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Global Trends in Literacy and Science Skills: Analysis and Future Projections Based on PISA Data

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ABSTRACT

Reading, mathematics, and science literacy are crucial for individual and societal progress. This study explored and projected global trends in these essential skills, with particular emphasis on the countries of the Organisation for Economic Co-operation and Development (OECD). Using data from the Programme for International Student Assessment (PISA) between 2000 and 2022, we performed a time-series analysis employing Auto-Regressive and Moving Average algorithms to uncover trends. Our key findings reveal a stable global reading literacy rate, with expected increases in the future; a stable global mathematics literacy rate, accompanied by short-term improvements; and a stable global science literacy rate, demonstrating short-term gains followed by consistently high levels. The findings also point to a concerning decline in mathematical literacy among OECD countries since 2005. This troubling trend, likely to persist, emphasises the urgent need for effective strategies to enhance mathematical competence to ensure future economic sustainability.

تحليل عالمي لاتجاهات معرفة القراءة والرياضيات والعلوم باستخدام نهج السلاسل الزمنية

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الكلمات المفتاحية:
برنامج تقييم الطلاب الدوليين.
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الملخص

تُعدّ معرفة القراءة والرياضيات والعلوم أمرًا بالغ الأهمية للتقدم الفردي والمجتمعي. تستكشف هذه الدراسة وتتوقع الاتجاهات العالمية في هذه المهارات الأساسية، مع التركيز بشكل خاص على دول منظمة التعاون الاقتصادي والتنمية (OECD) باستخدام بيانات من برنامج تقييم الطلاب الدولي (PISA) من عام 2000 إلى عام 2022، تم أجراء تحليل السلاسل الزمنية باستخدام خوارزميات الانحدار التلقائي والمتوسط المتحرك للكشف عن الاتجاهات معرفة القراءة والرياضيات والعلوم. تكشف النتائج الرئيسية عن معدل عالمي مستقر لمعرفة القراءة، مع زيادات متوقعة في المستقبل؛ ومعدل عالمي مستقر لمعرفة الرياضيات، مصحوبًا بتحسينات قصيرة الأجل؛ ومعدل عالمي مستقر لمعرفة العلوم، مما يدل على مكاسب قصيرة الأجل تليها مستويات عالية باستمرار. النتائج تشير أيضًا إلى انخفاض مقلق في معرفة الرياضيات بين دول منظمة التعاون الاقتصادي والتنمية منذ عام 2005. يؤكد هذا الاتجاه المقلق، والذي من المرجح أن يستمر، على الحاجة الملحة إلى استراتيجيات فعالة لتعزيز الكفاءة الرياضية لضمان الاستدامة الاقتصادية في المستقبل.

1. Introduction

Reading, mathematics, and science skills are crucial for the development of individuals and society as a whole. These skills contribute to individual growth, as well as social, economic, and technological advancement. As society evolves, the demand for skilled individuals who can solve problems becomes increasingly essential.

Reading skills enable effective communication and provide access to

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information. The importance of reading skills can be highlighted through three main points: access to information, enhancement of critical thinking, and support for academic success. Proficient reading skills allow individuals to easily obtain information, interact with various resources, engage in lifelong learning, and adapt to a rapidly changing world [1]. Furthermore, reading enhances a person's ability for critical analysis and comprehension, which are vital for problem-solving and making informed decisions [2]. There is a clear correlation between strong reading skills and performance in mathematics and science, as comprehension is crucial for understanding complex concepts in these subjects [3]. Consequently, excelling in mathematics and science contributes to academic achievement.

Mathematical skills are essential for various aspects of life and work. They play a significant role in economic development, enhance problem-solving abilities, and foster technological proficiency. A mathematically literate workforce is crucial for driving innovation and efficiency in industries, particularly in science, technology, engineering, and mathematics (STEM), which are vital for modern economies [3]. As mathematical skills improve, so too do problem-solving abilities. These abilities depend on mathematical knowledge, foster logical reasoning, and enable individuals to effectively address real-world challenges [4]. In today's technology-driven environment, strong mathematical skills are necessary for understanding and utilising technological tools and systems, thereby enhancing proficiency within societies [5]. Developing robust mathematics skills is essential for individuals to thrive in a competitive job market and for societies to achieve economic stability and growth.

Science skills are important for understanding the natural world and empowering individuals to make informed decisions. The significance of science skills can be observed through scientific literacy, innovation and research, and interdisciplinary collaboration. Scientific literacy involves understanding scientific principles, which is crucial for addressing contemporary issues related to health, the environment, and technology. Individuals who grasp scientific concepts can make informed choices that improve their lives and communities [6]. A solid foundation in science fosters advancements in research and innovation, which in turn enhance quality of life and help solve global challenges [4]. Moreover, science education emphasises the interconnectedness of various disciplines, which is essential in tackling complex societal issues [7]. By improving science skills, individuals can contribute to a more informed and innovative society capable of addressing pressing challenges.

Conducting a comprehensive global analysis of trends in reading, mathematics, and science literacy is essential for understanding the overall level of education worldwide and identifying areas for improvement. Such an analysis enables policymakers to make informed decisions regarding curriculum enhancement, teacher training, and resource allocation. This paper analyses global reading, mathematics, and science literacy trends over time and forecasts future developments. The analysis and forecasting are based on an International Large-Scale Assessment (ILSA), known as the Programme for International Student Assessment (PISA), conducted by the Organisation for Economic Co-operation and Development (OECD). This study examines the performance of countries participating in PISA, both internationally and among OECD member nations, in terms of reading, mathematics, and science literacy using historical PISA data.

The forecasting portion utilises time-series analysis algorithms to predict how these countries will perform regarding reading, mathematics, and science literacy in the future. The paper is structured into seven sections: Section Two reviews research limitations and gaps; Section Three introduces education measurement indicators and international large-scale assessments; Section Four explores time-series analysis algorithms; Section Five details the methodology; Section Six presents the results; and Section Seven offers the conclusion.

2. Literature Review Limitations and Research Gaps

Despite the significant advancements in understanding global literacy trends through the ILSAs and time series analysis, several limitations persist within the existing literature. A primary constraint highlighted implicitly throughout the reviewed studies is the scarcity of long-term, continuous time series data across diverse countries [8], [9]. While the ILSAs like the PISA, the TIMSS, and the PIRLS have provided comprehensive data over the past five decades, the continuity and comparability of these datasets over extended periods remain challenging [10], [11]. Short or intermittent data series significantly reduce the ability to detect sustained changes in literacy levels or accurately assess the long-term impacts of educational policies and interventions [12], [13]. This fragmentation weakens the validity of conclusions drawn about the evolution of global literacy, making it difficult to discern genuine improvements from methodological artifacts [11], [14].

Furthermore, the methodological consistency and data comparability across different assessments and cycles present ongoing challenges [9], [11]. While sophisticated linking methodologies and item response theory have been employed to harmonize data [10], [15], inherent differences in assessment frameworks, target populations, and testing conditions can introduce biases and limit the precision of longitudinal comparisons. The uneven coverage of developing regions also constrains the generalizability of findings, leading to an incomplete global picture of literacy development [16]. Additionally, existing studies often focus on particular regions or single assessments, which, while valuable, limits a comprehensive understanding of worldwide patterns and their evolution without regional bias [8], [9]. The complexity of integrating socio-economic and equity factors, and establishing causal inferences, also remains a significant hurdle [16], [17].

To address these critical limitations and advance the field of global literacy research, future studies must prioritize the development and utilization of more robust and continuous long-term time series data. This research aims to fill the identified gap by utilizing data from proper ILSAs and employing appropriate time series analysis algorithms to identify the international current level of reading literacy, mathematics literacy, and science literacy. By focusing on the continuous and comparable data streams available from established ILSAs, this approach will enable a more accurate and sustained trend analysis, overcoming the limitations posed by short or intermittent data series.

Specifically, this research will leverage the longitudinal capabilities of ILSAs to provide a clearer understanding of sustained changes in literacy over time. The application of advanced time series analysis algorithms will allow for the detection of subtle patterns, identification of turning points, and more precise forecasting of future literacy trends. This identification of current and evolving international literacy levels will be instrumental in providing policymakers with actionable insights, enabling them to plan for the future with greater confidence and develop targeted interventions to enhance educational outcomes worldwide [16], [18]. Such an approach will not only contribute to a more comprehensive understanding of global literacy evolution but also strengthen the evidence base for effective educational strategies and policy formulation.

3. Education Measurement Indicators and International Large-Scale Assessments

Different indicators are used to measure the quality of education, which are essential tools for assessing the effectiveness of educational systems. These indicators are divided into four categories: input indicators, process indicators, outcome indicators, and context indicators.

Input indicators focus on the educational system's resources, including financial investments, teacher qualifications, and student-to-teacher ratios. They aim to provide insights into the educational system's foundational aspects, along with demographic information such as student population data, socioeconomic status, and diversity [19].

Process indicators assess teaching practices and the implementation of curricula. Teaching practices are evaluated by examining instructional methods and levels of classroom engagement. Curriculum implementation examines how well the curricula are followed and adopted within schools [20].

Outcome indicators are divided into two key areas: student standardized test scores and graduation rates. Standardized test scores measure student performance and are commonly used to gauge educational effectiveness. In contrast, graduation rates reflect the educational system's ability to retain and graduate students [21].

Context indicators examine the broader school environment and policy frameworks, including safety, resource availability, and community involvement. These indicators are crucial for understanding how national and local policies can significantly impact educational outcomes and equity [22].

This research specifically focuses on measuring international students' reading, mathematics, and science outcomes. Outcome indicators, particularly standardized test scores, are the most relevant in this context. The ILSAs play a vital role in evaluating student performance in these subjects globally. The most prominent ILSAs include the PISA, the Trends in International Mathematics and Science Study (TIMSS), and the Progress in International Reading Literacy Study (PIRLS).

The PISA, conducted by the OECD, evaluates 15-year-old students in reading, mathematics, and science every three years. The focus is on problem-solving and the practical application of knowledge. The PISA aims to assess students' abilities to apply their skills in real-world contexts [23].

The TIMSS is managed by the International Association for the Evaluation of Educational Achievement (IEA). The IEA is a global network of researchers dedicated to improving education worldwide. This assessment focuses on fourth and eighth graders, evaluating their knowledge in mathematics and science while ensuring alignment with educational standards and practices in participating countries [24].

The PIRLS, also overseen by the IEA, assesses reading literacy among primary school students every five years. Its results provide valuable insights into educational practices and student performance across participating nations. Additionally, the PIRLS highlights the impact of socioeconomic factors, teaching methods, and school environments on reading achievement [25]. Table 1 provides a comparison of the ILSAs.

Table 1: A Comparison of the ILSAs

Feature	PISA	TIMSS	PIRLS
Age group	15-year	4th and 8th grade	4th grade
Focus	Real-world application of knowledge and skills	Curriculum-based assessment of mathematics and science achievement	Reading literacy
Subjects	Reading, Mathematics, Science	Mathematics, Science	Reading
Methodology	Cyclical assessment every 3 years	Cyclical assessment every 4 years	Cyclical assessment every 5 years
Responsible Organization	The OECD	The IEA	The IEA

This research selected the PISA as the ILSA for a comprehensive analysis of trends in reading, mathematics, and science literacy using time series analysis. The PISA was chosen because it uniquely evaluates all three subjects: reading, mathematics, and science. In contrast, the TIMSS focuses exclusively on mathematics and science, while the PIRLS is dedicated solely to reading. The PISA targets 15-year-old students, who are at the conclusion of their compulsory education; assessing students at this age ensures their readiness for further academic pursuits [26]. Furthermore, proficiency in reading, mathematics, and science is vital for these students, as these skills are essential for meaningful contributions to modern society. The PISA also assesses how students can apply their knowledge in unfamiliar contexts, making it particularly relevant to today’s economies [27].

The PISA encompasses both member countries and OECD partner economies. To select participating schools, The PISA employs stratified random sampling methods, ensuring diverse representation across various demographic groups [28].Within each participating school, students are randomly selected, resulting in a sample that accurately reflects the national student population [29].

To assess students’ abilities, The PISA utilizes a combination of multiple-choice and open-ended questions. Furthermore, The PISA requests that students, teachers, and schools complete questionnaires to collect contextual information, including socioeconomic background and learning environment [27], [30].

Student results are determined based on assessment performance, with scores standardized for international comparison. School results aggregate the scores of all participating students, while national performance averages are calculated using the mean scores from all participating schools within each country [31]. The PISA offers a standardized assessment of students' reading, mathematics, and science literacy, with scores ranging from 100 to 1000. A higher score indicates superior performance; however, the scale is not linear, which means that a 10-point difference between two countries does not correspond to a tenfold difference in capability. Furthermore, a country's score may vary over time, even if its actual level of knowledge remains constant, due to changes in the performance of other participating nations.

4. Time Series Analysis Algorithms

Time series data refers to observations arranged in chronological sequence, reflecting the state of a variable over time. This data type can be gathered at different frequencies, such as daily stock prices or monthly rainfall [32]. Time series analysis is frequently used to forecast economic trends, predict weather conditions, and examine health data during pandemics [33]. Its ability to detect trends, patterns, and relationships over time renders it a crucial tool across various domains, including education. In this setting, time series analysis can provide insights into how skills develop in different populations and over time, especially in a global evaluation of reading, mathematics, and science literacy trends.

Time series forecasting includes a variety of algorithms, each with unique traits and suitability for different situations. Table 2 compares the most commonly utilized time series analysis algorithms, emphasizing key features of Auto Regressive (AR), Moving Average (MA), Auto Regressive Moving Average (ARMA), Auto Regressive Integrated Moving Average (ARIMA), Vector Auto Regression, Matrix Profile, and Informer algorithms, particularly regarding their appropriateness for diverse applications.

Table 2: A Comparison among the most common time series algorithms

Algorithm Name	Definition	Suitability
Auto Regressive	The AR model excels at forecasting future values by analyzing historical data, effectively revealing the connections between current observations and their preceding ones [34].	AR models are appropriate for situations with limited data, as they can effectively leverage the available points to identify a pattern, since they need fewer parameters to estimate than more complex models [34].
Moving average	The MA model predicts future outcomes by analyzing previous forecast errors, helping to smooth over temporary variations [35].	Beneficial for limited datasets since they can reduce noise and offer clearer understanding of the underlying factors [36].
Auto Regressive Moving Average	Combines AR and MA [37].	Suitable for stationary time series, it delivers a concise model with a reduced number of parameters [38].
Auto regressive integrated Moving Average	The ARIMA enhances the ARMA by incorporating differencing to manage non-stationary data [39].	It is adaptable for a range of uses, such as predicting economic trends and sales [40].
Vector Auto Regression	VAR serves as an advanced extension of the ARIMA, specifically designed for analyzing multivariate time series data [41].	Ideal for multivariate time series, it captures the linear relationships between various time series and is frequently utilized in economic modelling [42].
Matrix Profile	The Matrix Profile is a data structure and a set of algorithms designed to efficiently identify patterns, anomalies, and motifs within time series data [43].	Ideal for handling extensive datasets and intricate patterns, appropriate for use in the IoT and financial applications [43].
Informer Algorithms	A method based on deep learning techniques [44].	The algorithm works well with long sequences; it is most useful in applications where precise prediction is most important, such as predicting equipment vibration trends [44].

The first iteration of the PISA as an ILSA occurred in 2000 and is conducted every three years. Consequently, the historical data available for time series analysis is relatively limited, consisting of just eight observations, as detailed in Table 3. As a result, the AR and the MA are deemed the most suitable algorithms for this forecasting. The AR and the MA are fundamental components of time series analysis, particularly advantageous for small datasets containing around ten observations. They capitalize on the inherent temporal dependencies within the data, making them effective for forecasting and understanding trends.

5. The Methodology

5.1 Data Collection

Historical data was obtained from the official PISA website. The first PISA test was conducted in 2000, and subsequent assessments have been carried out every three years, with the most recent test in 2022. Data from 2000 to 2022 were analyzed, emphasizing the overall averages for the global and the OECD countries' in reading, mathematics, and science. Tables 3 and 4 present the collected data, which has been used for analysis and forecasting.

Table 3: The global averages for reading literacy, mathematics literacy, and science literacy from the year 2000 to 2022

The Year	Count of Participating Countries	The Global Mean of Reading Literacy	The Global Mean of Mathematics Literacy	The Global Mean of Science Literacy
2000	41	473	472	474
2003	40	480	485	485
2006	57	460	469	473
2009	65	464	468	472
2012	65	474	473	479
2015	70	462	462	466
2018	78	784	459	714
2022	81	435	437	446

Table 4: The OECD mean in reading literacy, mathematics literacy and science literacy from 2000 and 2022

The Year	The OECD Mean of Reading Literacy	The OECD Mean of Mathematics Literacy	The OECD Mean of Science Literacy
2000	500	500	500
2003	497	498	500
2006	497	496	502
2009	496	497	501
2012	496	494	503
2015	493	490	501
2018	487	483	499
2022	477	478	498

5.2 Data Preprocessing

The dataset used for forecasting and time series analysis is comparatively small, as shown in Tables 3 and 4. The pre-processing operations encompassed handling missing values, detecting outliers, assessing stationarity, and selecting appropriate models. The data in Table 3 indicates no missing values; however, some outlier values are present. The mean value addresses outlier issues, while the data illustrated in Table 4 confirms the absence of missing and outlier values.

Although the Augmented Dickey-Fuller (ADF) test can be utilised to evaluate stationarity, its reliability may be compromised due to the limited size of the dataset. Similarly, tests such as the Autocorrelation Function (ACF) and Partial Autocorrelation Function might also lack reliability for selecting time series algorithms owing to the restricted dataset size. Consequently, this limitation necessitates the adoption of simpler time series algorithms, such as the MA and the AR, which are essential for effective forecasting.

The MA algorithm, incorporating window sizes ranging from 2 to 7, has been assessed using simple, weighted, and exponential types. Typically, the lag order (p) of the AR algorithm should not exceed half the total number of observations. This principle establishes that p must remain less than or equal to 4. The AR model includes lags 01 and 02. Given the limited dataset of Eight observations, utilising a higher-order AR model (such as AR(3) or greater) would result in an excessive number of parameters to estimate relative to the available data. This imbalance can render the model overly sensitive to specific characteristics of the training data, thereby hindering its ability to generalise effectively to new datasets. Therefore, it is prudent to implement lower-order AR models, such as AR(1) or AR(2), which are less susceptible to overfitting. As a result, the efficacy of twenty distinct models evaluated to identify the most suitable forecasting model. The models under consideration include:

- Window Size: 2, Moving Average Type: Simple
- Window Size: 3, Moving Average Type: Simple
- Window Size: 4, Moving Average Type: Simple
- Window Size: 5, Moving Average Type: Simple
- Window Size: 6, Moving Average Type: Simple
- Window Size: 7, Moving Average Type: Simple
- Window Size: 2, Moving Average Type: Weighted
- Window Size: 3, Moving Average Type: Weighted
- Window Size: 4, Moving Average Type: Weighted
- Window Size: 5, Moving Average Type: Weighted
- Window Size: 6, Moving Average Type: Weighted
- Window Size: 7, Moving Average Type: Weighted
- Window Size: 2, Moving Average Type: Exponential
- Window Size: 3, Moving Average Type: Exponential
- Window Size: 4, Moving Average Type: Exponential
- Window Size: 5, Moving Average Type: Exponential
- Window Size: 6, Moving Average Type: Exponential
- Window Size: 7, Moving Average Type: Exponential
- Auto-Regressive: Lag 01
- Auto-Regressive: Lag 02

The effectiveness of the aforementioned models was assessed using several performance metrics, including Mean Absolute Error (MAE), Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). The MAE quantifies the average magnitude of prediction errors in absolute terms, reflecting the typical discrepancy between predicted and actual outcomes. The MSE calculates the average of the squared differences between predicted values and actual figures, thereby emphasising larger errors through squaring. The RMSE is subsequently derived by taking the square root of the MSE, providing a measure in the same units as the original data [45], [46]. Lastly, the MAPE assesses the average percentage deviation of the predicted values from actual figures, facilitating a relative evaluation of forecast accuracy [47]. Generally, more favourable model performance is indicated by lower values across all four metrics: MAE, MSE, RMSE, and MAPE.

Table 5 displays the results achieved for the MAE, MSE, RMSE, and MAPE for each optimised model for forecasting the count of the global countries participating in PISA.

Table 5: Performance metrics of optimized models for forecasting the count of global countries participating in the PISA

Model Name	Performance Metric Values
Window Size: 2, Moving Average Type: Simple	MAE: 9.916666666666666 MSE: 124.125 RMSE: 11.141139977578597 MAPE: 14.955366812091956%
Window Size: 3, Moving Average Type: Simple	MAE: 11.799999999999999 MSE: 153.8444444444444 RMSE: 12.403404550543549 MAPE: 16.796364129697462%
Window Size: 4, Moving Average Type: Simple	MAE: 13.1875 MSE: 174.984375 RMSE: 13.228165972650933 MAPE: 18.16934608601275%
Window Size: 5, Moving Average Type: Simple	MAE: 16.333333333333332 MSE: 270.3066666666667 RMSE: 16.441005646452005 MAPE: 21.519558630669742%
Window Size: 6, Moving Average Type: Simple	MAE: 20.083333333333332 MSE: 405.8472222222222 RMSE: 20.14565020599291 MAPE: 25.30864197530864%
Window Size: 7, Moving Average Type: Simple	MAE: 21.57142857142857 MSE: 465.3265306122448 RMSE: 21.57142857142857 MAPE: 26.63139329805996%
Window Size: 2, Moving Average Type: Weighted	MAE: 8.88888888888889 MSE: 103.70370370370371 RMSE: 10.183501544346312 MAPE: 13.483312586626429%
Window Size: 3, Moving	MAE: 9.566666666666666

Model Name	Performance Metric Values
Average Type: Weighted	MSE: 105.03888888888889 RMSE: 10.248848173765133 MAPE: 13.564193008637455%
Window Size: 4, Moving Average Type: Weighted	MAE: 9.999999999999998 MSE: 101.14499999999997 RMSE: 10.057087053416609 MAPE: 13.67165242165242%
Window Size: 5, Moving Average Type: Weighted	MAE: 12.155555555555553 MSE: 149.65777777777774 RMSE: 12.233469572356721 MAPE: 15.975338790153604%
Window Size: 6, Moving Average Type: Weighted	MAE: 14.642857142857146 MSE: 216.95804988662138 RMSE: 14.729495914206344 MAPE: 18.46312124089902%
Window Size: 7, Moving Average Type: Weighted	MAE: 15.17857142857143 MSE: 230.38903061224497 RMSE: 15.17857142857143 MAPE: 18.73897707231041%
Window Size: 2, Moving Average Type: Exponential	MAE: 9.592592592592593 MSE: 110.19650205761319 RMSE: 10.497452169817835 MAPE: 14.47451593000651%
Window Size: 3, Moving Average Type: Exponential	MAE: 12.1125 MSE: 160.22890625 RMSE: 12.65815572072014 MAPE: 17.186474019807353%
Window Size: 4, Moving Average Type: Exponential	MAE: 14.152 MSE: 201.89339600000002 RMSE: 14.208919592988062 MAPE: 19.402889702889702%
Window Size: 5, Moving Average Type: Exponential	MAE: 16.985185185185177 MSE: 290.494979423868 RMSE: 17.043913266144838 MAPE: 22.329589934528194%
Window Size: 6, Moving Average Type: Exponential	MAE: 20.07142857142857 MSE: 405.40702947845796 RMSE: 20.134721986619482 MAPE: 25.29394473838918%
Window Size: 7, Moving Average Type: Exponential	MAE: 21.57142857142857 MSE: 465.3265306122448 RMSE: 21.57142857142857 MAPE: 26.63139329805996%
Auto Regressive: Lag 01	MAE: 4.112024193018201 MSE: 28.856288212477818 RMSE: 5.371804930605524 MAPE: 7.703667322544526%
Auto Regressive: Lag 02	**MAE: 2.528650741500011** **MSE: 9.102152166528295** **RMSE: 3.016977322839583** **MAPE: 3.661825355072061%**

Based on the metrics presented in Table 5, the AR model with lag 02 exhibits the best performance, yielding the lowest values for MAE, MSE, RMSE, and MAPE. The optimisation detailed in Table 5 was repeated to identify the best-performing models for reading literacy forecasting, mathematics literacy forecasting, and science literacy forecasting for global countries and countries within the OECD framework. The results are shown in Table 6.

Table 6: The performance metrics for the top models used in the forecasting tasks

Task Name	Best Model Performance	Performance Metrics Values
Reading literacy forecasting of global countries	Window Size: 6, Moving Average Type: Simple	MAE: 0.4166666666666572 MSE: 0.34722222222220644 RMSE: 0.5892556509887762 MAPE: 0.089031339031337%
Mathematics literacy forecasting of global countries	Window Size: 7, Moving Average Type: Weighted	MAE: 1.1785714285714448 MSE: 1.3890306122449363 RMSE: 1.1785714285714448 MAPE: 0.2518315018315053%
Science literacy forecasting of global countries	Window Size: 6, Moving Average Type: Weighted	MAE: 0.2619047619047592 MSE: 0.0963718820861727 RMSE: 0.3104382097715626 MAPE: 0.055370985603543164%
Reading literacy forecasting of OECD countries	Auto Regressive: Lag 02	MAE: 0.7761674718196426 MSE: 1.0353764090177142 RMSE: 1.0175344755917188 MAPE: 0.15814490130671416%
Mathematics literacy forecasting of OECD countries	Window Size: 2, Moving Average Type: Weighted	MAE: 4.388888888888886 MSE: 27.092592592592524 RMSE: 5.205054523498531 MAPE: 0.904070114141541%
Science literacy forecasting of OECD countries	Window Size: 2, Moving Average Type: Simple	MAE: 1.5833333333333333 MSE: 3.375 RMSE: 1.8371173070873836 MAPE: 0.3165044565006828%

6. The Results

6.1 The Result of Forecasting the Participation of Global Countries in the PISA

The AR algorithm with a lag of two type simple was employed to forecast the number of countries globally participating in the PISA over the upcoming two decades. Table 7 presents the actual participation figures of global countries in PISA from 2000 to 2022, alongside the projected values for participation from 2025 to 2046.

Table 7: The Number of the global countries participating in the PISA from 2000 to 2046

The Year	The Number of the Global Countries Participating in PISA
2000	41
2003	40
2006	57
2009	65
2012	65
2015	70
2018	78
2022	81
2025	82
2028	83
2031	83
2034	84
2037	84
2040	84
2043	85
2046	85

Figure 1 illustrates the number of global countries participating in PISA over a designated timeframe.

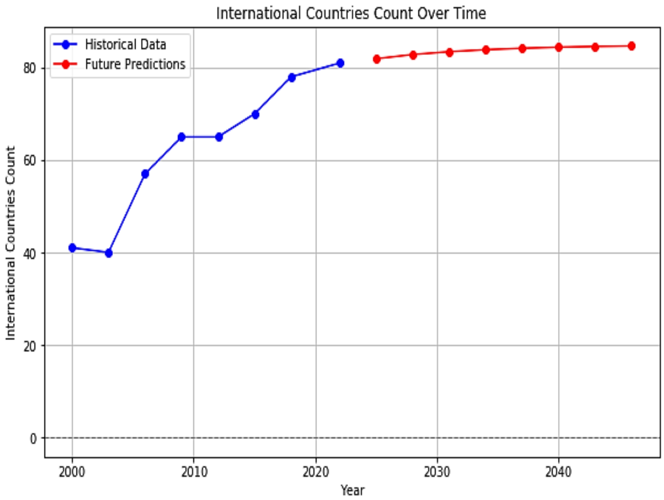

Fig. 1: The number of the global countries participating in the PISA from 2000 to 2046

The historical data indicates a clear upward trend among the countries examined, demonstrating an exponential growth pattern with a particularly marked increase in recent years. However, the projected trend suggests that, while this growth is expected to persist, it will occur at a decelerated rate relative to the historical data. The number of participating countries is anticipated to stabilize around the year 2030.

6.2 The Result of Global Countries' Performance Forecasting in Reading Literacy

The MA algorithm type simple with a window size of Six has was employed to forecast the global mean of reading literacy for the next twenty years. Table 8 presents the actual values for the global mean from 2000 to 2022 alongside the projected values for the global mean from 2025 to 2046.

Table 8: Illustrating the performance of countries worldwide in reading literacy from 2000 to 2046

The Year	The Global Mean of Reading Literacy
2000	473
2003	480
2006	460
2009	464
2012	474
2015	462
2018	784
2022	435
2025	467.61
2028	467.61
2031	467.61
2034	467.61
2037	467.40
2040	467.30
2043	467.52
2046	467.51

Figure 2 depicts the performance of countries worldwide in terms of reading literacy from 2000 to 2046

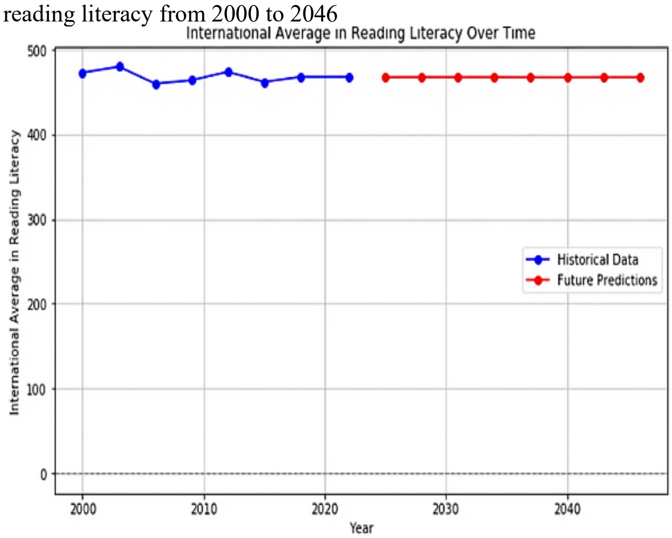

Fig. 2: Illustrating the performance of countries worldwide in reading literacy from 2000 to 2046

Analysis of historical data indicates that global reading literacy has remained relatively stable over the past two decades, exhibiting neither significant improvements nor declines. However, future projections indicate a potential increase in reading literacy in the near term, followed by the maintenance of elevated levels thereafter.

6.3 The Result of Global Countries' Performance Forecasting in Mathematics Literacy

The MA algorithm, specifically weighted with a window size of seven, was employed to predict the global mean of mathematics literacy over the next two decades. Table 9 presents the actual values for the global mean of mathematics literacy from 2000 to 2022 alongside the forecasted values for the global mean of mathematics literacy projected from 2025 to 2046.

Table 9: Illustrating the performance of countries worldwide in mathematics literacy from 2000 to 2046

The Year	The Global Mean of Mathematics Literacy
2000	472
2003	485
2006	469
2009	468
2012	473
2015	462
2018	459
2022	437
2025	466.60
2028	466.60
2031	466.60
2034	466.60
2037	466.60
2040	466.60
2043	466.57
2046	466.60

Figure 3 depicts countries worldwide' mathematics literacy performance across a specified timeframe.

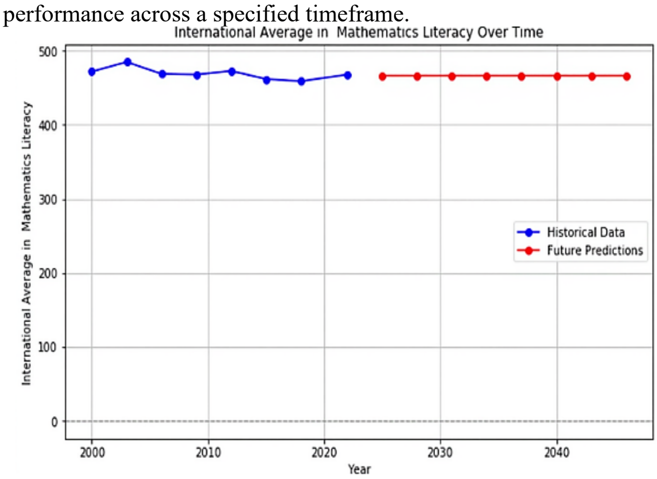

Fig. 3: Illustrating the performance of countries worldwide in Mathematics Literacy from 2000 and 2046

The historical data indicates global mathematics literacy has exhibited relative stability over the past twenty years, with no marked improvements or declines. However, future projections suggest a potential increase in the near term, which is anticipated to be succeeded by a prolonged period of elevated levels.

6.4 The Result of Global Countries' Performance Forecasting in Science Literacy

The MA algorithm, specifically weighted with a window size of six, was employed to project the global mean of science literacy over the next two decades. Table 10 presents the actual values reflecting the global mean of science literacy from 2000 to 2022, alongside the forecasted values for the global mean of science literacy from 2025 to 2046.

Table 10: Illustrating the performance of countries worldwide in science literacy from 2000 to 2046

The Year	The Global Mean of Science Literacy
2000	474
2003	485
2006	473
2009	472
2012	479
2015	466
2018	714/
2022	446/
2025	472.92
2028	472.92
2031	472.92
2034	472.92
2037	472.83
2040	472.82
2043	472.89
2046	472.88

Figure 4 shows worldwide' science literacy performance across a specified timeframe.

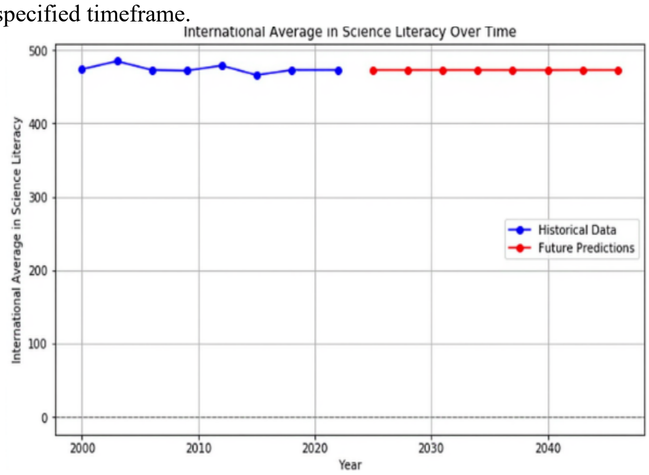

Fig. 4: Illustrating the performance of countries worldwide in science literacy from 2000 to 2046

Historical data indicates that the global science literacy levels have exhibited relative stability over the past twenty years, showing neither significant gains nor declines. However, projections for the near future suggest a potential increase in science literacy, followed by a period characterized by sustained elevated levels.

6.5 The Result of OECD Countries' Performance Forecasting in Reading Literacy

The AR algorithm with a lag of two type simple was employed to forecast the OECD mean reading literacy over the next two decades. Table 11 displays the values for the OECD mean reading literacy from 2000 to 2022 and the projected values from 2025 to 2046.

Table 11: Illustrating the performance of the OECD countries in reading literacy from 2000 to 2046

The Year	The OECD Mean of Reading Literacy
2000	500
2003	497
2006	497
2009	496
2012	496
2015	493
2018	487
2022	477
2025	484.66
2028	482.5
2031	483.58
2034	483.04
2037	483.31
2040	483.17
2043	483.24
2046	483.21

Figure 5 showcases the performance of OECD member countries in reading literacy over a designated timeframe.

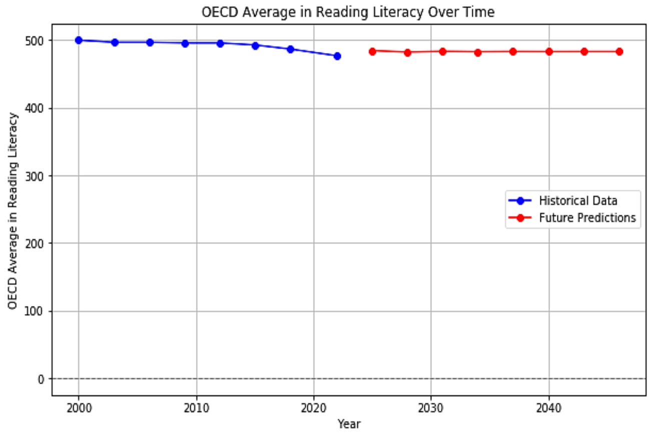

Fig. 5: Illustrating the performance of the OECD countries' in reading literacy from 2000 to 2046

As illustrated in Figure 5, the OECD average for reading literacy has continuously declined since 2005. Predictions suggest that this downward trajectory will likely continue, with reading literacy expected to stabilize at lower levels.

6.6 The Result of OECD Countries' Performance Forecasting in Mathematics Literacy

The MA algorithm, specifically weighted with a window size of Two employed to forecast the OECD average in mathematics literacy for the next twenty years. Table 12 presents the values for the OECD mean in mathematics literacy from 2000 to 2022 and the forecasted values for mathematics literacy from 2025 to 2046.

Table 12: Illustrating the performance of the OECD countries' in mathematics literacy from 2000 to 2046

The Year	The OECD Mean of Mathematics Literacy
2000	500
2003	498
2006	496
2009	497
2012	494
2015	490
2018	483
2022	478
2025	470.42
2028	460.74
2031	448.37
2034	432.58
2037	412.42
2040	386.66
2043	353.76
2046	311.74

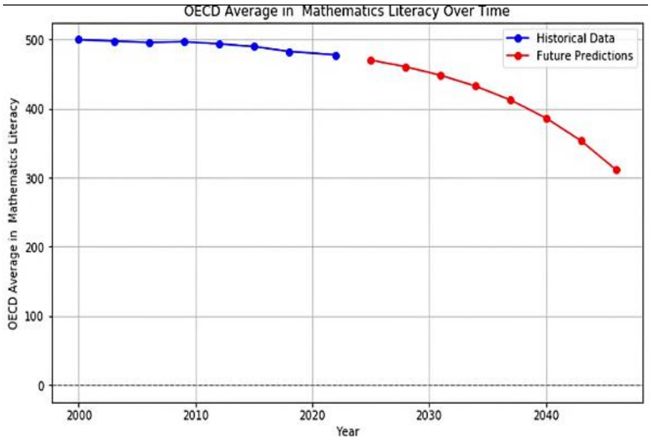

Fig. 6: Illustrating performance of the OECD countries' in mathematics literacy from 2000 to 2046

As depicted in the chart, the OECD has been experiencing a consistent decline in average mathematics scores since 2005. Projections for the future suggest that this negative trend will persist, with an anticipated acceleration in the decline.

6.7 The Result of OECD Countries' Performance Forecasting in Science Literacy

The MA algorithm, specifically simple with a window size of Two to forecast the OECD mean in science literacy for the next twenty years. Table 13 displays the OECD science mean values from 2000 to 2022 and the projected figures for 2025 to 2046.

Table 13: Illustrating the performance of the OECD countries' in science literacy from 2000 to 2046

The Year	The OECD Mean of Science Literacy
2000	500
2003	500
2006	502
2009	501
2012	503
2015	501
2018	499
2022	498
2025	499.10
2028	499.67
2031	499.96
2034	500.11
2037	500.18
2040	500.22
2043	500.24
2046	500.25

Figure 7 illustrates the performance of OECD countries in science literacy over a designated timeframe.

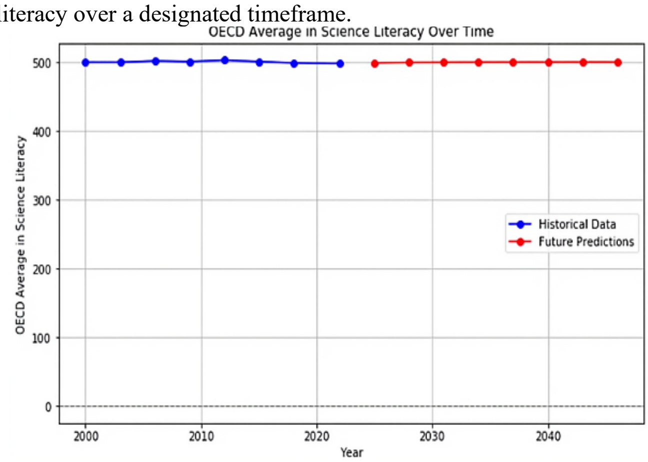

Fig. 7: Illustrating the performance of the OECD countries' in science literacy from 2000 to 2046

1. Figure 7 depicts a slight stability in the OECD's average science scores OECD since 2000. Future projections indicate that this stable trend is expected to persist, with only minor fluctuations anticipated in the years to come.

7. The Conclusion

Reading, mathematics, and science competencies are important for human and economic development. The OECD monitors and compares the competencies of its member and partner states. This analysis provides a comprehensive overview of historical trends and future projections of average reading, mathematics, and science skills in OECD countries and globally.

Worldwide, historical data from 2000 to 2020 indicate that literacy rates in reading, mathematics, and science have shown a relatively stable trend. Over the past two decades, global literacy rates have experienced only minor fluctuations. The increasing number of countries participating in educational assessments indicates a heightened international commitment to monitoring educational progress. The plateau in literacy gains can be attributed to inequities in access to education, especially in developing nations, which could potentially impede progress. Additionally, limitations in pedagogical practices and curricular structures may restrict students' learning potential, while issues of poverty and other socio-economic conditions adversely impact educational outcomes.

However, the projected gains in literacy rates appear optimistic and may reflect potential positive changes in educational policies, technological innovations, and international collaborations. These developments have several major implications, particularly given the rising number of nations participating in PISA. A greater number of participating countries facilitates broader international comparison and benchmarking. Furthermore, it provides insights into trends and patterns from PISA data for practical implications in educational policy and reform, while participation in PISA increases accountability in educational outcomes.

At the OECD level, reading and science literacy levels have remained comparatively stable over the past twenty years and are expected to continue this trend for the next twenty years. A marginal decline in reading literacy has been observed, but this change is not statistically significant. In mathematics literacy, the decline is more pronounced, with a clearer downward trend in the later parts of the time-series data. The relative stability in reading and science literacy suggests that OECD countries have been able to sustain consistent educational policies and standards. Increased access to technology and digital resources may have contributed to maintaining or improving literacy levels.

The declining trend in mathematics literacy requires policymakers and educators to revise the way mathematics is taught. This may involve renewed investment in teacher training, the development of new curricula, and efforts to reduce socio-economic disparities. Collaborative initiatives by OECD countries, including the sharing of best practices and research on mathematics teaching, will be instrumental in addressing this issue. Further research is needed to establish the underlying causes of this decrease in mathematics literacy and to develop effective intervention strategies.

This study provides a clear picture of reading, mathematics, and science literacy levels from 2000 to 2046, based on both global trends and the performance of OECD countries. However, it is important to acknowledge a limitation of this study. While the analysis is based on the historical performance of countries in the PISA assessments, it does not incorporate other crucial factors such as socio-economic status, family background, and country-level economic indicators. There is a strong consensus in the literature that these factors significantly influence literacy outcomes and contribute to achievement gaps across all domains. Future research should integrate these multifaceted variables to provide a more comprehensive understanding of literacy evolution and to inform more targeted policy interventions.

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