

Data Analysis

In the domain of machine learning, Support Vector Machines (SVM) are supervised learning models that scrutinize data for classification purposes. They hold a high reputation as reliable prediction methods, stemming from their foundation in statistical learning frameworks (Pallathadka et al., 2022). The SVM training process crafts a non-probabilistic binary linear classifier from an array of training instances, each labeled as pertaining to one of two classes (viz., unsuccessful, and successful). SVM situates training instances into points in a dimensional space with the objective of maximizing the gap between the two classes (Avolio & Fuduli, 2021). Subsequently, new instances are projected into the same dimensional space, and their class is predicted based on the partition of the gap they fall under. SVM has been recognized as an optimal machine learning methodology in educational research that dissect large-scale international databases (Pallathadka et al., 2022). Nevertheless, the substantial processing time and resources entailed suggest that SVM may be a lengthy process in determining the optimal model.

While suitable for both classification and regression tasks, SVM is more commonly applied for classification dilemmas. There exist multiple ways in which SVM can augment studies in educational research. By considering a spectrum of variables, SVM can be employed to predict student performance or outcomes, assisting in pinpointing the essential elements influencing student success and enabling interventions to enhance outcomes. SVM can also detect students susceptible to dropout or academic lag, paving the way for early support and intervention. The competency of SVM to manage high-dimensional data empowers it to contemplate a myriad of variables simultaneously (Bernardo et al., 2021). SVM fabricates hyperplanes in this multidimensional space, allowing for the classification of students based on diverse aspects of their reading performance and associated factors (Latif et al., 2021). This helps in revealing intricate relationships and interactions between multiple elements that may elude conventional statistical methods. SVM, equipped with its method termed regularization, serves as a reliable model for educational data, which often incorporates numerous variables, and aids in mitigating overfitting (Bernardo et al., 2021).

Support Vector Machines (SVMs) display substantial resilience to outliers, an essential quality in educational research. Outliers often represent unique or atypical instances that may not typify wider trends or patterns (James, 2019). While these outliers could significantly bias alternate machine learning algorithms, SVMs largely remain impervious, thereby ensuring a more accurate portrayal of the overarching educational context.

In the context of predictive accuracy, SVMs frequently surpass many other machine learning methodologies, an attribute of critical importance to educational research (Shimoda et al., 2018). Superior predictive precision enhances the validity of the results, aiding in formulating models to forecast student performance, attrition rates, or the efficacy of distinct teaching methodologies. The ability of SVM to deliver accurate predictions, even when confronted with smaller datasets, stands out as one of its key benefits (Alruwais & Zakariah, 2023). This advantage is especially beneficial in an academic environment where class sizes may be limited, and there may be scant data available per student.

In addressing the first question, the L2-regularized SVM with a linear kernel method was employed using 5-times repeated 10-fold cross-validation (CV) via the caret (Classification And REgression Training) package available for R program. The accuracy, sensitivity, and specificity scores are frequently used metrics in SVM to assess the model's classification capacity. In an SVM model with impeccable predictions, these metrics would return a value of 1. Scores above 0.8 are generally deemed good, and those above 0.7 are considered fair. The data were randomly split into two segments. 70% of the data (n= 2513) was allocated for training, and the remaining 30% (n= 1076) was employed to test the trained SVM model.

To address the second research question, the same caret package was harnessed, coupled with the 5-times repeated 10-fold CV outer resampling method. The technique of recursive feature elimination (RFE) was engaged to discern the key contextual elements predicting the reading aptitude of fourth-grade students. RFE arranges all factors in a descending hierarchy based on their import in classification. The amalgamation of SVM and RFE is a prevalent strategy for feature selection in machine learning (Albashish et al., 2021). This method functions by systematically eliminating features and then constructing a model with the remaining ones, appraising the performance of the model each time to pinpoint which characteristics primarily contribute to the model's accuracy. The RFE procedure was employed with a 5-times repeated 10-fold CV. CV is utilized to ascertain how effectively a machine learning model generalizes to a disparate dataset (i.e., the test set). For the k-fold CV, the original sample is randomly segregated into k subsamples of equivalent size.

In addressing the third question, the ranked factors were juxtaposed with previous research (Bozkuş, 2025), which examined the entire PIRLS 2021 dataset from 65 countries using a similar approach.

RESULTS

Results to Answer the First Question

The accuracy of the SVM model, representing the proportion of true results in the population, is recorded at 0.957. This indicates that the model accurately predicted the reading performance approximately 95.7% of the time. The 95% Confidence Interval for accuracy ranges from 0.943 to 0.968, further confirming the model's reliability.

The Kappa statistic measures the agreement between the predictions and actual outcomes, correcting for chance agreement. The value of 0.914 shows a high level of agreement, signifying the model's excellent performance.

The P-value [Acc > NIR], which compares the accuracy of the model to the No Information Rate (NIR), is less than 0.001, demonstrating that the model's accuracy is statistically significant and not due to random chance.

The SVM model exhibited a sensitivity (also known as recall) of 0.956, suggesting that it correctly identified approximately 95.60% of low-performing students. Similarly, the model's specificity was 0.958, meaning that it correctly identified about 95.84% of the high-performing students.

The Positive Predictive Value (PPV) and Negative Predictive Value (NPV) were both reported as approximately 0.956 and 0.958, respectively. These high values represent the model's strength in accurately predicting both positive (low-performing) and negative (high-performing) classes.

The Balanced Accuracy, an average of sensitivity and specificity, was found to be 0.9572, reinforcing the robustness and balanced performance of the SVM model in predicting student reading performance.

These results substantiate the efficacy of the SVM model in predicting the reading performance of fourth-grade students based on the selected contextual factors. Therefore, the first research question was answered successfully.

Results to Answer the Second Question

A crucial component of the SVM model's performance was the variable selection process. This process was conducted using recursive feature selection, a machine learning technique that successively eliminates the least important features based on their predictive power, aiming to improve the model's efficiency and prevent overfitting. The analysis began with the 405 independent variables, progressively selecting subsets of the 4, 8, and 16 most influential features. Performance across the subsets was validated using a robust method of cross-validation (10-fold, repeated 5 times).

The resampling performance statistics show a clear trend of improving model performance as the number of variables included increased, up to the point of 16 variables (Table 1). For the model trained with just four variables, the relatively high RMSE and MAE values and a low R2 value suggest a model with limited predictive power. However, as the number of variables is increased to eight and then to sixteen, all performance indicators improved significantly. With eight variables, the RMSE decreased to 0.4917, the R2 increased to 0.03607, and the MAE also decreased to 0.4820. The improvements were more significant with sixteen variables - the RMSE further reduced to 0.4784, the R2 increased notably to 0.08714, and the MAE also decreased to 0.4546, suggesting an improved fit of the model with these key variables. The full model with all 405 variables displayed the best performance, with an RMSE of 0.2618, R2 of 0.72766, and MAE of 0.2131. These statistics suggest a high degree of fit between the model's predictions and actual reading performance, but it is also important to note the computational complexity and potential overfitting when including this many variables in the model. Based on these results, the predictive power of the SVM model improved substantially as more relevant variables were included, with the top 16 variables delivering a satisfying balance between performance and model complexity.

The top four factors come from the school level, emphasizing the significant role schools play in shaping students' reading performance. This role is primarily reflected through the major emphasis on instruction and the students' ability to borrow books.

Teacher-level factors play an equally crucial role in predicting students' reading performance, encompassing a range of strategies for teaching and assessment, teacher's sentiments, and professional development. Interestingly, the frequency of monitoring homework was ranked as the 16th most important factor.

The only family-level factor that made it to the top 16 is the parental commitment to ensuring that students are ready to learn, indicating the importance of a supportive home environment in enhancing students' reading performance. These results answered the second question.

Table 1.
The Rank Order of the Factors

Rank	Code	Factor	Questionnaire	Answers	Level
1	ACBG14B	“Knowing letter-sound relationships” receives a major emphasis in instruction in the school	School	Ranking	School
2	ACBG14A	“Knowing letters of the alphabet” receives a major emphasis in instruction in the school	School	Ranking	School
3	ATBR13E	Students can borrow books from the classroom library or reading corner to take home	Teacher	Yes/No	School
4	ACBG14C	“Reading words” receives a major emphasis in instruction in the school	School	Ranking	School
5	ATBR18A	The importance placed on “observing students as they work" as an assessment strategy in reading	Teacher	3-point	Teacher
6	ATBR18C	The importance placed on “short, regular written assessments (paper or digital)” as an assessment strategy in reading	Teacher	3-point	Teacher
7	ATBR10C	Frequency of teacher’s asking the students to “explain or support their understanding with text evidence” to help develop reading comprehension skills or strategies	Teacher	4-point	Teacher
8	ATBR08A	Teacher “reads aloud to students” during reading instruction and/or reading activities	Teacher	4-point	Teacher
9	ATBG12E	Frequency of teacher’s feeling proud of the work done	Teacher	4-point	Teacher
10	ACBG14D	“Reading isolated sentences” receives a major emphasis in instruction in the school	School	Ranking	School
11	ATBR18B	The importance placed on “asking students to answer questions during class” as an assessment strategy in reading	Teacher	3-point	Teacher
12	ATBG10G	Parental commitment to ensure that students are ready to learn	Teacher	5-point	Family
13	ATBG12C	Frequency of teacher’s feeling enthusiastic about the job	Teacher	4-point	Teacher
14	ATBR10D	Frequency of teacher’s asking the students to “compare what they have read with experiences they have had” to help develop reading comprehension skills or strategies	Teacher	4-point	Teacher
15	ATBG07AF	In the past two years, teacher participated in formal professional development (e.g., workshops, seminars, lesson studies) in reading on addressing differentiation of instruction for students’ needs and interests	Teacher	Yes/No	Teacher
16	ATBR17C	Frequency of teacher’s “monitoring whether or not the homework was completed”	Teacher	3-point	Teacher

Results to Answer the Third Question

To answer the third question, the 16 factors were schematized, as shown in Figure 1. The factors and their representative higher-order dimensions (the assessment strategy, motivation…) in the figure are different compared to previous research (Bozkuş, 2025).

In the previous research, the main factors were at the family level and were related to socioeconomic background, which is about providing students with a personal study environment through an internet connection, their own study desk, room, books, and smartphone. The student-level factors were reading motivation, gender, and age. School-level factors were ineffective classroom rules, absenteeism, library, and access to digital resources.

In this research, the main factors were at the school level and were related to placing a major emphasis on instruction and the ability of students to borrow books. The teacher-level factors were the assessment strategy, helping students develop reading comprehension skills or strategies, and motivation. The only family-level factor was the parental commitment to ensure that students are ready to learn.

The comparative examination of the current study's findings with those of prior research provides a fascinating insight into the shifting landscape of influential factors affecting student reading performance. Such a comparison underscores the intricate and context-specific nature of these factors, demonstrating their variable emphasis in different educational settings.

In the previous study (Bozkuş, 2025), socioeconomic factors, including the provision of a personal study environment and digital resources, were found to be key predictors at the family level. In contrast, the current study identifies a parental commitment to ensure student readiness for learning as the sole significant family-level factor. This suggests a shift from tangible resources to more intangible aspects of parental engagement, underscoring the importance of a supportive learning atmosphere at home.

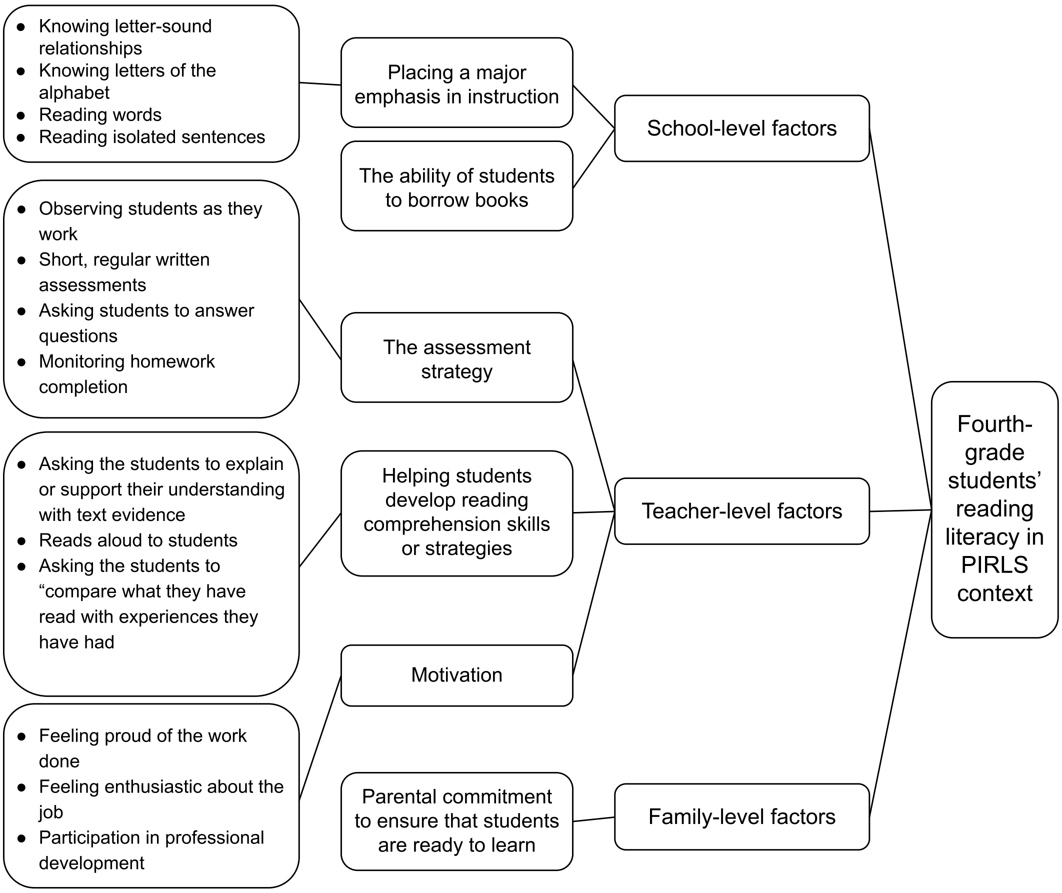
At the student level, the prior research emphasizes demographic factors like age and gender, and intrinsic attributes such as reading motivation. Interestingly, the current study does not identify any student-level factors as significant, indicating a potential shift of influence toward external contextual factors.

The school-level factors highlighted in the previous research, such as absenteeism, library resources, and digital access, seem to reflect a broader institutional framework. On the contrary, the current study points to more specific instructional factors, like the emphasis placed on certain learning areas and the opportunity for students to borrow books. This might indicate a growing focus on the pedagogical aspects within the school environment.

Teacher-level factors emerge as significant in the current study, with a focus on assessment strategies, reading comprehension skill development, and teacher motivation. This new insight underscores the crucial role teachers play in shaping the learning environment and instructional processes.

While both studies underscore the multilayered nature of the factors affecting reading performance, the variations noted call attention to the unique interplay of contextual factors within different educational settings. This comparison suggests that, while overarching factors do exist, the weight of each factor may fluctuate, influenced by the nuances of individual, family, school, and societal contexts. It underscores the need for tailored, context-responsive approaches in shaping educational policies, interventions, and practices to enhance reading performance.

Figure 1.
Illustration of the Key Contextual Factors



DISCUSSION

The successful deployment of an SVM model, trained on PIRLS 2021 data, to distinguish between high- and low-performing fourth graders on the basis of 16 pivotal contextual factors, bears significant implications. SVMs excel in the classification of data. It can potentially discern between high- and low-performing students based on a set of factors, suggesting that these variables may possess potent predictive capacity. This understanding can assist educators and policymakers to discern the components that are most consequential for student performance. By identifying the salient variables that forecast reading success, targeted interventions can be developed to augment outcomes. For instance, interventions could be designed to provide supplemental support to students hailing from lower socioeconomic backgrounds. Knowledge of the most crucial criteria can influence resource allocation. If specific resources are associated with improved performance, additional funding could be invested to ensure that all students have access to these resources.

Adding more features beyond the top 16 does not significantly boost the model's efficacy in forecasting reading success. This could suggest that the bulk of significant predictors of reading performance are encapsulated within these 16 factors. Such knowledge could be immensely beneficial in focusing educational interventions and resources where they will most likely have an impact.

The findings of this research underscore the critical interplay of various factors at school, teacher, and family levels in predicting the reading performance of fourth-grade students. The SVM model's high accuracy and sensitivity in distinguishing between high- and low-performing students corroborate the validity of our approach and the 16 factors it has identified. Yet, as these factors are closely tied to the Turkish context, the intriguing differences to the broader PIRLS 2021 data warrant further exploration.

At the school level, the emphasis on basic literacy skills such as knowing letters of the alphabet, letter-sound relationships, and reading words stood out as the most impactful. This emphasis reaffirms the foundational role of these literacy skills in students' reading development, mirroring previous findings (Ouellette & Haley, 2013). Moreover, the ability of students to borrow books from the classroom library was also a critical predictor. This highlights the importance of accessibility to reading materials, an aspect that aligns with Krashen's (2004) assertion that access to books positively influences reading acquisition and development.

At the teacher level, various teaching and assessment strategies, along with teachers' attitudes and ongoing professional development, emerged as significant predictors. Importantly, practices that promoted students' interaction with the text, such as asking students to support their understanding with text evidence and comparing their readings with personal experiences, proved influential. These findings are in harmony with the transactional theory of reading which advocates for the active role of readers in constructing meaning from the text (Rosenblatt, 1995). Also noteworthy is the importance of teachers' positive sentiments and participation in professional development activities, suggesting that teachers' motivation and continuous learning have notable repercussions on students' reading performance.

The singular family-level predictor, parental commitment to ensure that students are ready to learn, confirms the crucial role of families in facilitating learning readiness, mirroring the research of Park (2008). This finding underscores that family engagement is an important factor, although often overlooked in educational policy discussions.

The differences observed between the results of the current study, which analyzed PIRLS 2021 data from Türkiye, and the previous study which encompassed the entire dataset of 65 countries, may be attributed to numerous factors reflecting the specificity of sociocultural, educational, and economic contexts.

First, the variance in essential factors may be the result of countries' varied sociocultural settings. Türkiye's own cultural norms, attitudes, and traditions, especially in relation to education, may have influenced its dynamics differently than those of other nations. As indicated by the current study, the commitment of Turkish parents to ensuring their children are ready to learn is a significant factor of reading performance. This component may represent cultural values that differ from those of other nations, such as an emphasis on education and its role in social mobility.

Second, disparities in educational systems may possibly be a major factor in the observed variances. The increasing significance of teacher and school-level factors in the present study, particularly in relation to instructional and assessment procedures, may be a result of the structure and pedagogical approaches of the Turkish education system. Educational policies and practices, such as teacher training, curriculum design, and resource allocation, vary widely throughout nations and can have major effects on student performance.

Finally, economic disparities across countries might contribute to the variations. In the previous research, socioeconomic factors such as internet connection, personal study desk, and smartphone availability emerged as prominent determinants of reading performance. In the context of Türkiye, these factors might be more evenly distributed among the population, leading to their decreased significance in the current study.

The implications of this research for educational policy and practice are multi-fold. Firstly, it emphasizes the necessity for a systemic approach to improving reading performance, targeting school, teacher, and family levels simultaneously. Secondly, it underscores the need for contextualized policies and practices, considering the uniqueness of each educational context. Lastly, it suggests the potential of machine learning, specifically SVM, as a tool to make sense of the complex, multi-dimensional nature of student performance.

Limitations

While the binary classification and selection of the top 16 factors improved the model's interpretability, it remains a machine learning model that might not fully capture the complex, multifaceted nature of reading performance. The identified factors should be viewed as important predictors but not as definitive explanations for students' reading abilities.

The study relies on data from a specific cohort of fourth-grade students who participated in PIRLS 2021. As such, the findings may not be directly applicable to students in different educational contexts or grade levels. Variations in curriculum, teaching methods, and socio-economic factors across different regions or countries might influence reading performance differently. Replicating this study in diverse educational settings would strengthen the generalizability of the results.

The study's cross-sectional design provides a snapshot of the factors associated with reading performance at a single point in time. This design limits the ability to infer causality or examine how these factors might change over time. Longitudinal studies would be valuable for understanding the dynamic nature of reading development and the long-term impact of various predictors.

PIRLS assessments are designed to be culturally neutral; however, subtle cultural and linguistic differences might still influence how students interpret and respond to the test items. These differences could impact the generalizability of the model to populations with diverse cultural and linguistic backgrounds.

Suggestions

The insights derived from this study point towards several suggestions for educational policies, interventions, and research practices, drawing upon the particular context of fourth-grade students in Türkiye participating in PIRLS 2021.

At the policy level, an approach that systemically addresses school, teacher, and family factors may yield more meaningful improvements in reading performance. Policymakers should be encouraged to develop comprehensive strategies that encompass these three levels, rather than implementing isolated policies targeting one level at a time. For instance, at the school level, policies may be crafted to emphasize fundamental literacy skills in the curriculum and enhance access to reading materials. Simultaneously, support for teachers in terms of continued professional development, especially in the area of differentiated instruction, should be bolstered. Lastly, initiatives to foster parental engagement in students' readiness to learn could also be beneficial.

In terms of interventions, the findings suggest a focus on interactive teaching and assessment strategies that involve students actively interacting with text, supporting their understanding with evidence, and drawing connections between their readings and personal experiences. Schools and educators can be encouraged to adopt such pedagogical approaches. Besides, interventions to enhance teachers' motivation and satisfaction can be considered, such as peer support groups, mentorship programs, and stress management workshops. At the family level, programs that help parents understand their role in their children's learning process and equip them with strategies to foster their children's readiness to learn could be introduced.

As for research practices, this study highlighted the potential of machine learning as a valuable tool to understand the complex, multi-dimensional nature of student performance. Future research could further explore other machine learning techniques and how they can be harnessed to illuminate the nuanced interplay of various factors in educational outcomes. Longitudinal research designs, involving multiple data sources and methods, can provide more in-depth and comprehensive insights into the predictors of reading performance.

Moreover, in light of the differences between this study's findings and the overall PIRLS 2021 data, it would be worthwhile to explore the context-specific nature of the influential factors in other educational settings. Comparative studies can yield rich insights into how educational and socio-cultural dynamics shape the key factors influencing students' reading performance across different contexts.

CONCLUSION

This study illuminates the intricate tapestry of factors that influence the reading performance of fourth-grade students in Türkiye, offering a nuanced exploration into the role of school, teacher, and family-level variables. Utilizing machine learning techniques, specifically SVM has unveiled 16 key factors that distinguished between high- and low-performing students, providing an innovative lens to understand the multi-dimensional nature of student performance. Interestingly, these factors, while consonant with some broader educational theories, diverge from the overall PIRLS 2021 data, highlighting the role of context-specific dynamics in educational outcomes.

The results underline the essentiality of an integrative, systemic approach in educational policies and interventions, targeting school, teacher, and family levels simultaneously. They also underscore the need for contextualized practices, considering the uniqueness of each educational setting, as well as the potential of machine learning to navigate the complexities of educational research.

Future research can build on these insights, diving deeper into the context-specific nature of influential factors across various educational settings. This study also suggests harnessing advanced research methods, like longitudinal designs and machine learning techniques, to contribute to a more comprehensive understanding of educational outcomes.

In closing, the findings of this research reveal a landscape of interacting factors influencing reading performance, inviting a broader discourse on contextually-responsive and evidence-informed educational policies, interventions, and research practices. By doing so, we hope to continue advancing towards more effective and equitable educational practices that foster the reading development of all students.

REFERENCES

Albashish, D., Hammouri, A. I., Braik, M., Atwan, J., & Sahran, S. (2021). Binary biogeography-based optimization based SVM-RFE for feature selection. *Applied Soft Computing*, *101*, 107026-107026. https://doi.org/10.1016/j.asoc.2020.107026

Allington, R. L., & McGill-Franzen, A. M. (2021). Reading volume and reading achievement: A review of recent research. *Reading Research Quarterly*, *56*(S1), 231-238. https://doi.org/10.1002/rrq.404

Alruwais, N., & Zakariah, M. (2023). Evaluating student knowledge assessment using machine learning techniques. *Sustainability, 15*(7), 6229-6229. https://doi.org/10.3390/su15076229

Ameyaw, S. K., & Anto, S. K. (2018). Read or perish: Reading habits among students and its effect on academic performance: A case study of Eastbank Senior High School-Accra. *Library Philosophy and Practice*, 1-23.

Archibald, S. L. (2006). Narrowing in on educational resources that do affect student achievement. *Peabody Journal of Education, 81*(4), 23-42. https://doi.org/10.1207/s15327930pje8104_2

Avolio, M., & Fuduli, A. (2021). A semiproximal support vector machine approach for binary multiple instance learning. *IEEE Transactions on Neural Networks and Learning Systems*, *32*(8), 3566-3577. https://doi.org/10.1109/tnnls.2020.3015442

Bannister, S. L., Hanson, J. L., Maloney, C. G., & Dudas, R. A. (2015). Practical framework for fostering a positive learning environment. *Pediatrics*, *136*(1), 6-9. https://doi.org/10.1542/peds.2015-1314

Bernardo, A. B. I., Cordel, M. O., Lucas, R. I. G., Teves, J. M. M., Yap, S. A., & Chua, U. (2021). Using machine learning approaches to explore non-cognitive variables influencing reading proficiency in English among Filipino learners. *Education Sciences*, *11*(10), 628-628. https://doi.org/10.3390/educsci11100628

Bozkuş, K. (2025). *Predictors of reading performance of fourth-graders*. Manuscript submitted for publication.

Chen, F., Sakyi, A., & Cui, Y. (2022). Identifying key contextual factors of digital reading literacy through a machine learning approach. *Journal of Educational Computing Research*, *60*(7), 1763-1795. https://doi.org/10.1177/07356331221083215

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*, 129-158. https://doi.org/10.1007/s11165-019-9835-y

Dong, X. L., & Hu, J. (2019). An exploration of impact factors influencing students' reading literacy in Singapore with machine learning approaches. *International Journal of English Linguistics*, *9*(5), 52-52. https://doi.org/10.5539/ijel.v9n5p52

Eker, C. (2014). The effect of teaching practice conducted by using metacognition strategies on students' reading comprehension skills. *International Online Journal of Educational Sciences*, *6*(2), 269-280. https://doi.org/10.15345/iojes.2014.02.002

Frijters, J. C., Tsujimoto, K. C., Boada, R., Gottwald, S., Hill, D. E., Jacobson, L. P., Lovett, M. W., Mahone, E. M., Willcutt, E. G., & Wolf, M. (2018). Reading-related causal attributions for success and failure: Dynamic links with reading skill. *Reading Research Quarterly*, *53*(1), 127-148. https://doi.org/10.1002/rrq.189

Gorostiaga, A., & Rojo-Alvarez, J. L. (2016). On the use of conventional and statistical learning techniques for the analysis of PISA results in Spain. *Neurocomputing*, *171*, 625-637. https://doi.org/10.1016/j.neucom.2015.07.001

Hill, N. E., & Tyson, D. F. (2009). Parental involvement in middle school: A meta-analytic assessment of the strategies that promote achievement. *Developmental Psychology*, *45*(3), 740-763. https://doi.org/10.1037/a0015362

Hu, J., Dong, X., & Peng, Y. (2022). Discovery of the key contextual factors relevant to the reading performance of elementary school students from 61 countries/regions: insight from a machine learning-based approach. *Reading and Writing, 35*, 93-127. https://doi.org/10.1007/s11145-021-10176-z

James, N. D. (2019). A novel robust kernel for classifying high-dimensional data using Support Vector Machines. *Expert Systems with Applications, 131*, 116-131. https://doi.org/10.1016/j.eswa.2019.04.037

Jeynes, W. H. (2007). The relationship between parental involvement and urban secondary school student academic achievement: A meta-analysis. *Urban Education*, *42*(1), 82-110. https://doi.org/10.1177/0042085906293818

Kettler, T. (2014). Critical thinking skills among elementary school students: Comparing identified gifted and general education student performance. *Gifted Child Quarterly*, *58*(2), 127-136. https://doi.org/10.1177/0016986214522508

Kikas, E., Soodla, P., & Mägi, K. (2018). Teacher Judgments of Student Reading and Math Skills: Associations With Child- and Classroom-Related Factors. *Scandinavian Journal of Educational Research*, *62*(5), 783-797. https://doi.org/10.1080/00313831.2017.1307271

Krashen, S. D. (2004). *The Power of Reading: Insights from the Research.* Libraries Unlimited.

Latif, G., Alghazo, J., Butt, M. J., & Kazimi, Z. (2021). Fast parallel SVM based arrhythmia detection on multiple GPU clusters. *2021 10th IEEE International Conference on Communication Systems and Network Technologies (CSNT)*, 669-673. https://doi.org/10.1109/csnt51715.2021.9509589

Law, Y. (2011). The role of teachers' cognitive support in motivating young Hong Kong Chinese children to read and enhancing reading comprehension. *Teaching and Teacher Education*, *27*(1), 73-84. https://doi.org/10.1016/j.tate.2010.07.004

Leahy, M. A., & Fitzpatrick, N. M. (2017). Early readers and academic success. *Journal of Educational and Developmental Psychology*, *7*(2), 87-95. https://doi.org/10.5539/jedp.v7n2p87

Lee, J., & Shute, V. J. (2010). Personal and social-contextual factors in K–12 academic performance: An integrative perspective on student learning. *Educational Psychologist*, *45*(3), 185-202. https://doi.org/10.1080/00461520.2010.493471

Lewis, N. D. (2017). *Machine learning made easy with R*. ND Lewis.

Lim, H. J., Bong, M., & Woo, Y. K. (2015). Reading attitude as a mediator between contextual factors and reading behavior. *Teachers College Record*, *117*(1), 1-36. https://doi.org/10.1177/016146811511700108

Lin, X., & Powell, S. R. (2022). The roles of initial mathematics, reading, and cognitive skills in subsequent mathematics performance: A meta-analytic structural equation modeling approach. *Review of Educational Research*, *92*(2), 288-325. https://doi.org/10.3102/00346543211054576

Mullis, I.V.S., von Davier, M., Foy, P., Fishbein, B., Reynolds, K.A., & Wry, E. (2023). *PIRLS 2021 International Results in Reading*. Boston College, TIMSS & PIRLS International Study Center. https://doi.org/10.6017/lse.tpisc.tr2103.kb5342

Ouellette, G., & Haley, A. (2013). One complicated extended family: The influence of alphabetic knowledge and vocabulary on phonemic awareness. *Journal of Research in Reading*, *36*(1), 29-41. https://doi.org/10.1111/j.1467-9817.2010.01483.x

Pallathadka, H., Sonia, B., Sanchez, D. T., De Vera, J. V., Godinez, J. A. T., & Pepito, M. T. (2022). Investigating the impact of artificial intelligence in education sector by predicting student performance. *Materials Today: Proceedings*, *51*, 2264-2267. https://doi.org/10.1016/j.matpr.2021.11.395

Park, H. (2008). Home literacy environments and children's reading performance: A comparative study of 25 countries. *Educational Research and Evaluation*, *14*(6), 489-505. https://doi.org/10.1080/13803610802576734

Rosenblatt, L. M. (1995). *Literature as exploration* (5th ed.). Modern Language Association.

Savolainen, H., Ahonen, T., Aro, M., Tolvanen, A., & Holopainen, L. (2008). Reading comprehension, word reading and spelling as predictors of school achievement and choice of secondary education. *Learning and Instruction*, *18*(2), 201-210. https://doi.org/10.1016/j.learninstruc.2007.09.017

Shimoda, A., Ichikawa, D., & Oyama, H. (2018). Using machine-learning approaches to predict non-participation in a nationwide general health check-up scheme. *Computer Methods and Programs in Biomedicine, 163,* 39-46. https://doi.org/10.1016/j.cmpb.2018.05.032

Swain-Bradway, J., Pinkney, C., & Flannery, K. B. (2015). Implementing schoolwide positive behavior interventions and supports in high schools: Contextual factors and stages of implementation. *Teaching Exceptional Children*, *47*(5), 245-255. https://doi.org/10.1177/0040059915580030

Wang, M. T., & Degol, J. L. (2016). School climate: A review of the construct, measurement, and impact on student outcomes. *Educational Psychology Review*, *28*(2), 315-352. https://doi.org/10.1007/s10648-015-9319-1

Wolniak, G. C., & Engberg, M. E. (2010). Academic achievement in the first year of college: Evidence of the pervasive effects of the high school context. *Research in Higher Education, 51*, 451-467. https://doi.org/10.1007/s11162-010-9165-4

TÜRKÇE GENİŞLETİLMİŞ ÖZET

Okuduğunu anlama eğitimin temel taşıdır. Tüm akademik disiplinlerde öğrenme için temel oluşturur ve bireyin gelecekteki akademik ve profesyonel gidişatının güçlü bir belirleyicisidir (Leahy ve Fitzpatrick, 2017). Önemine rağmen, özellikle geniş ve çeşitli öğrenci popülasyonlarında okuma performansının doğru tahmin edilmesi bir zorluk olmaya devam etmektedir. Karmaşıklık, okuma performansını etkileyen birbiriyle ilişkili çok sayıda faktörün dikkate alınması ihtiyacıyla daha da artmaktadır (Dong ve Hu, 2019). Yüksek performanslı öğrencileri düşük performans gösterenlerden ayırabilecek faktörler konusunda literatürde bir boşluk bulunmaktadır (Chen vd., 2022; Hu vd., 2022). Bu faktörlerin sağlam bir şekilde kavranamaması, kapsamlı eğitim politikasının ve kişiye özel müdahale stratejilerinin oluşturulmasını engellemektedir (Lee ve Shute, 2010; Swain-Bradway vd., 2015). Dijitalleşmeye ve bilgi bolluğuna doğru hızla ilerleyen bir dünyada, öğrencileri yetkin okuma becerileriyle donatmak sadece arzu edilen değil, aynı zamanda mutlak bir gerekliliktir.

En önemli zorluk, öğrencinin okuma performansını şekillendirmede çeşitli okul, öğretmen ve aile faktörlerinin rolünü anlamak ve incelemektir. Bu faktörlerin iç içe geçmiş doğası göz önüne alındığında, eğitim paydaşlarının etkili müdahaleler tasarlarken bir ikilemle karşılaşması alışılmadık bir durum değildir. Önceki çalışmalar, okuma performansının bazı genel yordayıcılarını belirleyip anlayarak bu alana katkıda bulunmuş olsa da (Chen vd., 2022; Hu vd., 2022), daha kapsamlı, derinlemesine ve incelikli bir analiz Türkiye bağlamındaki literatürde eksiktir.

Dahası, önceki araştırmalarda kullanılan geleneksel istatistiksel yaklaşımlar genellikle öğrenci performansını etkileyebilecek çok çeşitli bağımsız değişkenleri ele almak için gereken karmaşıklıktan yoksundur. Destek Vektör Makinesi (SVM) gibi makine öğrenimi modelleri, büyük veri kümelerini verimli bir şekilde işleyerek ve bunların içindeki karmaşık modelleri aydınlatarak bu sınırlamanın üstesinden gelmeyi vaat etmektedir.

Bu çalışma Türkiye'deki dördüncü sınıf öğrencilerinin okuma performansını yordayan faktörlerin karmaşık etkileşimini anlama sorununu ele almayı amaçlamaktadır. Bu araştırma, SVM modelini kapsamlı PIRLS 2021 veri kümesine uygulayarak okul, öğretmen ve aile düzeyindeki değişkenlerin karmaşık ağında gezinmeyi ve bunların okuma performansı üzerindeki etkilerini ortaya çıkarmayı amaçlamaktadır. Ayrıca bu çalışma, bu bulguları PIRLS 2021'in kapsamlı sonuçlarıyla karşılaştırmayı, Türkiye bağlamında etkili olan benzersiz faktörleri tanımlamayı ve açıklamayı amaçlamaktadır. Dolayısıyla bu araştırma şu sorulara cevap vermeyi amaçlamaktadır:

1) Bağlamsal faktörler PIRLS 2021'in okumada iyi performans gösteren dördüncü sınıf öğrencilerini kötü performans gösterenlerden ayırabilir mi?
2) Eğer öyleyse, sınıflandırmada hangi faktörler en büyük öneme sahiptir?
3) Bu faktörler sıralanırsa 65 ülkenin PIRLS 2021 verilerinin tamamıyla karşılaştırıldığında ne gibi farklılıklar vardır?

İlk soruyu ele alırken, R programı için mevcut olan paketler aracılığıyla 5 kez tekrarlanan 10 kat çapraz doğrulama (CV) kullanılarak doğrusal çekirdek yöntemine sahip L2-düzenlenmiş SVM kullanılmıştır. Doğruluk, duyarlılık ve özgüllük puanları, modelin sınıflandırma kapasitesini değerlendirmek için SVM'de sıklıkla kullanılan ölçümlerdir. Kusursuz tahminlere sahip bir SVM modelinde bu ölçümler 1 değerini vermelidir. 0,8'in üzerindeki puanlar genellikle iyi kabul edilir ve 0,7'nin üzerindeki puanlar ise adil kabul edilir. Veriler rastgele iki bölüme ayrılmıştır. Verilerin %70'i (n= 2513) eğitime ayrılmış, geri kalan %30'u (n= 1076) ise eğitilen SVM modelini test etmek için kullanılmıştır.

İkinci araştırma sorusunu ele almak için, 5 kez tekrarlanan 10 kat CV dış yeniden örnekleme yöntemi kullanıldı. Dördüncü sınıf öğrencilerinin okuma yeteneğini öngören temel bağlamsal unsurları ayırt etmek için özyinelemeli özellik eleme tekniği (RFE) kullanıldı. RFE, sınıflandırmadaki önemlerine göre tüm faktörleri azalan bir hiyerarşide düzenler. SVM ve RFE'nin birleştirilmesi, makine öğreniminde özellik seçimi için yaygın bir stratejidir (Albashish vd., 2021). Bu yöntem, özellikleri sistematik olarak ortadan kaldırarak ve ardından geri kalanlarla bir model oluşturarak, her seferinde modelin performansını değerlendirerek, hangi özelliklerin modelin doğruluğuna öncelikli olarak katkıda bulunduğunu belirlemeye çalışır. RFE prosedürü 5 kez tekrarlanan 10 kat CV ile uygulandı. CV, bir makine öğrenimi modelinin farklı bir veri kümesine (yani test kümesine) ne kadar etkili bir şekilde genelleştirildiğini tespit etmek için kullanılır. K-katlı CV için, orijinal numune rastgele eşdeğer boyuttaki k alt numuneye ayrılır.

Üçüncü soruyu ele alırken sıralanan faktörler, benzer bir yaklaşım kullanarak 65 ülkeden PIRLS 2021 veri setinin tamamını inceleyen önceki araştırmayla (Bozkuş, 2025) yan yana getirildi.

PIRLS 2021 verileriyle eğitilmiş bir SVM modelinin, 16 önemli bağlamsal faktör temelinde yüksek ve düşük performans gösteren dördüncü sınıf öğrencilerini birbirinden ayırmak için başarılı bir şekilde uygulanması, önemli sonuçlar doğurmaktadır. SVM'ler verilerin sınıflandırılmasında mükemmeldir. Bir dizi faktöre dayalı olarak yüksek ve düşük performans gösteren öğrencileri potansiyel olarak ayırt edebiliyorlar. Bu, eğitimcilerin ve politika yapıcıların öğrenci performansı açısından en önemli bileşenleri ayırt etmelerine yardımcı olabilir. Okuma başarısını öngören belirgin değişkenleri belirleyerek sonuçları artıracak hedefe yönelik müdahaleler geliştirilebilir. Örneğin, müdahaleler düşük sosyoekonomik kökenden gelen öğrencilere ek destek sağlayacak şekilde tasarlanabilir. En önemli kriterlerin bilgisi kaynak tahsisini etkileyebilir. Belirli kaynakların performansın iyileştirilmesiyle ilişkilendirilmesi durumunda, tüm öğrencilerin bu kaynaklara erişebilmesini sağlamak için ek finansman yatırımı yapılabilir.

İlk 16'nın ötesinde daha fazla özellik eklemek, modelin okuma başarısını tahmin etmedeki etkinliğini önemli ölçüde artırmamıştır. Bu, okuma performansının önemli belirleyicilerinin çoğunun bu 16 faktör içinde kapsandığını gösterebilir. Bu tür bilgiler, eğitimsel müdahalelerin ve kaynakların büyük olasılıkla etki yaratacakları yere odaklanmasında son derece faydalı olabilir.

Bu araştırmanın bulguları, dördüncü sınıf öğrencilerinin okuma performansını tahmin etmede okul, öğretmen ve aile düzeyindeki çeşitli faktörlerin kritik etkileşiminin altını çizmektedir. SVM modelinin yüksek ve düşük performans gösteren öğrenciler arasında ayrım yapma konusundaki yüksek doğruluğu ve hassasiyeti, yaklaşımımızın ve tanımladığı 16 faktörün geçerliliğini desteklemektedir. Ancak bu faktörler Türkiye bağlamıyla yakından bağlantılı olduğundan, daha geniş PIRLS 2021 verilerindeki ilgi çekici farklılıklar daha fazla araştırmayı gerektirmektedir.