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Mathematical Modeling of Student Learning Outcomes using E-learning-Based Remedial Programs

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ABSTRACT

Research on mathematical modeling of learning outcomes remains limited, despite its potential to evaluate educational processes and inform placement decisions in schools, classes, learning resources, and remedial programs. This quantitative study aims to construct a mathematical model in the form of an ordinary differential equation (ODE) to represent the dynamics of students' learning in a remedial program. The model is developed using empirical data obtained from multiple-choice diagnostic tests designed to identify common learning difficulties and a series of three remedial assessments conducted after e-learning-based interventions. The dataset includes students' assessment scores and time records during the remedial learning process. The Nelder–Mead method was used to estimate the model parameters, followed by a stability analysis and an RMSE-based evaluation of the model's accuracy. The model captures changes in student understanding over time and reveals that students with lower initial scores tend to show greater improvements through remedial programs. However, as the duration of the remedial program increases, the rate of score improvement decreases—suggesting a decline in student focus and learning efficiency over time. These findings highlight the nonlinear nature of learning progress in remedial program. The model provides for predicting student outcomes and analyzing the effectiveness of remedial programs. It offers practical implications for optimizing the structure and timing of remedial programs and can support the development of adaptive learning systems tailored to student needs. This research demonstrates the potential of mathematical modeling for decision-making in education.

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A. INTRODUCTION

Mathematical modeling has been used in education as a tool to analyze, predict, and support student learning processes. Generally, mathematical models in education are employed to identify key factors influencing learning outcomes and to forecast student performance in various instructional settings (Ardianti & Marlena, 2020; Mailizar et al., 2022; Mutiawati et al., 2022). These models can reveal patterns in student behavior, monitor progress over time, and support data to decision making in teaching and assessment. Despite their potential, research on mathematical modeling within the Indonesian educational context remains limited. This concern is emphasized in an integrative review conducted by Vitoria et al. (2021), which highlights the scarcity of studies exploring educational modeling in Indonesia. This is unfortunate, considering that effective learning outcome modeling plays a crucial role in evaluating educational quality and enhancing instructional strategies (Chen & Cui, 2020).

Developing and implementing reliable models can thus provide significant contributions to both research and classroom practice.

A mathematical model used to predict learning outcomes is considered valuable if it exhibits a high degree of predictive accuracy. High accuracy models provide educators with meaningful tools to guide interventions and improve learning outcomes. For example, (Alamri et al., 2020) conducted experiments using a binary regression model to measure student learning outcomes, achieving a prediction accuracy of 93%. These findings demonstrate that precise predictive models can play a central role in identifying students who need additional support. Moreover, predictive modeling results can be used to inform instructional decisions such as grouping students based on ability and designing differentiated learning pathways. In educational systems around the world, learning outcome data are also used to place students in schools, classes, or learning tracks that align with their abilities and needs (Figlio & Ozek, 2024). Among these strategies, remedial programs are an essential component that provide extended learning opportunities for students with suboptimal performance.

Remedial learning emerges as an alternative to enhance students' competencies. It can assist students who are not yet ready by strengthening their foundational skills (Zhao et al., 2022) and supporting those with poor evaluation test results (Myllykoski, 2016). Remedial learning can be applied across various subjects and serves as a highly beneficial program for teaching mathematics to students experiencing learning difficulties (Vaughn & Bos, 2015). Mathematics, in particular, is a subject that commonly requires remedial learning (Cody Davidson, 2016), as it has been shown to improve student learning outcomes in schools (Sasalia S et al., 2016). Cut et al. (2023) revealed that the objectives of remedial learning are more effectively achieved when e-learning is utilized, showing a significant impact on improving student learning outcomes. The integration of information technology in remedial learning enables educators to gather extensive student performance data in a relatively short period.

Additionally, online learning and computerized assessments have led to an explosion of both structured and unstructured educational data, such as student problem-solving process data (Chen & Cui, 2020). These abundant data sources offer new opportunities for large-scale learning outcome modeling across various educational contexts. The increased availability of learning process data allows researchers to analyze student performance more deeply and to identify patterns that were previously inaccessible. Mathematical models for evaluating learning outcomes through computer-based assessments also underpin the success of student learning evaluations (Chen et al., 2023). These models enable the integration of assessment data to predict learning outcomes, serving as a foundation for instructional decision making. As a result, they play a crucial role in supporting adaptive learning. The development of accurate mathematical models is therefore essential for optimizing learning environments in the digital era.

Mathematical modeling in education has generally been applied to evaluate and predict student performance in various learning environments, both formal and digital. These models serve as valuable tools for understanding how students learn, identifying learning gaps, and designing interventions that are responsive to student needs. While considerable progress has been made in modelling general learning outcomes, limited attention has been given to modelling outcomes in remedial learning contexts. Remedial learning differs from mainstream instruction in that it targets students with prior learning difficulties and involves personalized, time-bound interventions. Consequently, it presents unique dynamics that require dedicated modelling approaches to accurately capture the learning process. Despite the increasing relevance of remedial programs in addressing learning loss and supporting at-risk students, mathematical models tailored to this context remain underdeveloped. In response to this gap, this study aims to develop a mathematical model for remedial learning that reflects the gradual improvement of student performance and supports data-driven decisions in instructional planning.

B. METHODS

Research on remedial learning has been ongoing since 2022, particularly in response to the growing need for personalized support following pandemic-related learning disruptions. This article focuses on modelling remedial learning based on data available from an e-learning platform. By using the model, we can identify patterns, test hypotheses, and make data-driven decisions supported by a solid mathematical foundation (Hirsch et al., 2013). Therefore, this study employs a quantitative research design, as it systematically investigates the phenomenon of remedial learning using measurable variables and mathematical modelling. Quantitative research is a structured approach that relies on numerical data to explain relationships between variables and to predict outcomes (Gnawali, 2022). In this context, the use of a mathematical model grounded in quantitative analysis provides an effective means of evaluating the effectiveness of remedial programs and informing educational practices.

This study involved junior high school students (grades 7 and 8), aged 12 to 14 years, from nine schools in Banda Aceh, Indonesia. A total of 547 students took part in the diagnostic test, and 314 of them (57%) participated in the remedial learning program. Figure 1 illustrates the proportion of students who passed and failed the diagnostic test. The learning materials addressed in this study included integer numbers, fraction numbers, linear equations and inequalities in one variable, and systems of linear equations in two variables.

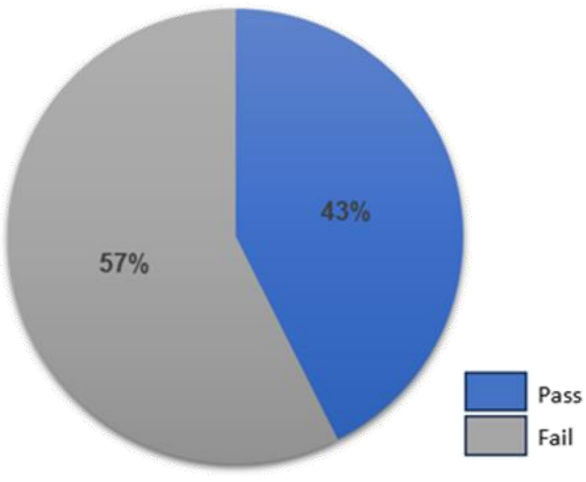

Figure 1. The Number of Diagnostic Tests Participants

Data were collected through the Getmath platform, an e-learning application that supports diagnostic assessment and remedial instruction. Multiple-choice diagnostic questions were administered to identify students' learning difficulties across the targeted topics. Following this, students participated in an e-learning-based remedial program and completed three follow-up assessments, each consisting of multiple-choice questions, to evaluate their understanding after the program. The data used in this study included student activity records, assessment results, and time logs recorded during the remedial program.

The instructional content delivered through Getmath has been developed and validated through a series of prior research studies to ensure its validity and practicality in the context of both junior and senior high school mathematics learning. While numerous studies have supported the effectiveness of this platform, several representative examples include research by Cut et al. (2023), Lestari et al. (2023), Lestari et al. (2024), and Suhartati et al. (2024). These studies confirm that the materials provided through the platform are pedagogically sound and appropriate for use in remedial learning contexts.The first stage in modelling involves observing real-world problems to gather information regarding the characteristics of the phenomena. The mathematical modelling flow diagram is presented in Figure 2.

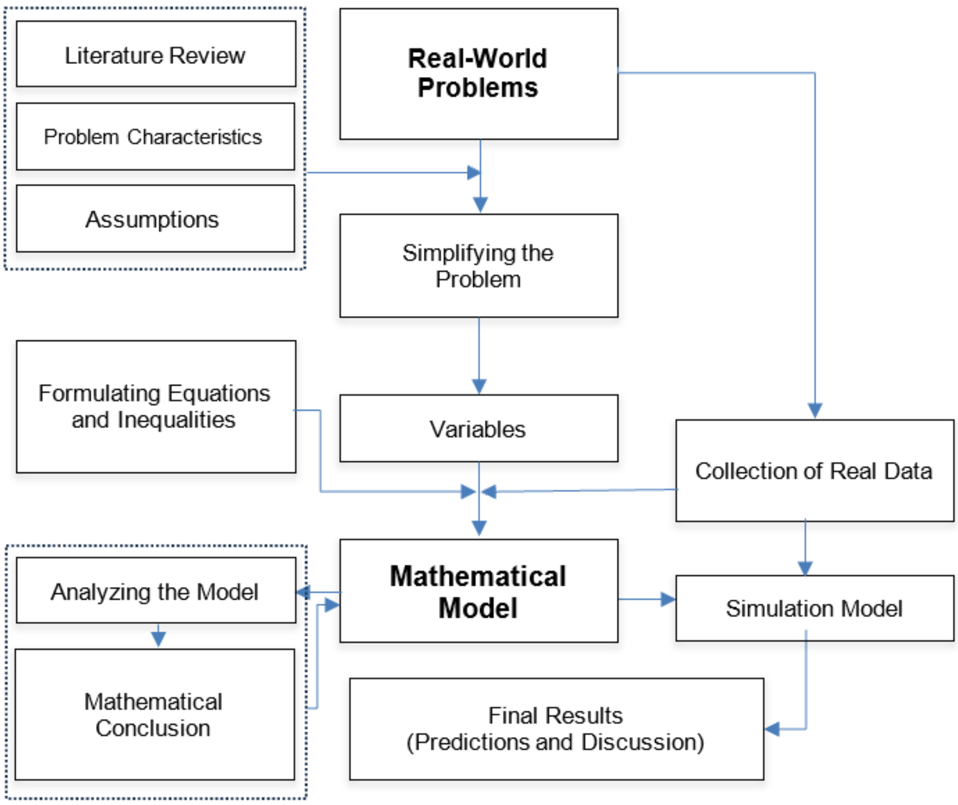

Figure 2. Flowchart of Mathematical Modelling

Following this, the next step is to establish assumptions that simplify the real-world problem without eliminating crucial variables. The following assumptions are based on observations:

1. Diagnostic Test: The diagnostic test serves as a means to assess students' learning outcomes before the remedial instruction, thus depicting their initial competence level.

Students are administered the diagnostic test using e-learning after receiving learning from teachers who utilize validated teaching materials.
2. Criteria for Remedial Participation: Students who score below 75 on the diagnostic test will participate in the remedial learning program. In general, secondary schools in Banda Aceh use a score of 75 as the threshold for mastery in mathematics learning.
3. Learning Outcomes Post-Remedial: It is assumed that students' learning outcomes will improve following the remedial learning program, relative to their performance before undergoing remediation. This assumption is supported by the findings of Cut et al. (2023)
4. Duration of Remedial Learning: The longer the time students spend engaging with remedial learning, the greater the improvement in their academic performance. This is based on the premise that extended remedial sessions allow students to cover additional enrichment materials, thereby increasing their knowledge, which, in turn, enhances their learning outcomes.

Various methods can be employed for mathematical modeling in education, such as Partial Least Square (PLS) (Alyani & Nurafni, 2019; Mardiana & Faqih, 2019), Linear Regression (LR) (Khasanah & Harwati, 2019), Multiple Linear Regression (MLR) (Santoso & Yulia, 2020), Decision Trees, and Support Vector Machines (SVM) (Sembiring et al., 2011). Each method offers different analytical strengths and model forms, depending on the characteristics of the phenomenon and the objectives of the study. Among these, continuous models formulated using Ordinary Differential Equations (ODEs) provide a powerful approach for representing processes that evolve over time. According to Banerjee (2021)), continuous models are systems in which inputs and outputs may change at any moment and are typically represented by a dependent variable that varies continuously with respect to one or more independent variables. When there is sufficient information or assumption about the rate of change of a dependent variable over time, the system can be effectively modeled using first-order ODEs. In this study, the learning process in a remedial setting is viewed as a dynamic and continuous phenomenon, where student performance changes gradually in response to interventions. Therefore, an ODE-based model is considered appropriate for capturing the time-dependent nature of learning progression in a remedial context. The following section presents the model developed to represent the remedial learning process.

$$\frac{dS(t)}{dt} = \alpha(S_{max} - S(t)) \tag{1}$$

t is learning time, α is rate of increase in student score, $S(t)$ is student score over time, S_{max} is the maximum score that can be obtained by students ($S_{max} = 100$). The solution of Equation (1) will be sought with direct integral as follows.

$$S(t) = S_{max} - (S_{max} - S_0)\, e^{-\alpha t} \tag{2}$$

for $t = 0$ and $S(0) = S_0$ where S_0 is the student's initial ability score before remedial learning is carried out. The rate of increase in student scores α can be obtained using numerical methods or non-linear regression based on diagnostic test data, time records, and remedial data. In this study, the rate of increase in student scores was obtained using a numerical method using The Nelder-Mead Method to identify a value that satisfies the equation derived from the transformed solution of the mode in the following form.

$$f(a) = a + \frac{1}{t}\ln\left|\frac{S_{max} - S(t)}{S_{max} - S_0}\right| \tag{3}$$

The Nelder-Mead algorithm is utilized to minimize the error (the discrepancy between the estimated and actual scores), yielding an optimal α $(f(a) = 0)$. The Nelder-Mead algorithm is a numerical optimization method for locating the minimum or maximum of a multivariable objective function without relying on derivatives (Olsson & Nelson, 1975; Selvam et al., 2022; Singer & Nelder, 2009). This optimization approach is particularly suitable because it does not require gradient information, making it ideal for objective functions that are non-differentiable or based on empirical data with irregularities. The computation of α using the Nelder-Mead algorithm is producing a value of α = 0.03575≈0.04.

Following the parameter estimation, the model is subjected to a stability analysis to examine the behavior of solutions around the equilibrium point and an accuracy evaluation. The equilibrium point of a differential equation represents the condition where the rate of change becomes zero, and stability is analyzed in relation to these equilibrium points (Roussel, 2019). Accuracy evaluation using the Root Mean Square Error (RMSE) to assess how well the model fits the empirical data. RMSE is a widely used metric to evaluate a model's accuracy (Bass et al., 1989; Genel & Altinsoy, 2021; Willmott & Matsuura, 2005) by measuring the average squared difference between the model's predicted values and the actual values. These analyses provide further validation of the model's reliability in capturing the characteristics of students' learning progression in remedial program

C. RESULT AND DISCUSSION

1. Equilibrium and Stability

Equilibrium points and the stability of a model are crucial for understanding the system's behavior over time, predicting future outcomes, developing control strategies, and ensuring that the model accurately reflects real-world systems. The condition $\frac{dS(t)}{dt} = 0$ yields an equilibrium point at (100,0), as shown in Figure 3.

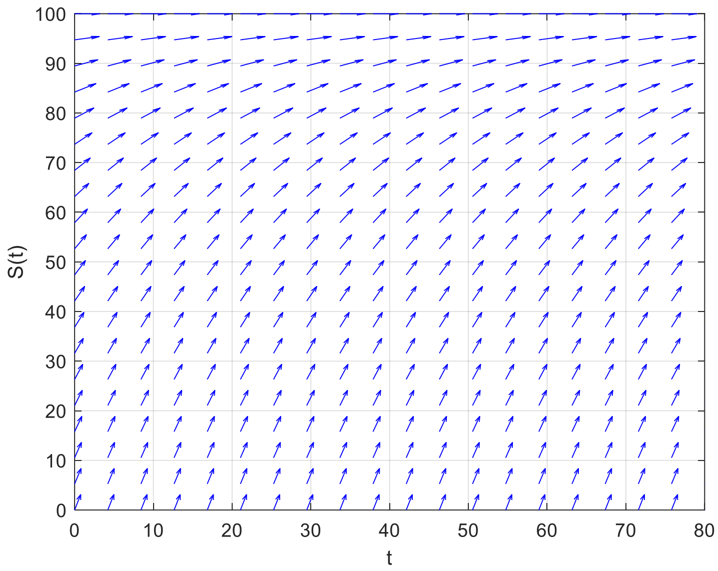

Figure 3. Slope Field of $S(t)$

The slope of $S(t)$as shown in Figure 3, which depicts all arrows converging towards an equilibrium value of $S(t) = 100$. This aligns with the equilibrium point, where no further increase in $S(t)$ occurs. The equilibrium point in this model is stable, because $t \to \infty$ as $S(t)$ approaches 100 regardless of the initial value S_0. This stability indicates that the system naturally tends towards its maximum value over time. In other words, the final outcome will be achieved naturally, even with variations in initial conditions.

2. Model Accuracy

The mathematical model of remedial learning was evaluated for accuracy using the Root Mean Square Error (RMSE). The resulting RMSE value was 21.5, which is considered relatively high. A lower RMSE value indicates greater accuracy in predicting outcomes; thus, this result suggests that the model is not yet sufficiently precise in forecasting students' scores. As illustrated in Figure 4, the data points are fairly dispersed, reflecting substantial variation in student performance that the model does not fully capture. This dispersion indicates that additional factors may be influencing student outcomes beyond those represented in the current model. Nevertheless, the model generally succeeds in capturing the overall trend of increasing student scores over time. However, notable deviations from the predicted trend remain, particularly among students with higher score values, indicating the need for further refinement.

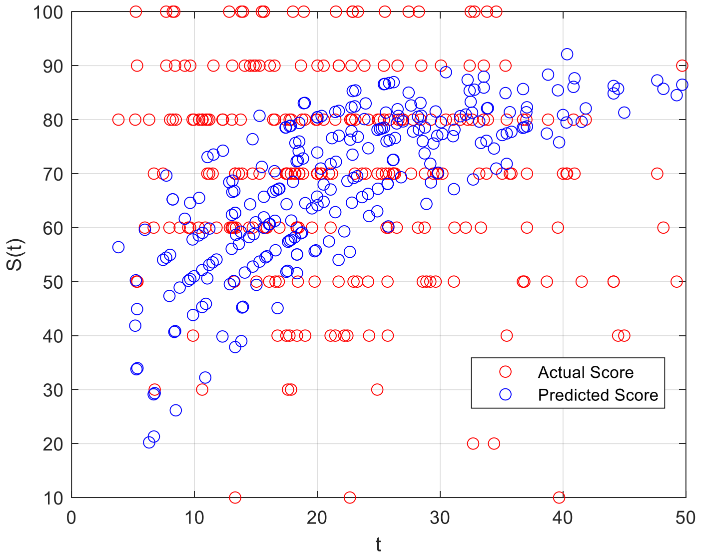

Figure 4. Distribution of actual scores and predicted scores

Several steps can be taken to improve the model's accuracy, one of which involves examining the dataset for potential outliers. According to Pearson (2002), the presence of outliers can adversely affect the performance and accuracy of a predictive model. These extreme values may distort the relationship between variables and lead to biased parameter estimates. Therefore, identifying and appropriately addressing outliers may significantly enhance the model's predictive capability. Implementing such data preprocessing steps is essential in refining the model to better reflect the actual learning patterns observed among students, as shown in Figure 5.

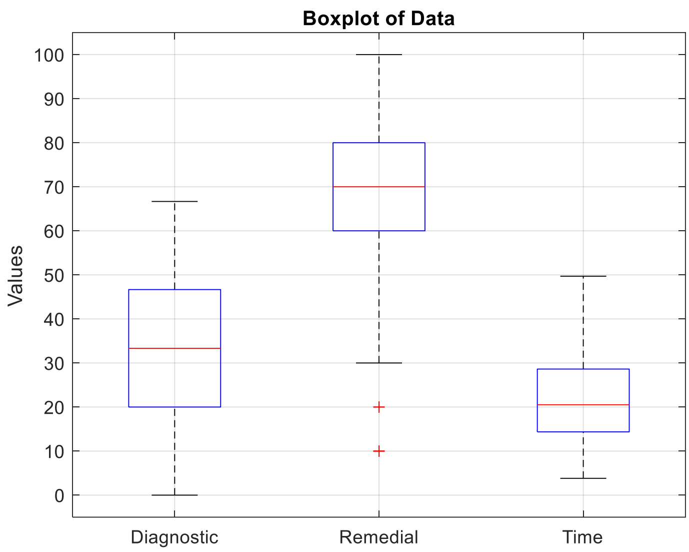

Figure 5. Boxplot of Data

The results of the outlier check on the data are presented in Figure 5. Five data points in the remedial dataset were identified as outliers, specifically 10, 10, 10, 20, and 20. After removing the outliers, an α value of 0.03886 was obtained, which is not significantly different from the previous α value. The RMSE with α = 0.03886 was calculated to be 20.5, which also shows no significant increase compared to the previous RMSE of 21.5. Therefore, it was decided to use the original dataset without excluding the outliers.

2. Model Simulation

This simulation aims to determine the extent to which the developed model can represent the actual dynamics of learning. According to Bretti (2021) simulations are effective tools for elucidating system dynamics. The simulated data reflect the most recent observations. A total of 17 students participated in the diagnostic test, with 15 of them being candidates for the remedial program.

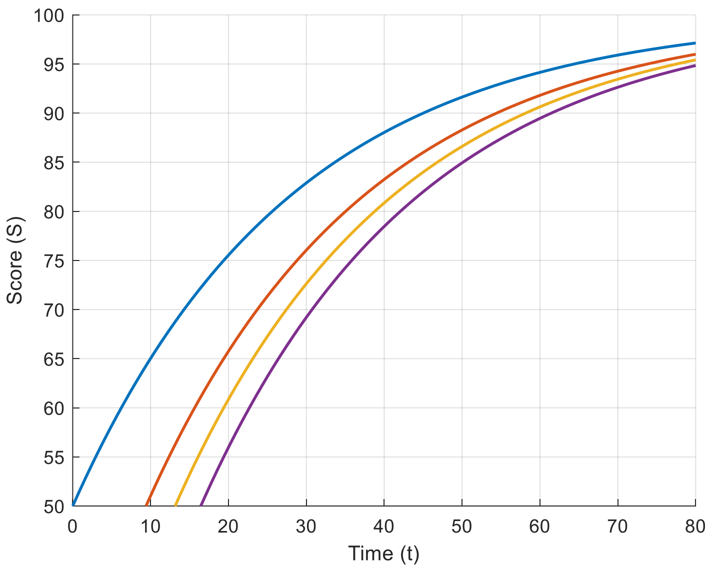

Figure 6. Illustrates the progression of students' scores over time

The mathematical model simulation of remedial learning is presented in Figure 6. It features four curves, each representing different initial ability levels of students who did not pass the diagnostic test. The simulation results indicate that 100% of the students can exceed the minimum mastery criteria through remedial learning, though there remains a possibility of predictive error at 21.5%. However, with their current initial abilities, none of the students are able to achieve the maximum score in remedial learning. Furthermore, the lower a student's initial score, the more significant the score improvement achieved through remedial learning. Thus, it can be concluded that the remedial learning model is effective for these students.

The slope field (Figure 4) and simulation results (Figure 6) reveal a decreasing rate of improvement as the maximum time is approached. This indicates that the longer the remedial learning process continues, the smaller the score improvements students achieve. This trend aligns with the diminishing focus ability of students towards the end of the session. Kamuche and Ledman (2005) explored how students' understanding or knowledge deteriorates over time, finding a significant and non-linear decline in their performance. Studies on student focus (Bradbury, 2017; Wilson & Korn, 2007) commonly report that student attention spans last about 15 minutes before declining. While this claim remains debated, Chaisricharoen et al.

(2019) support the notion, suggesting that shorter study periods with breaks yield better learning outcomes. Chang and Zhu (2018) proposed the "5:20:20:5" model for 50-minute classes, combining technology and varied activities to maintain student focus. Rosen (2017) identified modern communication technology as a factor contributing to the decline in students' focus and learning abilities. However, confiscating devices is not an effective solution, as it may increase anxiety and hinder learning. Instead, Rosen proposed strategies for educators to enhance student focus, such as helping them manage technology use, improve study habits, and create dedicated learning environments. Optimizing IT usage in both primary and remedial learning is a promising approach.

E-learning for remedial instruction emerges as a relevant solution to support the learning process, as evidenced by this study, which demonstrates that students can significantly improve their outcomes. The developed model captures this non-linear learning trajectory and represents it in the form of a continuous system through an ordinary differential equation (ODE). These findings contribute directly to the advancement of remedial learning models that can describe and predict student progress over time. the proposed model accounts for the dynamic nature of learning, allowing for more responsive and adaptive instructional design. This advancement supports teachers in planning more efficient remedial interventions by predicting when the learning impact will begin to plateau. Therefore, the model has practical usefulness in optimizing time allocation and resource use in remedial learning programs in addition to theoretical contributions to the field of educational modeling.

D. CONCLUSION AND SUGGESTIONS

The mathematical model of remedial learning has been found. The mathematical model for remedial learning provides a framework to understand how students' scores evolve over time under the influence of a learning intervention. The analysis obtained that the model is stable with an accuracy of 78.5%. Based on the results of the model simulation, it was found that students with lower initial scores tend to experience greater improvement through remedial learning. Conversely, as the duration of remedial instruction increases, the rate of score improvement diminishes, indicating a saturation point in learning efficiency. The mathematical model developed in this study is capable of predicting students' learning trajectories, where scores asymptotically approach a maximum value, and the rate of learning gradually slows over time. This behavior aligns with realistic learning patterns, where cognitive load and attention span affect performance gains.

The main contribution of this research lies in the development of a predictive model for remedial learning outcomes using an ordinary differential equation (ODE) approach. This model enables educators and researchers to better understand the dynamics of student learning in remedial settings and to evaluate the effectiveness of instructional strategies based on empirical data. Practically, the model can serve as a decision-making tool to personalize remedial program, estimate optimal learning durations, and support adaptive e-learning systems that respond to individual student needs. To enhance the model's predictive power and generalizability, future developments should consider integrating additional variables that influence learning outcomes. These may include student background, learning styles, motivation, external support, or individual learning strategies. Additionally, extending the model to a system of differential equations may allow for the representation of more complex and nonlinear interactions among variables, ultimately leading to more accurate and robust predictions.

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