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Comparative Estimation of Digital Device Ownership via Time Series Models Based on Pisa Data: Lstm, Gru, Arima and Prophet Models

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COMPARATIVE ESTIMATION OF DIGITAL DEVICE OWNERSHIP VIA TIME SERIES MODELS BASED ON PISA DATA: LSTM, GRU, ARIMA AND PROPHET MODELS

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ABSTRACT

This study aims to make projections regarding digital device ownership among 15-year-old students in Türkiye in 2031, using data from previous PISA cycles. To generate estimations for 2031, time series LSTM, GRU, ARIMA, and Prophet models were employed. To determine the models' performance, MAE, MSE, RMSE, DTW, and R^2 metrics were estimated by categorizing PISA's three-year cycles and dividing them into 80% training and 20% test data. When examining the metric scores, the GRU model demonstrated the highest performance with values of 0.96 R^2, 0.06 MAE, 0.008 MSE, 0.087 RMSE, and 18 DTW. The prediction results obtained using the GRU method indicate that the number of computers and mobile phones will increase much faster than the number of televisions in the future years.

The results of the study demonstrate that the data from PISA cycles can be analyzed using time series methods, while also showing that the GRU model yields better results in educational estimation studies. The GRU model's projections for 2031 not only illustrate how students' access to digital devices may evolve in the future but also provide a temporal window of opportunity for developing countermeasures and policies to address this situation.

Keywords: Artifical intelligence, Digital device ownership, Educational infrastructure, PISA, Time series estimation

1.INTRODUCTION

The rapid advancement of technology, which we struggle to keep up with, is causing parallel transformation and widespread adoption in digital devices, leading to fundamental changes in the field of education where these devices are heavily used and in students' learning activities (Alenezi et al., 2023; Alenezi, 2023; Mohamed Hashim et al., 2022; Timotheou et al., 2023). Digital devices with high usage rates, such as computers, cell phones, and televisions, positively impact students' academic success due to the quick and easy access to information they provide. However, excessive screen exposure has also brought negative effects to the forefront, such as distraction, focus problems, screen addiction, and a tendency to learn information superficially (Akhtar et al., 2023; Ben Youssef et al., 2022; Dontre, 2021; Lee et al., 2023; Limniou, 2021). Therefore, the issue of digital device ownership should be approached in a multifaceted manner, not only in terms of the increase in their number and the ease of access to these devices, but

also in terms of guiding their proper use (Komljenovic, 2022). In this context, understanding how digitalization in the home environment will change over time is critically important in terms of producing reliable predictions regarding digital device ownership and enabling the development of future-oriented policies based on these predictions.

Students have the opportunity to learn outside of school due to the ability to access online resources through digital devices such as computers and mobile phones with internet access, which allows them to create individual learning spaces outside of group learning areas (Aquino et al., 2023; Vitalis et al., 2025). While the positive effects of digital device use are being evaluated, it is also necessary to assess the potential negative effects that may arise in connection with the duration and purpose of use outside of learning (Qanash et al., 2021; Veronica et al., 2022; Veronica & Lopez, 2022). Therefore, along with analyzing current digital device ownership indicators and their effects, future possible scenarios and their effects should also be addressed (Arizmendi et al., 2023; Timotheou et al., 2023). In this context, the data collected within the framework of PISA (Programme for International Student Assessment) administrations from participating countries every three years have provided an accessible source for many studies, as well as enabling this study to examine students' digital device indicators in their home environment (Acıslı & Yesilkanat, 2023).

With the growing importance of artificial intelligence in recent years, deep learning-based approaches have become quite widespread, particularly in the fields of education and engineering. However, due to the limited adequacy of traditional statistical approaches, these methods also offer innovative analysis opportunities for the social sciences and education (Gupta et al., 2021). This study, which uses deep learning-based time series methods to forecast digital device ownership among 15-year-old students for the coming years, lies at the intersection of educational sciences and engineering, making a significant contribution to the gap in the literature regarding the application of machine learning to educational datasets.

1.1. Literature Review

The study intersects topics relevant to different themes such as digital device ownership and artificial intelligence in a single study using PISA data. Therefore, studies in the literature on digital device ownership, studies using PISA data, and studies on artificial intelligence and time series will be examined separately before being addressed as studies that evaluate these themes together.

When examining the topic of digital device ownership, with a particular focus on recent studies in the literature, it is observed that some studies have addressed the situation where not all students have equal access to digital devices and the impact this has on their educational lives (Afzal et al., 2023; Ben Youssef, 2022; Berkley et al., 2024; Elliott, 2023; George et al., 2020). Some of these studies emphasize that socioeconomic status is a factor in students' access to digital devices, while others focus on the positive and negative effects on students based on the purpose and duration of use among those who have access to digital devices.In addition, many studies have addressed the issue of equal access to digital devices (Afzal et al., 2024; Lembani et al., 2020), the use of digital devices for academic purposes (Bozkuş, 2021), and effective use of digital devices (Kong et al., 2022).

Some of the studies focus on how the COVID-19 pandemic and the subsequent widespread adoption of online classes (Peimani & Kamalipour, 2021) and increased demand for digital education platforms (Mittal, 2022) have made the use of computers and smartphones mandatory (Adedoyin, 2023). This situation necessitates the presence of multiple digital devices within the same household. For these and similar reasons, the effects of increased digital device use on student behavior are assessed as likely to cause academic failure (Arizmendi, 2023), while educational use is expected to support educational motivation (Berei, 2022).

Studies addressing PISA datain terms of students' academic achievement (Antonelli-Ponti et al., 2021; D'agostino et al., 2022; Gamazo& Martínez-Abad, 2020; Wang et al., 2023), the impact of socio-economic and cultural back ground on education (Bilican & Yıldırım, 2021; Cingöz & Gür, 2020; Esen & Adıgüzel, 2023; Lagravinese et al., 2020; Pehlivan & Aslan, 2023) and the effects of digital devices on student achievement (Bozkuş, 2025; Kong et al., 2022; Navarro-Martinez & Navarro-Martinez, 2022; Nyberg, 2024; Wang, 2023) are included in the literature. Studies in the literature that use PISA data with artificial intelligence, deep learning-based approaches have generally been preferred because statistical analyses of students' current academic achievement are insufficient (Alanya-Beltran, 2024; Cruz-Jesus et al., 2020; Meini et al., 2025; Yu et al., 2024). Deep learning-based time series methods trained with past data yield highly successful results for future years (Spiliotis, 2023; Yapıcı et al., 2025). Deep learning-based time series analyses are widely used in the field of education, as applied in many studies. Studies in the literature have addressed students' academic achievements (El Hajoui et al., 2024; Perkash et al., 2024)and the socio-economic and cultural effects related to students' education (Anitha, 2025; Gonzales et al., 2025) using deep learning-based approaches. Studies using PISA data have examined the differences between countries based on PISA indicators to investigate how learning outcomes achieved through the digital infrastructure of education systems vary nationally (Kim & Liou, 2025). Furthermore, studies on PISA are ideal for both statistical and deep learning-based approaches because they address broad topics such as the effects of student academic achievement, educators, and school resources and opportunities (Cheung et al., 2024; Pan & Cutumisu, 2024). An important area of research on this topic is to make predictions about education performance by making future projections in the field of education using time series methods. In this context, most of the forecasting studies are based on classical statistical studies, and no studies using deep learning-based estimation have been encountered.

The vast majority of studies addressing the effects of socioeconomic variables on digital device ownership highlight inequality in access to these devices (Dodel, 2024) emphasizing that parents' educational status, cultural possessions, and wealth indicators are particularly decisive factors in this inequality (Van Der Wal, 2024).

The growing interest in research in the field of education necessitates predictions for future years based on large-scale datasets and the use of digital devices by students. However, current studies focus on the relationship between digital device use and student achievement for a single time period in past years (Baert et al., 2020; Sapci et al., 2021). Therefore, making future projections using time series based on PISA's long-term cycles will provide a novel methodological contribution in terms of digital device usage in education.

1.2. Contribution and Organization of the Article

The study distinguished itself from other works in the literature by not only examining PISA data through descriptive analyses but also adapting time series methods to make future projections that would contribute to future research.

Deep learning-based time series methods were used to predict students' digital device ownership, enabling a comparative evaluation of these models in the field of education and the identification of the best one. GRU (Gated Recurrent Unit), identified as the most suitable approach, yielded prediction results that were highly compatible with PISA data, thanks to its high performance. To the best of our knowledge, there is no study that uses data from PISA cycles and deep learning-based time series methods to predict students' computer, mobile phone, and television ownership for future years.

Digital device ownership in PISA cycles was detailed to include computers, televisions, and mobile phones within the study, and by additionally including the average value of students' cultural and socioeconomic indicators, highly realistic results were obtained.

The remaining sections of the article are as follows: Section 2 analyzes the PISA data used in the study, Section 3 discusses time series models LSTM (Long Short-Term Memory), GRU, ARIMA (Autoregressive Integrated Moving Average), Prophet, and evaluation criteria MAE (Mean Absolute Error), MSE (Mean Squared Error), RMSE (Root Mean Squared Error), R^2 (Coefficient of Determination), and DTW (Dynamic Time Warping); Section 4 presents performance results based on metric scores and graphs and tables for 2031 projections; and Sections 5 presents the evaluation of analysis results and future work plans.

2.DATASET

The data used in this study is based on survey data collected every three years by the Programme for International Student Assessment (PISA) from 15-year-old students in many countries (Navarro-Martinez & Peña-Acuña, 2022). The dataset is publicly available on the webpage of OECD addressing PISA data files and for this study the dataset was downloaded from this webpage (https://webfs.oecd.org/pisa2022/index.html). PISA is coordinated by the Organisation for Economic Co-operation and Development (OECD) and is a regular assessment of specific topics every three years. The assessments provide summary information on educational outcomes and home learning environments, with careful consideration given to influencing factors.

The 2006, 2009, 2012, 2015, 2018, and 2022 cycles of PISA used in this study have sufficient historical data for time series analysis and forecasting. Tables 1, 2, and 3 show the rates of computer, television, and cell phone ownership among 15-year-old students in Türkiye from 2006 to 2022.

Table 1. Computer ownership in the household reported by 15-year-old students in Türkiye from 2006 to 2022

Computer ownership by year (%)	None	One	Two	Three and more
2006	59.4	35.9	3.1	0.5
2009	37	51	7.8	1.7
2012	28.9	52.3	14.2	4.1
2015	21.2	35.6	25.4	15.9
2018	20.3	34.1	26.8	17.4
2022	17.4	33.3	27.5	20.3

Table 1 shows that the percentage of participants who reported owning a computer increased over time. While the percentage of students who stated that they did not own a computer decreased over time, there was an increase in the percentage of students who stated that they had two, three, or more computers at home. When examining the changes between 2006 and 2022, the fact that multiple computer use in the home environment reached 20.3% in 2022 indicates that it is quite widespread in households. The increase in the "One" category, which continued until 2012, has remained stable since 2015, indicating that digital device ownership in households has evolved from a single computer to multiple computers. The change in the "None" category indicates that there will be virtually no computerless home environments in the coming years, while these numerical changes emphasize the need for further work on this topic.

Table 2. Television ownership in the household reported by 15-year-old students in Türkiye from 2006 to 2022

Television ownership by year (%)	None	One	Two	Three and more
2006	0.6	47.8	40.6	10.6
2009	0.5	49.5	39.4	10
2012	0.8	55.2	34.6	8.1
2015	0.6	58.2	32.5	8.1
2018	0.8	55.8	33.5	9
2022	1.3	46.6	35	12.6

When Table 2 is examined, no consistent change in the number of televisions is observed over time, and fluctuations are seen. However, it is observed that the percentage of those who do not have a television at home exceeded 1% for the first time in 2022. Nevertheless, it is seen that the percentage of those who own three or more televisions at home is higher than in previous cycles. Overall, it is thought that television entered the saturation phase earlier than computers and mobile phones because it is an older technological product. Therefore, almost every student has a television at home, demonstrating that television has been accepted as a universal device for a very long time. Although no significant difference is expected for television, which reached saturation level long ago, in the 2031 forecast, it is crucial to compare and analyze the development and evolution of newer technological devices like computers and mobile phones with a more stable digital device.

Table 3. Mobile phone ownership in the household reported by 15-year-old students in Türkiye from 2006 to 2022

Cellular phone ownership by year (%)	None	One	Two	Three and more
2006	3.3	15.3	27.8	53.4
2009	1	7.3	20.9	70.3
2012	0.6	6.2	20.7	71.5
2015	9.7	21.5	21.1	45.9
2018	2.8	9.2	13.9	72.5
2022	3.1	10	15	69.1

Table 3 shows that the change in mobile phone ownership did not follow a consistent trend over time. However, mobile phone ownership peaked in 2012. The fact that the percentage in the "Three and more" category reached 53% in 2006 indicates that mobile phones reached saturation in multiple usage in the early years. Since mobile phone ownership reached an early saturation level and maintained this rate in subsequent years, the stability of multiple usage in the 2031 projections is of critical importance.

In addition to the dependent variables, independent variables were also selected in the study. This was done with the aim of obtaining more realistic prediction results. Under the general heading of digital device ownership, the variables of computer, television, and mobile phone ownership represent the dependent variables of the study, while the factors affecting the dependent variables are the *Cultural possessions at home (CULTPOS), Home educational resources (HEDRES), Index of home possessions (HOMEPOS), Highest parental education in years (PAREDINT), and Wealth*. Mean values were used for the independent variables for the Turkish sample. Table 4 indicates the mean values pertaining to independent variables by year for Türkiye data.

Table 4. Mean values pertaining to independent variables

Independent variables	2006	2009	2012	2015	2018	2022
CULTPOS	-.001304	0.5171	-0.1246	-0.259707	-0.771617	-1.081836
HOMEPOS	-1.058728	-0.7361	-1.3151	-1.432295	-1.179025	-
HEDRES	-.653613	0.4801	-0.6092	-0.583278	-0.48112	-
PAREDINT	8.648	-	-	-	11.4041	11.4259
WEALTH	-1.058728	-0.7361	-0.5433	-1.487698	-1.356178	-

The OECD estimates index scores for certain variables. These index scores are converted into standard scores with an arithmetic mean of zero and a standard deviation of one (Robitzsch & Lüdtke, 2023). In this study, students' ownership of digital devices at home was not only considered in terms of time, but estimates were also made taking into account students' socioeconomic and cultural factors.

2.1.Data Sources, Data Preprocessing and Simulation Environment

The data preprocessing process was carried out in accordance with deep learning approaches, involving the variables in the PISA cycle: alignment, category transformation, and time series creation. First, after examining the measurement scales and category structures of the variables, the state space was defined and mappings were made to create the temporal counterpart of the variables. Then, to prevent artificial jumps, the probabilistic redistribution approach was used to separate nested categories. Finally, to scale the numerical data, max-min normalization, which is preferred in deep learning approaches, was applied to convert the variables to the [0,1] range.

In this study, analyses and simulations were performed using the Pandas, NumPy, Sklearn, Flask, and Keras libraries available in Python version 3.12.2. After the model training and testing process was carried out in a controlled simulation environment, the best model was identified using MAE, MSE, DTW, and R^2 error metrics, and predictions were made using this model.

When evaluating the computational infrastructure and model operating environment, inference processes utilized an Intel Xeon Silver 4310 (16 cores, 2.1 GHz) processor, 64 GB system memory, and NVIDIA A100 (80 GB VRAM) graphics processing unit, enabling the stable and efficient training of computationally intensive deep learning models such as LSTM and GRU. Model training times averaged around 27 minutes, and after training was completed, the estimation performance of the models was recorded at an average of 0.85 seconds. This value represents the response time measured for each prediction request made through a Flask-based application interface. The average power consumption of the graphics processing unit was 155 W, and 0.07 kWh of energy was consumed during the training process. These values show that it is appropriate in terms of energy costs in practical applications.

3. METHOD

The study aimed to predict future trends by modeling the digital device ownership of 15-year-old students in Türkiye in previous PISA cycles. In the study, the data from PISA cycles were applied to the proposed deep learning-based time series approaches, namely ARIMA, Prophet, LSTM, and GRU, and the performance of these models was compared. The comparison aimed to identify the model with the best performance. Based on the model with the best performance and PISA's three-year assessment cycle, the study made predictions for digital device ownership in the 2031 cycle. The year 2031 was selected to create a time frame that would allow for more meaningful long-term predictions.

Figure 1 shows the flowchart of the study, illustrating the data preprocessing, category conversion, model creation, training, identification of the best performance, and forward-looking predictions.

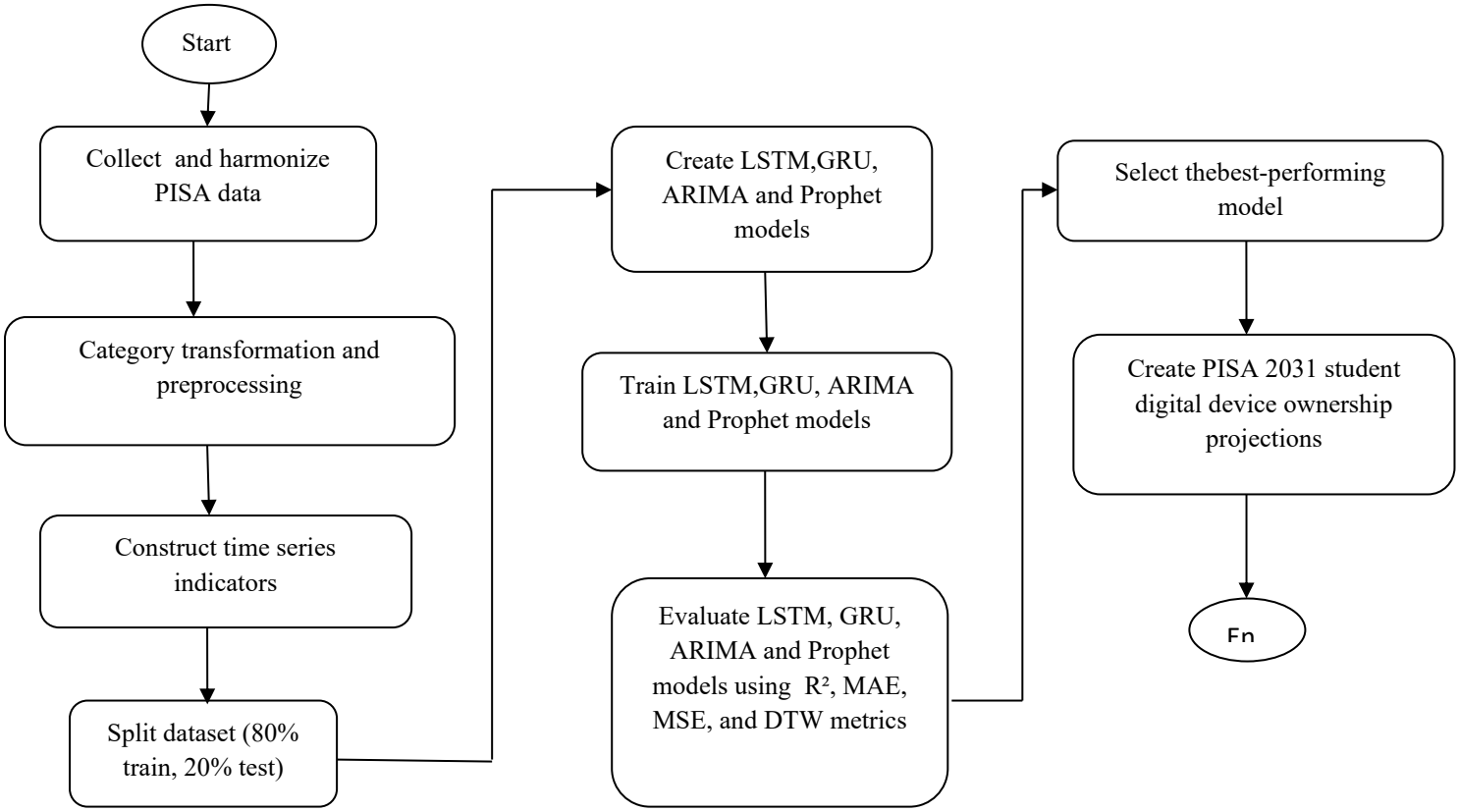


Figure 1. Flowchart of the study

3.1.Category Conversion

Due to differences in category structures based on student survey results in the years when PISA assessment cycles were conducted, time series analysis could not be directly applied. As a result of the category conversion and harmonization process applied to data on digital device ownership among 15-year-old students, a comparable category structure was obtained in the time series models used in the study for the 2006-2022 cycles.

The mathematical expressions used in the category conversion are defined below:

*t:*PISA's cycle from 2006 to 2022

C^*: Data set subject to the harmonization process

C_t: PISA's non-harmonized dataset

$N_{t,k}$: PISA's category frequency

The original PISA data were converted into categories and harmonized for Ct, resulting in C^* data suitable for time series modeling after the harmonization process. The category classification applied to the obtained C^* is shown in Equation 1.

$$C^* = \{None, one, two, threeormore\} \quad [1]$$

In some cycles of PISA, data was combined directly without any loss. For the 15-year-old age group, digital device ownership was considered as *3-5 device ownership* and *5 or more* device ownership in some cycles, while in other cycles it was calculated as *3 or more device ownership*. Here, since there was no data overlap in the cycles and the interval boundaries matched exactly, a deterministic transformation was applied and the data was directly aggregated. This process is shown in Equation 2.

$$N_{t,threeormore} = N_{t,3and5} + N_{t,morethan5} \quad [2]$$

In some PISA cycles, data were intertwined, so instead of applying deterministic transformation, combined categories were separated using the proportional distribution method, with reference to years that had detailed categories. Specifically, in the latest PISA cycles, *1 and 2 device ownership* were treated as a single category, whereas in earlier cycles, *1 device ownership* and *2 device ownership* were treated separately. This process is illustrated in Equation 3 and Equation 4.

$$p_{one} = \frac{N_{one}}{N_{two} + N_{one}} \quad [3]$$

$$p_{two} = 1 - p_{one} \quad [4]$$

At the end of the category conversion and alignment process, the dataset was made ready for training and testing for time series models.

3.2. Estimation Methods

This study aims to predict the digital device ownership of 15-year-old students in Türkiye for the PISA 2031 cycle using deep learning-based time series approaches such as ARIMA, GRU, LSTM, and Prophet. The method showing the best performance among the time series approaches was selected for the prediction. When deciding on the model with the best performance, the test and prediction results were evaluated using MAE, MSE, R^2, and DTW metric scores.

3.2.1. LSTM

LSTM is a method that can decide how much of the past data to retain and how much to forget using gate mechanisms developed to solve the gradient vanishing problem of classical recurrent neural networks (RNN), and it is a highly preferred method in time series (Noh, 2021). Since PISA collects data in three-year intervals, making long-term modeling appropriate, LSTM is a highly suitable model for capturing changes in students' digital device ownership over time.

The LSTM has three gates: the input gate (i_t), the forget gate (f_t), and the output gate (o_t). The mathematical expression of the LSTM cell is described by Equations (5-8) (Zang et al., 2020).

$$i_t, f_t, o_t = \sigma(W_{xt} + Uh_{t-1} + b) \quad [5]$$

$$\hat{C}_t = \tanh(W_C[h_{t-1}, x_t] + b_C) \quad [6]$$

$$C_t = f_t C_{t-1} + i_t \hat{C}_t \quad [7]$$

$$h_t = o_t \tanh(C_t) \quad [8]$$

Figure 2 shows the block diagram of an LSTM cell.

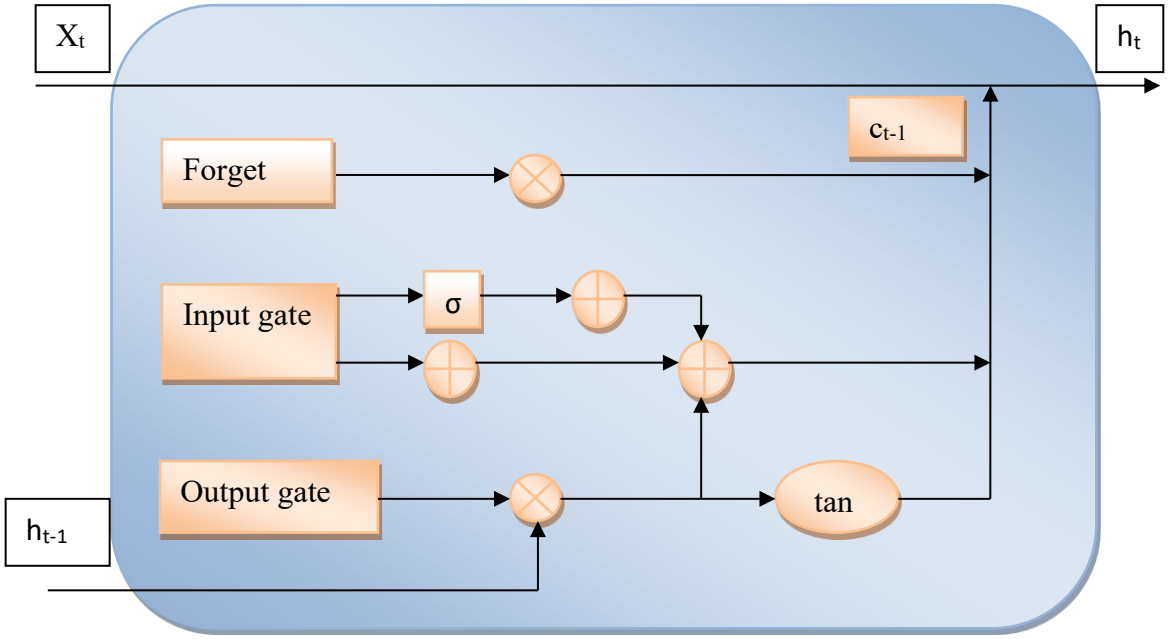


Figure 2. Block diagram of an LSTM cell.

3.2.2. GRU

GRU is a method developed to solve the gradient vanishing problem in classical recurrent neural networks (RNN) such as LSTM, but requires fewer parameters and computations due to its simpler structure (Jiao et al., 2020). GRU's structure with fewer parameters and computations is well suited for time series structures with long periods such as PISA.

The GRU has two gates: an update gate (z_t) and a reset gate (r_t). The mathematical expression of the GRU cell is described in Equations (9-12) (Chen & Huang, 2020).

$$z_t = \sigma(W_z[h_{t-1}, x_t] + b_z) \quad [9]$$

$$r_t = \sigma(W_r[h_{t-1}, x_t] + b_r) \quad [10]$$

$$\hat{h}_t = \tanh(W_h[r_t h_{t-1}, x_t] + b_h) \quad [11]$$

$$h_t = z_t h_t + (1 - z_t)\hat{h}_t \quad [12]$$

Figure 3 shows the block diagram of the GRU cell.

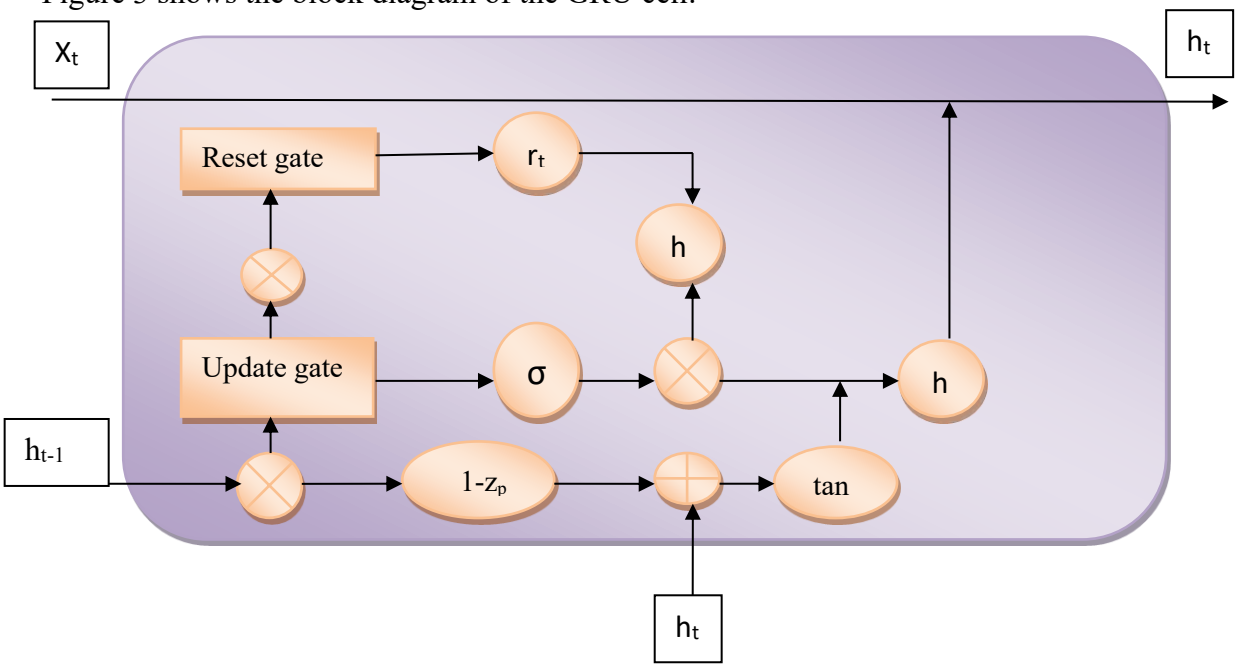


Figure 3. Block diagram of a GRU cell.

3.2.3.ARIMA

ARIMA is particularly suitable for single-variable, especially short-term time series structures by combining past period data with error terms (Duan et al., 2023). Although ARIMA has more limited flexibility compared to other time series methods, it is preferred for its comparative function, as it allows for comparison between other models by creating a reference estimate.

ARIMA consists of three terms: the autoregressive term (p), the moving average term (q), and the differencing order (d), and is mathematically expressed by Equation 13 (Kaur et al., 2023).

$$\phi(B)(1-B)^d y_t = \theta(B)\varepsilon_t \quad [13]$$

Equation 13 shows the time series y_t, the lag B, the autoregressive polynomial, the moving polynomial, and the white noise (Ning, 2022).

Figure 4 shows the ARIMA cell block diagram.

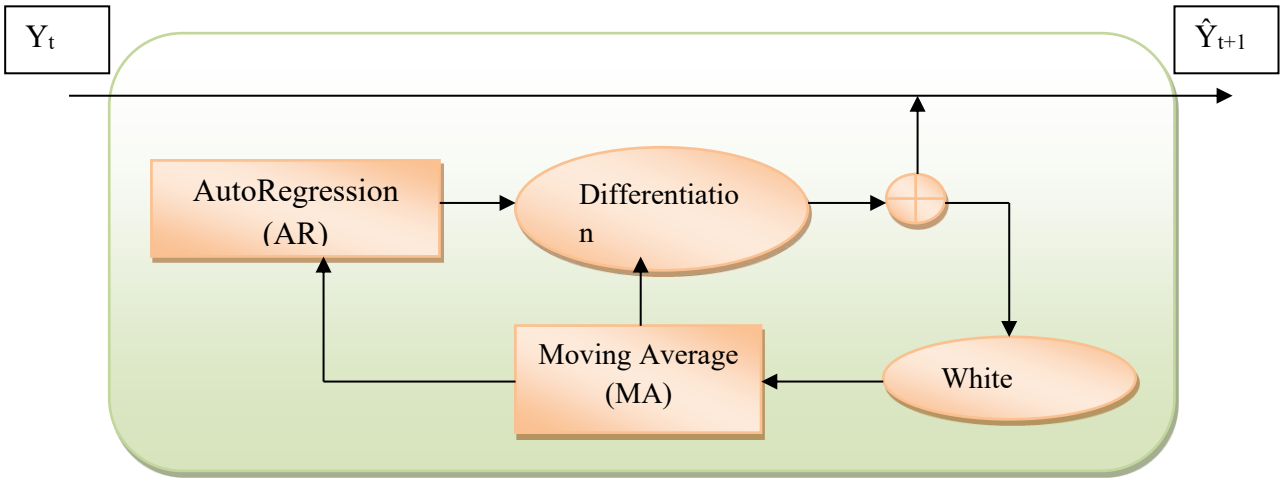


Figure 4. Block diagram of an ARIMA cell.

3.2.4.Prophet

Prophet provides more realistic results compared to other time series methods, especially in studies with more missing data and more irregular time intervals. When evaluated in terms of PISA estimation, although it was expected to yield relatively better results than ARIMA due to its trend-focused estimation structure, it can be noted that it was preferred for comparison with LSTM and GRU to demonstrate that other models provided more accurate results.

Prophet consists of three components: a trend component, a seasonal component, and an error term, and is mathematically expressed by Equation 14 (Stefenon, 2023) .

$$y(t) = g(t) + s(t) + \varepsilon_t \quad [14]$$

Figure 5 shows the block diagram of the Prophet cell.

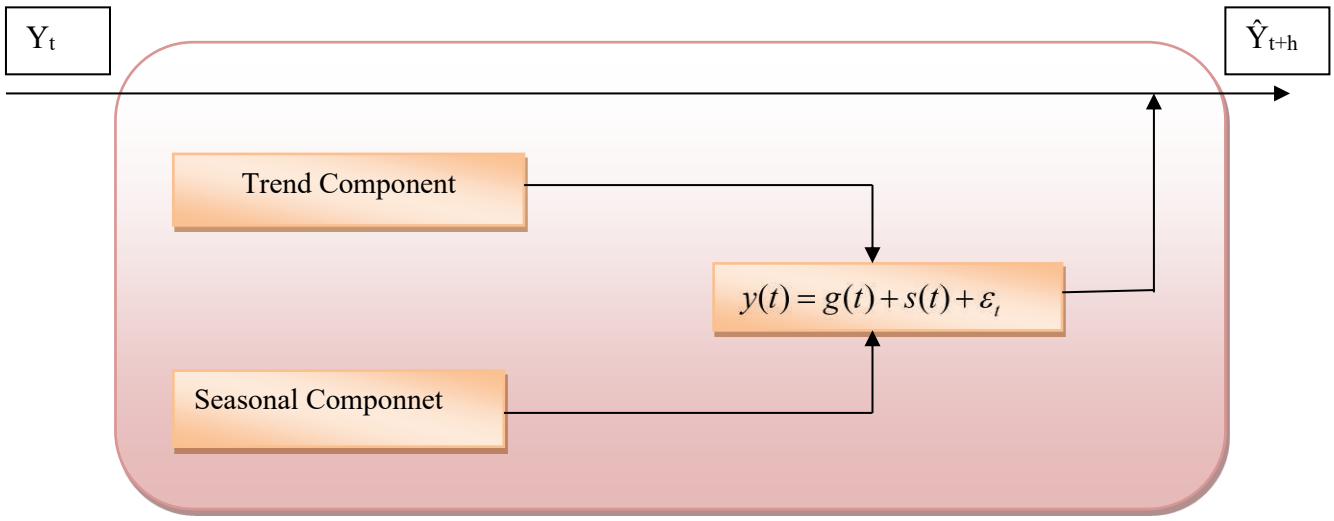


Figure 5. Block diagram of a Prophet cell.

3.3.Model Training and Validation

The estimation models used in this study—LSTM, GRU, ARIMA, and Prophet—were trained using Türkiye's 15-year-old PISA digital device ownership data. In time series studies, preserving the temporal structure of the data is crucial to prevent data leakage and obtain realistic results. In this context, the digital device ownership data from the 2006-2022 PISA cycles were divided into test and training data in a way that preserves the temporal structure. The data set was divided chronologically into 80% training data and 20% test data, eliminating data leakage and enabling predictions for the future based on past observations.

In the study, after all models were trained with the same training data, the validation process analyzed model performance using error metrics based on test data. The model with the best performance was then used to obtain Türkiye's 2031 PISA 15-year-old digital device ownership rates across different categories. Using the best model determined by MAE, MSE, and RMSE error metrics, R^2 success, and DTW distance metric scores, predictions were made for the 2031 household TV, computer, and mobile phone rates.

3.3.1.Evaluation Metrics

In this study, preferred metrics were used to measure the differences between actual values and prediction results in order to decide on the best model for estimation. During the evaluation process, MAE, MSE, and RMSE metrics were preferred to measure the error rate between the predictions resulting from training the models and the chronological test data separated by 20%. R^2 was used to measure higher success among these scores, and DTW was used to measure the distance between the scores.

MAE (Mean Absolute Error)

MAE is calculated by taking the average value after taking the absolute value of the difference between the actual values and the estimated results. Equation 15 is used in the calculation of MAE (Hodson, 2022).

$$MAE = \frac{1}{n}\sum_{t=1}^{n}\left|\hat{y}_t - y_t\right| \quad [15]$$

In this study, the MAE value was calculated by taking the difference between the estimated results obtained from the values found in the six cycles of PISA between 2006 and 2022 and then computing the average.

MSE (Mean Squared Error)

In MSE, unlike MAE, the average value is taken after squaring the difference between the actual values and the estimated results. Equation 16 is used in the calculation of MAE (Chicco, 2021).

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(y_t - \hat{y}_t\right)^2} \quad [16]$$

In this study, the MSE value was calculated by computing the average of the squares of the differences between the estimated results obtained using the values from the six cycles of PISA between 2006 and 2022.

RMSE (Root Mean Squared Error)

RMSE is calculated by taking the square root of the value found in MSE. Equation 17 is used in the calculation of RMSE (Wang et al., 2022).

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}\left(y_t - \hat{y}_t\right)^2} \quad [17]$$

R^2(Coefficient of Determination)

R^2 is a success metric that can take values between 0 and 1, with values closer to 1 indicating higher performance. Equation 18 is used to calculate R^2 (Tao et al., 2023).

$$R^2 = 1 - \frac{\frac{1}{n}\sum_{t=1}^{n}(y_t - \hat{y}_t)^2}{\frac{1}{n}\sum_{t=1}^{n}(y_t - \bar{y}_t)^2}, \qquad \bar{y}_t = \frac{1}{n}\sum_{t=1} y_t \quad [18]$$

DTW (Dynamic Time Warping)

DTW is a metric that measures the distance between two time series with actual and predicted values, where the lower value indicates higher performance. Equation 19 is used in DTW calculation.

$$DTW = \sum_{t=1}^{n} \|(\hat{y}_t - y_t)\|_2^2 \quad [19]$$

In the metrics, y_t represents actual values, while $\hat{y}_t$ represents the estimated values produced by the models.

The study evaluated multiple metrics, enabling a comparison between models and confirming the accuracy of the results obtained. When calculating the preferred metrics in the study, only test data was used; the data used for training was not included in this process, ensuring more realistic measurements.

4. RESULTS

The estimation results obtained from PISA's past cycles and the comparative performance results for time series models are presented in this section. The study consists of two stages: the first stage involves performance evaluations of LSTM, GRU, ARIMA, and Prophet models using MAE, MSE, RMSE, and DTW metrics, and the second stage involves making predictions for 2031 using the model that demonstrated the best performance.

Time series models were implemented in a Python 3.12.2 simulation environment, Numpy 2.1.2 for numerical calculations, Pandas 2.2.2 for data processing, Statsmodels 0.14.4 for statistical evaluation, Scikit-learn 1.5.2 for evaluation and scaling, and Keras 2.4.3 for neural network modeling.

All estimation methods used in the study were evaluated using the same training and test data with manually adjusted hyperparameter values that were kept constant throughout the study to ensure a fair comparison. Table 5 shows the hyperparameters used in the study.

Table 5. Model hyperparameters

Hyperparameter	**Value**
Units	50
Learning Rate	0.001
Epoch	50
Dropout	0.0
Batch Size	16
Optimizer	Adam

The R^2 and DTW metric scores of the models are shown in Figure 6. R^2 is a success metric, and the value closest to 1 indicates the highest performance. When examining Figure 6, the R^2 metric score shows that GRU has the highest performance with 0.96, while LSTM shows a value of 0.94, which is quite close to GRU. Prophet shows a slightly lower performance with 0.88, and ARIMA with 0.83. DTW is a distance metric and, as it evaluates the distance between actual data and prediction scores, a smaller value indicates higher performance. Examining Figure 6, the DTW metric score shows that GRU has the highest performance with 18, while LSTM has a value of 22, Prophet has 35, and ARIMA has 60, showing slightly lower performance.

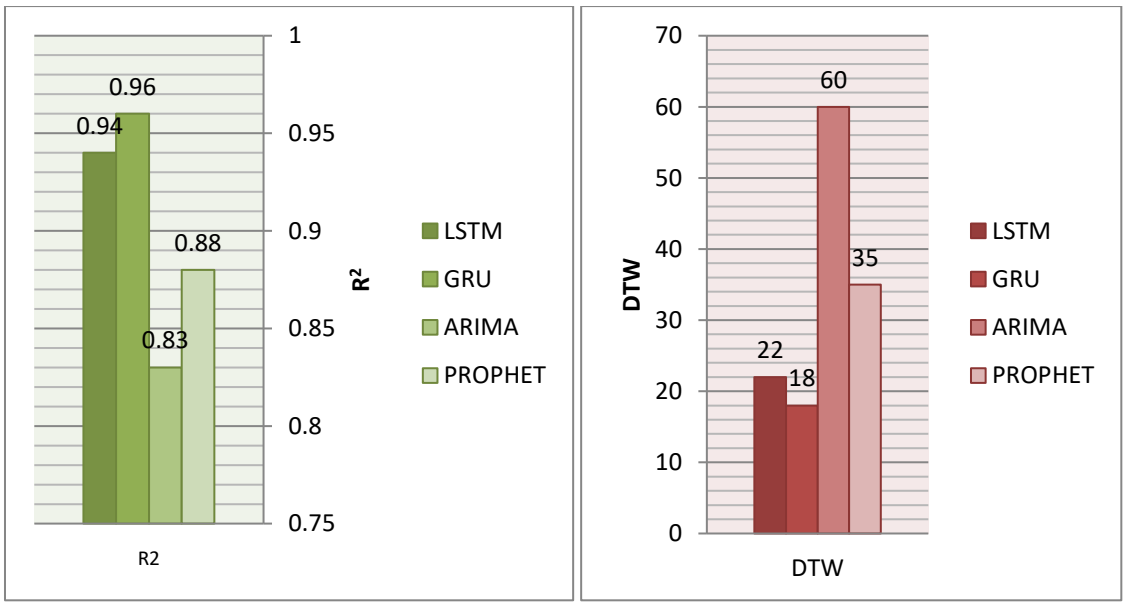


Figure 6.R^2 and DTW scores for LSTM,GRU, ARIMA and Prophet models

The MAE, MSE, and RMSE metric scores of the models are shown in Figure 7. Since these metrics are error metrics, the lowest value indicates the highest performance. When examining Figure 7, the MAE metric score shows that GRU has the highest performance with 0.06, while

LSTM has a value of 0.08, Prophet 0.14, and ARIMA 0.22, indicating lower performance. The MSE metric score shows that GRU has the highest performance with 0.008, while LSTM has a value of 0.012, Prophet has 0.028, and ARIMA has a relatively lower performance with 0.050. The RMSE metric score showed the highest performance for GRU at 0.087, while LSTM scored 0.112, Prophet 0.157, and ARIMA 0.216, indicating relatively lower performance.

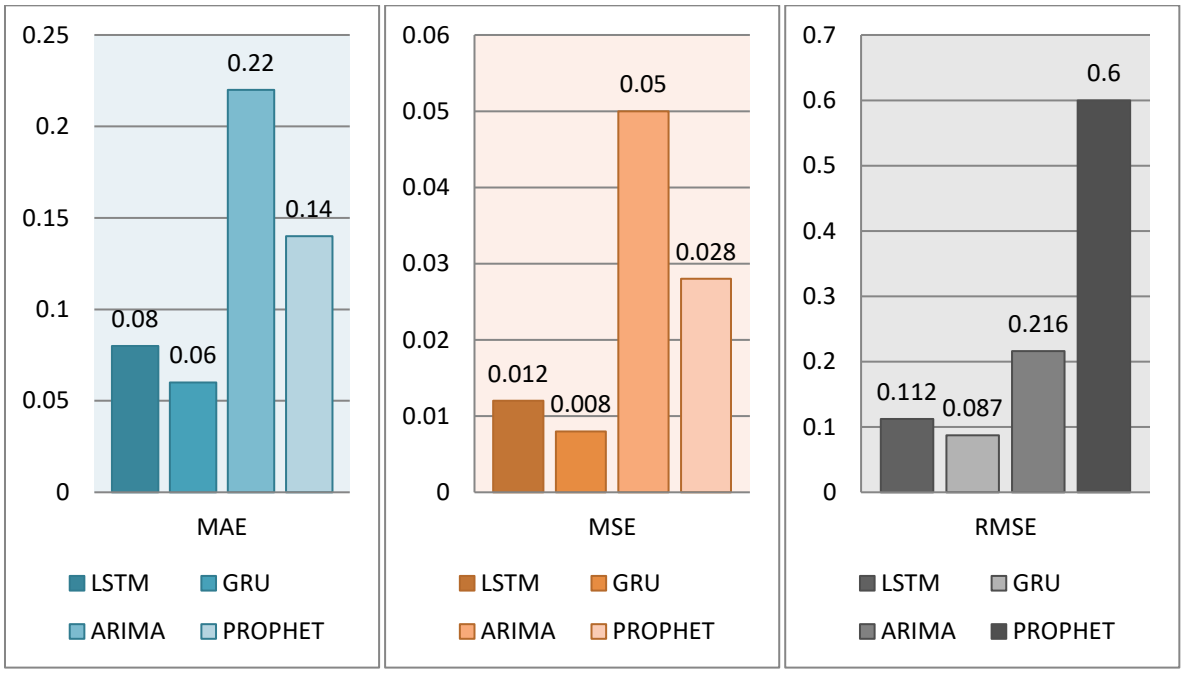


Figure 7. MAE, MSE and RMSE scores for LSTM, GRU, ARIMA and Prophet models

When Figures 6 and 7 are examined, it can be seen that the GRU model performs quite well compared to other models in terms of metric scores. Therefore, the results of the GRU model were obtained in the estimation process.

The aim of the first stage of the study was to determine the time series model with the best performance, and then to complete the estimation process with the model determined in the second stage. In this context, the GRU model showed the best performance among the LSTM, GRU, ARIMA, and Prophet models, with lower error and higher success scores. The estimation for digital device ownership among 15-year-old students in Türkiye in 2031 was made using the GRU model, which was determined to be the best time series model. The 2031 predictions were made by dividing digital device ownership into subcategories: television, computer, and mobile phone.

Table 6 shows the predictions for computer ownership among 15-year-old students in Türkiye in 2031, as determined by PISA.

Table 6. Computer ownership among 15-year-old students in Türkiye from 2006 to 2022

Computer ownership (household)	Percentage(%)
None	0
One	30.44
Two	40.57
Three and more	29.09
Total	**100, 1**

In Figure 8, the number of computers for 15-year-old students in Türkiye in 2031 is shown with a solid line for the years 2006-2022, and the projections are shown with a dashed line.

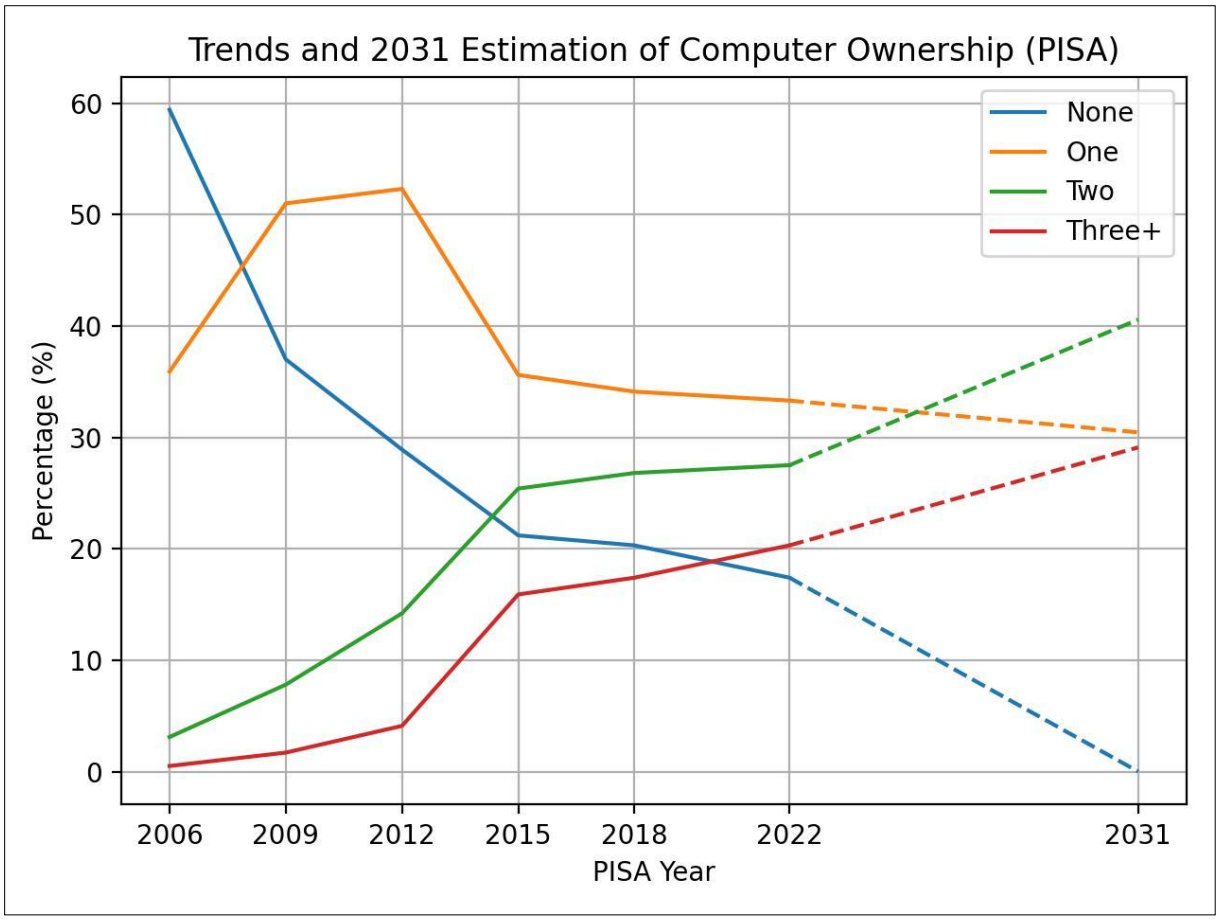


Figure 8. Computer ownership from 2006 to 2022 and 2031 estimation

Table 7 shows Türkiye's projections for 2031 PISA 15-year-old students' digital device ownership under the mobile phone subheading.

Table 7. Cellular phone ownership among 15-year-old students in Türkiye from 2006 to 2022

Cellular phone ownership (household)	Percentage(%)
None	5.27
One	11.32
Two	9.81
Three and more	70.22
Total	**96.62**

In Figure 9, the percentage of 15-year-old students in Türkiye with mobile phones in 2031 is shown as a solid line for the years 2006-2022, while the projections are shown as a dashed line.

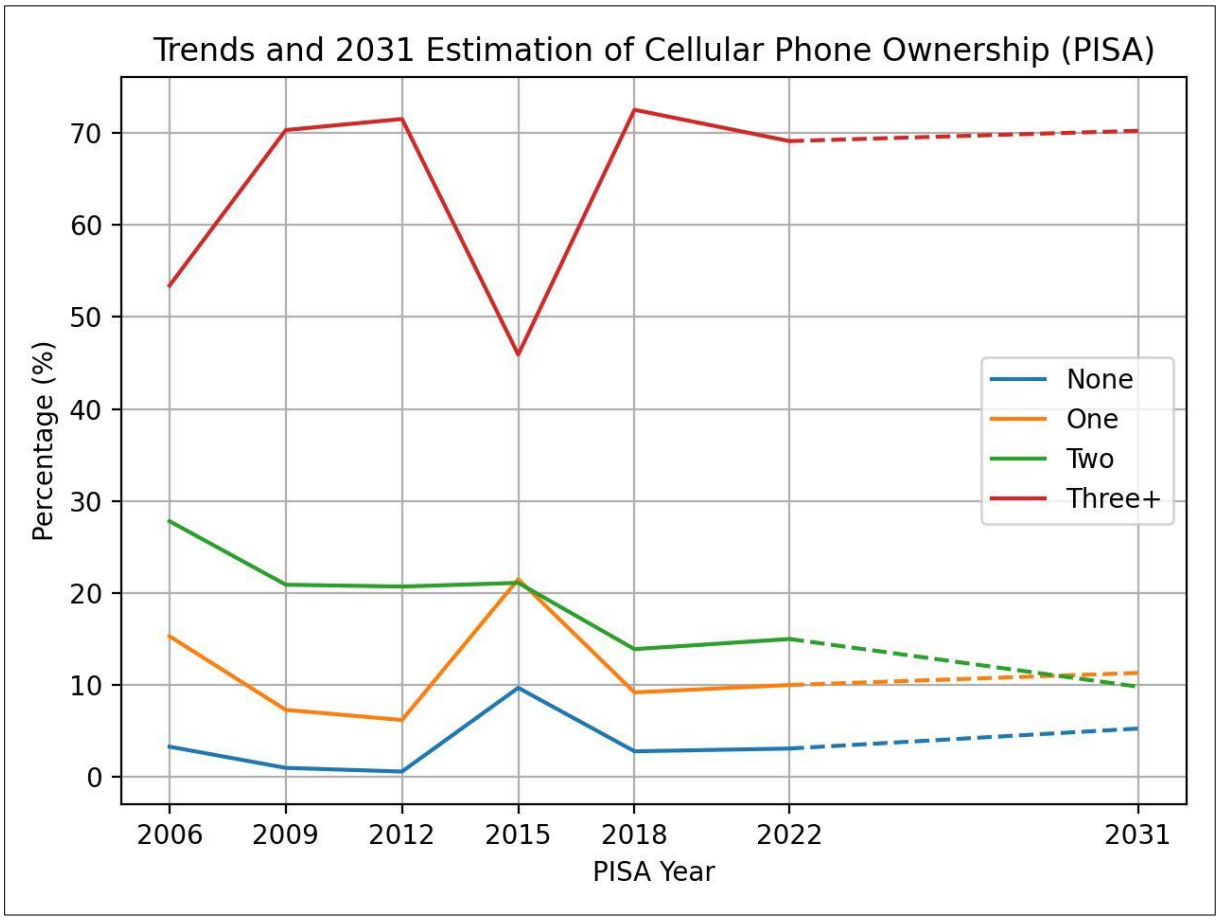


Figure 9.Cellular phone ownership from 2006 to 2022 and 2031 estimation

Table 8 shows Türkiye's projections for television ownership among 15-year-old students in the 2031 PISA assessment.

Table 8. Television ownership among 15-year-old students in Türkiye from 2006 to 2022

Television ownership (household)	**Percentage(%)**
None	5.27
One	11.32
Two	9.81
Three and more	70.22
Total	**96.52**

In Figure 10, Türkiye's television ownershiprate among 15-year-old students in the 2031 PISA assessment is shown as a solid line for the years 2006-2022, while the projections are shown as a dashed line.

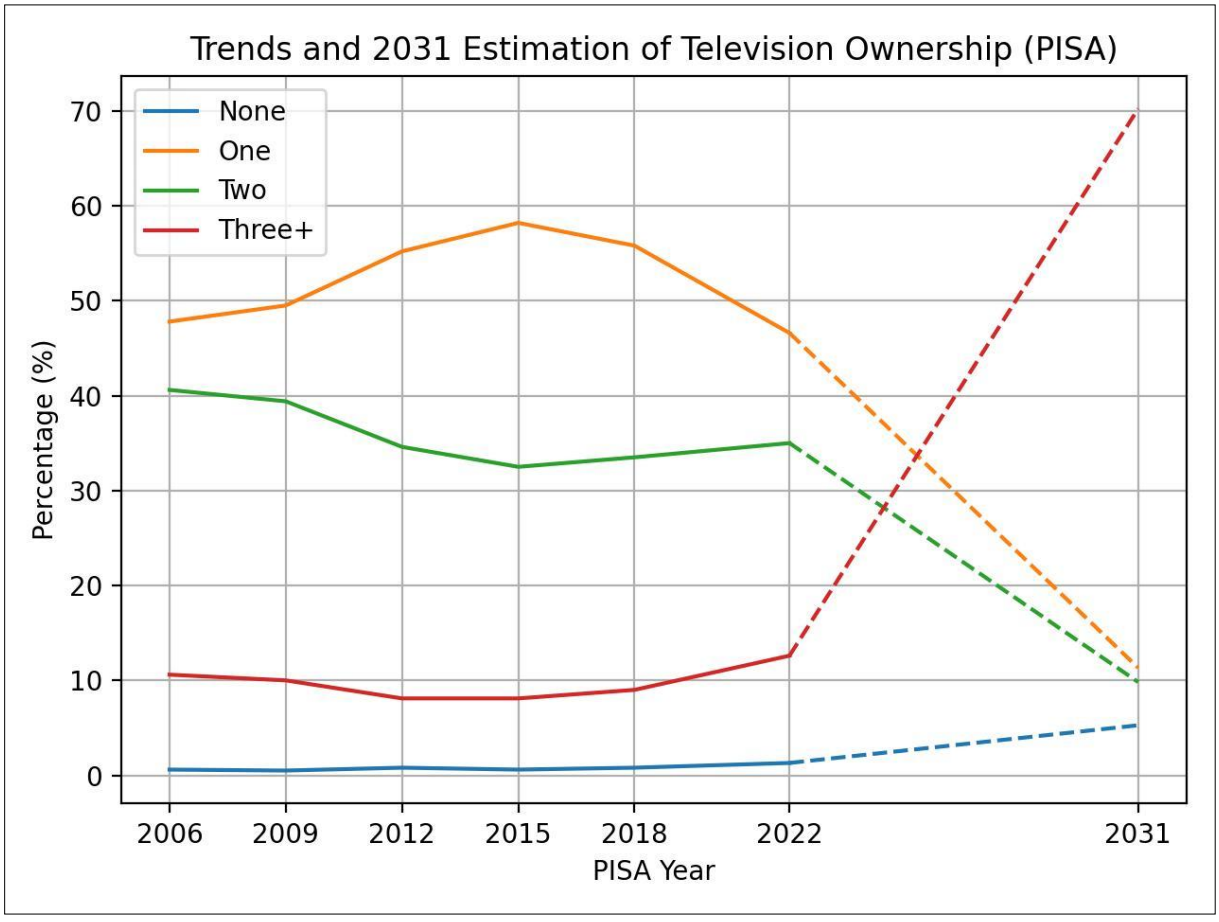


Figure 10.Television ownership from 2006 to 2022 and 2031 estimation

6.CONCLUSION AND DISCUSSION

This study uses data on digital device ownership and changes among 15-year-old students from previous PISA cycles to generate projections for the 2031 cycle. Digital device ownership can have positive or negative effects on students' academic achievement, social life, and study habits, depending on how it is used. For this reason, establishing a long-term forecast horizon on this topic provides education experts and policymakerswith an opportunity to assess potential positive or negative effects and take necessary measures.

The study utilized deep learning-based time series models, demonstrating that LSTM and GRU models, in particular, yielded better results when applied to PISA data. These findings will provide insights for future studies using similar datasets. The study elaborated on the subject by considering not only the number of digital devices but also subcategories based on device types, such as computers, televisions, and mobile phones. Among deep learning-based models, the GRU model provided the best results, while LSTM showed performance very close to GRU. ARIMA and Prophet models were observed to fail to achieve similar success rates.

When evaluating the 2031 projections, it is seen that the "Three and more" category will reach up to 70% in 2031 and the "One" category will decline to 11%, indicating that multiple usage will be dominant and households with single usage will transition to multiple usage. This result indicates that the number of televisions, which remained stable between 2006 and 2009, will give way to multiple usage. In the mobile phone estimation, while the current saturation rate is expected to continue at around 70% in 2031, particularly in the "Three and more" category, the 5% rate in the "None" category indicates that although mobile phones are widely accepted by a large part of society, they remain inaccessible to a limited segment. Computer projections indicate that the transformation in the number of computers will become more noticeable in the coming years. By 2031, almost every student will have access to a computer, and it is clear that computer ownership is evolving towards multiple use. The rise of the "Two" category to 40% and the "Three and more" category to 29% indicates that multiple computer ownership in student households is generally accepted.

The estimation results obtained were not based solely on the temporal dimension; students' socioeconomic and cultural indicators were also used. Thus, the estimations produced results that were consistent with an educational approach that took into account existing inequalities, rather than merely evaluating digitization on a yearly basis. Anitha (2025) evaluated the impact of ICT (Information and Communication Technology) on student achievement using variables such as course grades and computer usage skills with the GRU model. The model demonstrated 98% accuracy in the study. This result confirms the GRU model's performance both on educational data and on the prediction results obtained using the GRU model with PISA data in this study. Wekerle and colleagues (2022) reported positive correlation between the level of student participation in learning activities using digital devices in the classroom and learning outcomes. In this context, our study's prediction of an upward trend in device ownership by 2031 highlights the importance of planning future education policies in a way that encourages the effective and purposeful use of digital tools. In this context, our study's prediction of an upward trend in device ownership by 2031 highlights the importance of planning future education policies in a way that encourages the effective and purposeful use of digital tools**.** In their study, Sunday and colleagues (2021) analyzed cell phone usage in a sample size of 147,943 students from 16 countries, emphasizing that it negatively affects academic achievement and the skills and potential necessary for learning. In this context, the study shows a contradiction between the predicted increase in student phone ownership by 2031 and academic achievement. Bozkuş and Kıvanç examined the effects of the digital device infrastructure in schools and the digital device usage skills of teachers who use these devices on student achievement in their study using PISA data. The study, conducted using PISA 2018

survey data, reported that the rate of digital device use and teachers' proficiency in using them had positive effects on students' reading, science, and mathematics achievement. The findings of the study show that there is a strong relationship between digital infrastructure and teacher competence and that, in order for digital technologies to be used effectively in education, not only access but also infrastructure and implementation capacity must be developed together. When evaluated in conjunction with our study's projection of an increase in digital device ownership by 2031, these findings support the notion that strengthening digital infrastructure is an important factor that could influence students' learning opportunities and academic outcomes in the future.

The current research predicts that the use of digital devices will increase by 2031. Türel and Dokumacı (2022) emphasize that the impact of digital device use on education is not always positive. Therefore, considering that technology use in the coming years may hinder students' social and academic development, it is recommended that policymakers take the necessary measures.

Future studies could be conducted using different time series methods and covering not only Türkiye but also other countries, thereby creating a broad field of application. Studies on variables such as frequency and duration of use, in addition to digital device ownership, will also make important contributions to the field of education.

Data availability

The datasets used and/or analysed during the current study are publicly available from the webpage of OECD addressing PISA data files (https://webfs.oecd.org/pisa2022/index.html).

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Contributions

AY**:** Methodology, Writing, Data curation. ATY: Methodology, Writing, Data curation

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Ethics declarations

Competing interests

The authors declare no competing interests.

Declaration of competing interest

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