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Students' achievement and e-learning acceptance in remedial mathematics: A case on sequences and series

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ABSTRACT

This study examines the impact of an e-learning-based remedial program in senior secondary schools in Indonesia, focusing on two main research areas: program outcomes and factors influencing students' acceptance of the e-learning platform. Using a quantitative pre-experimental design, 168 secondary school students participated, with data collected through pre-tests, post-tests (30 questions on sequences and series), and a 19-item questionnaire based on the unified theory of acceptance and use of technology (UTAUT) framework. Analysis included descriptive analysis, t-tests, and structural equation modeling. Results showed varying program effectiveness between two schools, with factors like effort expectancy, facilitating conditions, perceived enjoyment, and social influence positively influencing behavioral intention to use the platform.

Keywords: UTAUT, remedial, student achievement, e-learning, behavioral intention

INTRODUCTION

The landscape of education has undergone transformations catalyzed by the global pandemic (Soto-Acosta, 2020). The sudden shift to remote and online learning has not only brought the challenges faced by educational systems worldwide but has also forced educators and researchers to explore innovative approaches to address the learning gaps that have emerged (Engzell et al., 2021). This paper explores one of the crucial issues of education which is remediation in mathematics learning.

The disruption caused by the pandemic has led to a concerning learning loss in various academic disciplines, including mathematics (Fuchs et al., 2023; Huang et al., 2023; Schult et al., 2022). Studies have documented significant declines in students' mathematical proficiency during this period. For instance, Contini et al. (2022) reported that students in Italy experienced substantial learning gaps in mathematics, with performance levels dropping by 20-30% compared to pre-pandemic benchmarks. Similarly, Schult et al. (2022) found that German students lost approximately three months of learning in mathematics during the first wave of the pandemic

As schools transitioned to remote and hybrid learning models, many students found themselves grappling with the absence of face-to-face interactions, personalized guidance, and the structured learning environment that traditional classrooms offer. This learning loss is particularly noticeable in mathematics (Contini et al., 2022; Hevia et al., 2022; Schult et al., 2022) . As a result, the need for targeted remedial interventions has become more demanding than ever before.

Educators face a challenge when it comes to providing support for a large number of students, especially considering the limited time and resources available (Almusawi et al., 2021; Chen & Wu, 2020). Teachers, who are already under a lot of pressure have the job of meeting each students individual learning needs within time constraints (Gurfidan & Koc, 2016). The creation and use of customized e-learning platforms offer a solution to support teachers' efforts. Technology-enhanced remedial platforms can personalize learning pathways, provide targeted feedback, and adapt difficulty to address individual learning gaps more effectively than whole-class instruction, with documented gains in math from ICT-integrated remedial courses and intelligent tutoring systems (ITS) (Chen & Wu, 2020; Pai et al., 2021; Sayed et al., 2023); examples include intelligent tutors and commercial interactive courseware (e.g., MyMathLab) that sequence content based on learner performance.

This study will explore both the effectiveness of e-learning platforms in remedial mathematics instruction and investigate a critical aspect of their implementation: students' acceptance. The acceptance of technology by students plays a crucial role in determining its efficacy, as established by the UTAUT framework linking acceptance to intention and use, and corroborated in educational contexts where higher acceptance predicts better uptake and outcomes (Abbad, 2021; Chen & Wu, 2020; Venkatesh et al., 2016). To this end, the research examines students' perceptions of the e-learning platform and their willingness to engage with it as a remedial tool. The intertwined relationship between students' acceptance and their achievement in remedial mathematics forms a key central point of this investigation.

This research aims to investigate effective e-learning platforms in helping students with mathematics and the important aspect of whether students actually accept and engage with these platforms. The effectiveness was evaluated based on outcome of remedial and students' acceptance of the program. The acceptance of technology by students is crucial in determining its effectiveness. In this study we examine what students think about the e-learning platform and how willing they are to use it as a tool for learning.

The basis of this research is enriched by insights from existing studies that have examined the intersection of technology and education, particularly in the context of remedial mathematics. Notable among these is the work of Pai et al. (2021), who developed a dialogue-based mathematics ITS that demonstrated significant improvements in students' achievement in multiplication and division of fractions. Additionally, Additionally, recent evidence from remedial mathematics contexts shows that negative emotions such as boredom, frustration, and test anxiety are significantly associated with motivation (e.g., task value and self-efficacy) and self-regulation (effort and metacognitive regulation), underscoring the central role of motivation and self-regulatory skills in remedial courses (Park et al., 2024).

This paper aims to contribute to the discourse on e-learning, remedial education, and student acceptance by conducting a comprehensive study focused on topic of sequence and series in mathematics. The research objectives include the development and testing of an e-learning platform tailored for remediation, an exploration of students' acceptance of the platform, and an assessment of their achievement in the remedial program. The subsequent sections of this paper explore the methodology employed, the findings of the study, and their implications for enhancing remedial mathematics education.

Based on the literature and research objectives, we formulated the following hypotheses:

1. The implementation of an e-learning-based remedial program will significantly improve students' achievement in mathematics, specifically in the topic of sequences and series.
2. Students' acceptance of the e-learning platform for remedial mathematics will be positively influenced by effort expectancy (EE), facilitating conditions (FC), perceived enjoyment (PE), and social influence (SI), as outlined in the UTAUT framework.

RELATED LITERATURE AND CONCEPTUAL FRAMEWORK

Learning Loss in Mathematics Due to COVID-19

The COVID-19 pandemic has catalyzed unprecedented disruptions in the field of education, leading to widespread concerns about learning loss across various subjects, particularly in mathematics (Miller et al., 2023). The sudden transition to remote and hybrid learning resulted in lacking the structure and personalized attention of traditional classrooms (Alhusban, 2022). Mathematic, a subject that rely on cumulative, sequential mastery, is particularly vulnerable. Empirical reports document declines in mathematics performance, widening achievement gaps across grades and student groups, increased variability in attainment, and growing demand for remediation as prerequisite knowledge weakened (Contini et al., 2021; Soesanto & Dirgantoro, 2021; Tashtoush et al., 2023).

The consequences of this learning loss extend beyond immediate academic performance. Proficiency in mathematics underpins critical cognitive skills such as problem-solving and logical reasoning, (Chew et al., 2019). A weak foundation in mathematics not only hinders current learning but also has far-reaching implications for future academic success. Research highlights the urgency of addressing this learning loss, stressing the need for targeted interventions that mitigate the negative effects of learning loss (Osborne & Shaw, 2020).

Technology-driven solutions, such as e-learning platforms and ITS, have gained attention as potential tools to address learning loss and promote effective remediation (Osborne & Shaw, 2020). The integration of technology in remedial mathematics education holds promise in providing personalized and scalable interventions that provide individual learning needs (Chen & Wu, 2020). As educational institutions adapt to the circumstances, understanding the e-learning acceptance and student achievement becomes a critical area of investigation.

Technology-driven solutions, such as e-learning platforms and ITS, have gained attention as tools to address learning loss and support remediation (Osborne & Shaw, 2020). In this context, e-learning acceptance refers to students' willingness and intention to use an e-learning platform, conceptualized in the UTAUT framework as behavioral intention (BI) leading to actual usage (Venkatesh et al., 2003). Higher acceptance is associated with greater uptake, engagement, and improved outcomes in technology-supported mathematics remediation (Abbad, 2021; Chen & Wu, 2020). Determinants of acceptance include performance expectancy (PE) (perceived usefulness for learning), EE (perceived ease of use), SI, and FC (infrastructure and support), with extensions such as PE also shown to matter in educational settings (Abbad, 2021; Tan, 2013; Venkatesh et al., 2003). When students perceive low usefulness or ease, face weak social endorsement, or lack adequate technological support, acceptance–and thus impact–suffers. Accordingly, as institutions adapt, examining both acceptance and achievement is essential for designing effective, scalable remedial interventions (Abbad, 2021; Chen & Wu, 2020).

Students Need of a Personalized Online Platform for Remedial in Mathematics

The need for tailored interventions to address students' diverse learning needs is well-supported, particularly in the context of mathematics remediation. Research highlights that students in remedial programs often have varying levels of prior knowledge,

Table 1. Key feature of GetMath

Key features	Description
Diagnostic assessment	At the beginning, students engage in a diagnostic test that serves as a comprehensive assessment of their mathematical strengths and areas needing improvement. This assessment is crucial in creating a customized learning path for each student.
Personalized learning pathways	Leveraging the diagnostic assessment results, students are directed to specific topics that require attention. This ensures that learning is precisely targeted, maximizing the efficiency of the remedial process.
Micro-learning videos	The platform employs short, engaging video lessons, each lasting around 5 minutes. These tutorials deliver focused explanations of mathematical concepts.
Interactive quizzes	Following each video, students find a series of interactive questions designed to reinforce their understanding.
Adaptive progression	The platform adapts to individual progress, dynamically adjusting the difficulty of content based on mastery.
Real-time progress tracking	Students and educators can monitor progress in real time, gaining insights into performance, topic proficiency, and areas that demand further attention.

misconceptions, and learning paces, making a one-size-fits-all approach ineffective (Logue et al., 2019). For example, corequisite mathematics programs that provide targeted support alongside regular coursework have shown significant improvements in student outcomes by addressing individual needs. Similarly, McElwee (2020) emphasizes the importance of teacher autonomy and flexibility in designing interventions that align with the unique challenges and strengths of their students, further underscoring the value of personalized approaches in remediation.

Technology-enhanced personalized platforms offer several advantages for remedial mathematics. One key benefit is their ability to provide immediate and targeted feedback, such as highlighting specific errors in a student's solution or offering partial credit with explanations for partially correct answers. For example, if a student solves a problem on sequences and series but makes an error in applying the formula, the platform can identify the mistake, explain the correct application, and guide the student through similar practice problems to reinforce understanding. Such platforms also adapt content and instruction based on individual progress, ensuring that students are neither overwhelmed nor underchallenged. By tailoring the learning experience, personalized platforms empower students to take ownership of their learning journey, promoting self-directed learning and intrinsic motivation (Ferdianto & Anindita, 2023).

In a study conducted by Sayed et al. (2023), students engaging with a personalized online platform for mathematics remediation demonstrated significantly improved performance and increased confidence than students not engaging in personalized online learning platform. The platform's adaptive nature provided to individual learning trajectories, enabling students to progress at their pace. As educators attempt to create inclusive and effective learning environments, technology platforms have demonstrated their potential to enhance learning outcomes and bridge educational gaps by fostering personalized learning, improving accessibility, and addressing equity challenges (Timotheou et al., 2022).

Proposed Platform

For the purpose of the study, we develop an online platform for remedial programs. Here is the link of the platform https://getmath.id/. The "GetMath" platform is a dynamic and innovative online resource designed to address the learning needs of secondary school students in the field of mathematics. Tailored for remedial purposes, this platform offers a comprehensive and personalized approach to strengthening mathematical proficiency through intentional diagnostic assessment, personalized learning pathways, and more (see **Table 1**).

The Unified Theory of Acceptance and Use of Technology

The unified theory of acceptance and use of technology (UTAUT) is a theory that explains how and why people adopt and use new technologies. It was proposed by Venkatesh et al. (2003). The UTAUT model is based on the following four constructs:

PE: The degree to which an individual believes that using a new technology will help them achieve their goals.

EE: The degree of ease with which an individual believes they can use a new technology.

SI: The degree to which an individual believes that important others think they should use a new technology.

FC: The degree to which an individual believes they have the resources and support necessary to use a new technology.

The model suggests that these four constructs have a direct effect on an individual's BI to use a new technology. BI is defined as the individual's plan or expectation to use a new technology. BI, in turn, has a direct effect on the individual's actual use of the new technology.

The UTAUT model has been widely used to study the adoption and use of new technologies in various settings, including the workplace, education, and healthcare (Ward, 2013). For example, in the workplace, it has been used to predict employee adoption of enterprise software; in education, it has been applied to understand students' acceptance of e-learning platforms; and in healthcare, it has been utilized to examine the adoption of telemedicine and electronic health records. The model has been shown to be a reliable and valid tool for predicting the adoption and use of new technologies (Kim & Lee, 2022).

The UTAUT model has also been extended to include additional constructs, such as PE (Sarosa, 2019), trust (Arfi et al., 2021), and security (Khalilzadeh et al., 2017). These extensions have improved the model's predictive power in specific contexts, such as online shopping, mobile banking, and virtual learning environments.

The UTAUT model is a valuable tool for understanding how and why people adopt and use new technologies. It can be used to design and implement interventions to promote technological adoption in diverse settings. Therefore, we believe it can effectively

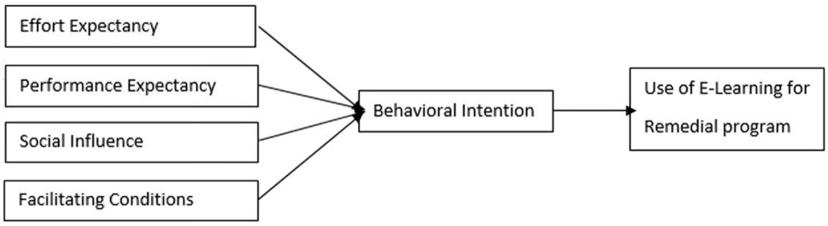

Figure 1. Initial model (Venkatesh et al., 2003)

be applied to understand students' acceptance of e-learning for remedial programs. The UTAUT model suggests that four constructs–PE, EE, SI, and FC–have a direct effect on an individual's BI to use a new technology.

PE: The degree to which an individual believes that using a new technology will help them to achieve their goals (Sewandono et al., 2023). In the context of e-learning for remedial programs, students may be more likely to accept e-learning if they believe that it will help them to improve their academic performance, if they believe that it is easy to use, if they believe that their friends and family think that they should use it, and if they believe that they have the necessary resources and support to use it. For example, a student who is struggling in math may be more likely to accept e-learning if they believe that it will help them to improve their math skills.

EE: The degree of ease with which an individual believes they can use a new technology (Sang et al., 2023). EE, within the context of e-learning for a remedial program, refers to the perceived ease of use and convenience associated with utilizing online learning tools and platforms to improve academic skills. It focuses on students' perceptions of the effort required to engage in e-learning activities and their expectations regarding the user-friendliness of the e-learning resources. Here are some key considerations related to EE in the use of e-learning for a remedial. It involves considering whether the online learning materials are easily accessible and available when needed.

SI: The degree to which an individual believes that important others believe they should use a new technology (Joa & Magsamen-Conrad, 2022). SI, within the context of e-learning for a remedial program, refers to the impact of social factors on students' intentions to use e-learning resources and their overall engagement in the learning process. SI in the use of e-learning for a remedial program is significantly shaped by peers and classmates, as their positive experiences and recommendations can motivate other students to adopt and engage with e-learning resources

FC: The degree to which an individual believes that they have the resources and support necessary to use a new technology (Abbad, 2021). It involves considering the external factors that support students' engagement and access to e-learning resources. FC for e-learning in a remedial program rely on reliable technological infrastructure, including access to devices, internet connectivity, and appropriate software or applications to effectively utilize e-learning resources. **Figure 1** shows the initial model.

METHOD

Research Design

In this study, we employed a pre-experimental design to examine the effectiveness of the remedial program in improving academic performance. As described by Ary et al. (2014), a pre-experimental design is a type of research design that does not require a control group or random assignment of participants. Instead, it focuses on assessing the impact of an intervention by comparing data collected before and after its implementation. In our study, we administered pre-tests prior to the program to measure participants' baseline performance. Following the completion of the program, post-tests were conducted to evaluate the participants' progress. By comparing the pre- and post-test scores, we aimed to determine whether the remedial program led to significant improvements in academic achievement. While pre-experimental designs lack the rigor of true experimental designs, they provide valuable insights into the potential effects of an intervention and serve as a foundation for future, more robust investigations (Ary et al., 2014).

Participants

The participants of this study were 168 students from two schools in Banda Aceh, Indonesia. School A represented a high-achievement school while school B represented the low-achievement school. From school A, 93 participated in this study, all of whom were identified as needing remedial education. Similarly, from school B, 75 students participated, and they were also identified as needing remediation. In this study, students who need remedial education were identified by their teachers, a particular group selected for intervention (Schwartz, 2012).

Ethical Considerations

This study adhered to ethical research practices to ensure the protection of participants' rights and privacy. Informed consent was obtained from all participants prior to their involvement in the study, and participation was entirely voluntary. Additionally, measures were taken to ensure anonymity and confidentiality; no identifiable information was collected or included in the study. The data were used solely for research purposes, and all findings were reported in aggregate to protect the privacy of individual participants.

Table 2. Results of remedial in each class

School	Class	Completeness
School A	1	100%
	2	96.15%
	3	100%
	4	88.46%
	5	61.53%
	6	100%
School B	1	2.00%
	2	36.84%
	3	8.34%
	4	9.09%

Instrument

We used mathematical tasks that were uploaded on the e-learning platform. There are 30 questions prepared by the researchers, consisting of 10 main questions and 20 backup questions. Furthermore, the questionnaire based on UTAUT model was adapted from Tan's (2013). The original questionnaire was modified to suit the remedial education context by focusing on students' experiences and challenges in using e-learning for remedial purposes. Specifically, the wording of some items was adjusted to reflect the unique needs of students requiring additional support in mathematics. The adapted questionnaire contains 19 items, with four items addressing the PE aspect, four items on the EE aspect, three items on the SI aspect, four items on the FC aspect, and three items on the BI aspect.

Data Collection

The data collection technique was carried out in several stages. Initially, we directed students to take a diagnostic test on the e-learning platform. Students who scored less than 75 were asked to participate in the remedial program. The remedial time was different for each class which depended on their working time is adjusted to the lesson hours of each class. The UTAUT model-based questionnaire was used to collect data on student acceptance of the e-learning-based remedial. Questionnaires were given after students completed the remedial course. Students filled out the questionnaire according to the conditions experienced by students. On average, it took 10-15 minutes for the students to complete the questionnaire

Data Analysis

This research aims to investigate effective e-learning platforms in helping students with mathematics and the important aspect of whether students actually accept and engage with these platforms. The acceptance of technology by students is crucial in determining its effectiveness. In this study we examine what students think about the e-learning platform and how willing they are to use it as a tool for learning. To analyze data, we used quantitative analysis. For the remedial tests, we calculated the average scores of each class. Students were considered have successfully completed the remedial when they reached score above 75. Furthermore, we examined differences of scores in pre- and post-test using t-test analysis. In addition, to analyze data from the questioner, we used structural equation modelling (SEM) using Smart PLS 4.0

RESULTS

As outlined in the introduction, this study tested two main hypotheses: The implementation of the e-learning-based remedial program would significantly improve students' achievement in mathematics, specifically in the topic of sequences and series; and students' acceptance of the e-learning platform would be positively influenced by EE, FC, PE, and SI, as described in the UTAUT framework. In this section, we present results of remedial and students' acceptance of the program. First, we present results of remedial for each class in terms of level of completeness of remedial. Furthermore, we provide results of analyses of pre- and post-test of remedial. In addition, we provide results of analysis data from questioners regarding students' acceptance of e-learning.

Result of Remedial

Table 1 presents percentage of completeness of remedial program at each school. As we mentioned previously, this study involved students from two schools (school A and school B). School A consisted of 6 classes while school B consisted of 4 classes. Results of students' remedial achievement in each class are presented in **Table 2**.

Table 2 shows that, overall, students from school A perform well in the remedial program. The results indicate that 100% of students from three classes in this school (class 1, class 3, and class 6) successfully achieved minimum requirement scores after they completed the remedial program. On the other hand, in the other school, less than 40% of students from all classes could achieve the requested score.

For group A (experimental group), the mean post-test score increased from 8.13 (standard deviation [SD] = 2.52) to 15.13 (SD = 2.67), $t(14) = 10.12$, $p < .001$. For group B (control group), the mean post-test score increased from 8.00 (SD = 2.38) to 10.00 (SD = 2.38), $t(14) = 4.47$, $p < .001$.

To examine students' improvement during the remedial program, we examined difference in students' pre- and post test scores. Results of the test are presented in **Table 3**.

Table 3. Results of t-test

	N	Mean	SD	t-value	p-value
Pre-test	98	54.67	14.29	-8.243	< 0.001
Post-test	98	77.65	23.28		

Table 4. Reflective indicator loading and internal consistency reliability

Item	Loading	α	Composite reliability	AVE
BI1	0.819	0.795	0.802	0.708
BI2	0.863			
BI3	0.841			
EE1	0.793	0.847	0.853	0.687
EE2	0.873			
EE3	0.863			
EE4	0.782			
FC1	0.779	0.821	0.826	0.651
FC2	0.827			
FC3	0.807			
FC4	0.813			
PE1	0.707	0.767	0.819	0.678
PE2	0.872			
PE3	0.880			
SI1	0.871	0.848	0.854	0.766
SI2	0.897			
SI3	0.858			

The results of the t-test show that there is a significant difference between the pre- and post-test scores. The mean difference between the pre- and post-test scores is -22.980, which is a large difference. The 95% confidence interval for the difference in means is -28.513 to -17.447. This means that we can be 95% confident that the true difference in means is between -28.513 and -17.447. The p-value for the t-test is < .001, which is very small. This means that we can reject the null hypothesis and conclude that there is a significant difference between the pre- and post-test scores. In other words, the data shows that there was a significant improvement in scores from pre-test to post-test. This suggests that the intervention that was implemented was effective. These findings support our first hypothesis, indicating that the e-learning-based remedial program led to a statistically significant improvement in students' mathematics achievement.

Students' Acceptance of Remedial

In this section, we will cover several important aspects. First, we explain our measurement model and then move on to results of the structural model. We also discuss all issues with collinearity and describe the relationships in our structural model. Lastly, we provide results of the coefficient of determination (R^2) and effect size (f^2) to show how well our model works and the impact of our findings

Measurement model

Indicator loadings and internal consistency reliability: **Table 4** shows the reflective indicator loading and internal consistency reliability for five constructs: BI, EE, PE, FC, and SI (see **Table 4**). Reflective indicator loading is a measure of the strength of the relationship between an indicator and the construct it is measuring. The higher the loading, the stronger the relationship. In **Table 4**, all of the loads are above 0.7, which is considered to be a good level of reliability. This suggests that the indicators are measuring the constructs they are intended to measure.

Internal consistency reliability is a measure of how well the indicators of a construct measure the same thing. The higher the reliability, the more consistent the indicators are. In **Table 4**, all of the alphas and CRs are above 0.7, which is considered to be a good level of reliability. This suggests that the indicators of the constructs are measuring the same thing. In **Table 4**, the AVEs for all five constructs are greater than 0.5, which is a good indication that they are measuring different things. Overall, the results in **Table 4** suggest that the indicators of the constructs are measuring the same thing and that the constructs are reliable. This suggests that the constructs are valid measures of the concepts they are intended to measure.

Validity: To assess discriminant validity, we employed Fronell-Larcker criteria. Discriminant validity is the extent to which different constructs are measuring different things. According to the Fornell-Larcker criterion, the square root of the average variance extracted (AVE) for a construct must be greater than the correlation between that construct and any other construct. The Fornell-Larcker criterion states that the correlation between a construct and its AVE must be greater than the correlation between that construct and any other construct. In **Table 5**, all of the correlations between the constructs are greater than the correlations between the constructs and any other construct. This suggests that the constructs are measuring different things. Overall, the results of the Fornell-Larcker criterion suggest that the constructs in **Table 5** have good discriminant validity.

Heterotrait-Monotrait (HTMT) ratio is a measure of the similarity between two constructs. In **Table 6**, the HTMT values are all below 0.9, which suggests that the constructs are distinct. A HTMT value of 0.9 or above would suggest that the constructs are measuring the same thing. This would be a problem, as it would make it difficult to interpret the results of a study. However, in

Table 5. Fornell-Larcker results

	BI	EE	FC	PE	SI
BI	0.841				
EE	0.646	0.829			
FC	0.640	0.718	0.807		
PE	0.574	0.597	0.546	0.824	
SI	0.655	0.583	0.618	0.520	0.875

Table 6. HTMT ratio results

	BI	EE	FC	PE	SI
BI					
EE	0.778				
FC	0.782	0.854			
PE	0.703	0.729	0.670		
SI	0.786	0.689	0.736	0.626	

Table 7. VIF values

	BI
EE	2.427
FC	2.396
PE	1.697
SI	1.806

Table 8. Bootstrapping results

	B	Mean	SD	t-statistics	p-values	Significance
EE -> BI	0.221	0.220	0.076	2.901	0.004	Supported
FC -> BI	0.190	0.192	0.090	2.122	0.034	Supported
PE -> BI	0.173	0.173	0.087	1.989	0.047	Supported
SI -> BI	0.319	0.323	0.076	4.180	0.000	Supported

Table 6, the HTMT values are all below 0.9, which suggests that the constructs are distinct. Overall, the HTMT values in **Table 6** suggest that the constructs are distinct.

Structural model assessment: To examine the structural model, we followed the steps m by Hair et al. (2016). We started by assessing collinearity issues, then continued to analyzing the path coefficients (β) in the second step. In the third step, we examine the coefficients of determination (R^2). In the fourth step, we measured the f^2 to understand its relevance in the endogenous constructs. Lastly, in steps five and six, we determined the Q2 and its impact, as outlined by Hair et al. (2016)

Collinearity issue: Variance inflation factor (VIF) is a measure of the collinearity between independent variables in a multiple regression model. Collinearity occurs when two or more independent variables are highly correlated. High collinearity can lead to problems with the regression model, such as unstable estimates and low significance levels. The VIF values in **Table 7** are all below the threshold of 5, which suggests that there is no serious collinearity problem.

Structural model relationship: **Table 8** shows the results of a multiple regression analysis, with BI as the dependent variable and EE, FC, PE, and SI as the independent variables. The beta coefficients (β) measure the strength of the relationship between each independent variable and the dependent variable. The higher the beta coefficient, the stronger the relationship. In **Table 7**, the beta coefficients for EE, FC, PE, and SI are all positive and significant, which suggests that they all have a positive relationship with BI. The SD of the provide information about the variability of the estimates. The lower the SD, the more precise the estimates. The results show that the SDs are relatively low, which suggests that the estimates are relatively precise. Furthermore, the results suggests that all of the beta coefficients are statistically significant. Finally, all of the p-values are less than 0.05, which suggests that the null hypothesis can be rejected. Overall, the results suggest that EE, FC, PE, and SI all have a positive and statistically significant relationship with BI (see **Figure 2**).

R^2: Hair et al. (2016) defined the R^2 as a value that assesses the predictive accuracy of a model. The R^2 value from 0 to 1, where a higher value designates a higher level of predictive accuracy. According to Hair et al. (2016), an R^2 value of .75 is regarded as strong, while .50 is moderate, and .25 is weak. **Table 9** shows the R^2 for BI is 0.572, which suggests that the proposed model has an acceptance level of predictive accuracy.

f^2: The f^2 is an effect size measuring the effect of an exogenous construct on an endogenous construct. When a particular predictor construct is removed from the model, the f^2 examines the change in the values of R^2. The effect size aims to measure the real effect of a predictor construct on an endogenous construct. Hair et al. (2016) suggested that the value of .02 is a small effect, .15 is a medium effect, and .35 is a large effect. **Table 10** shows that all exogenous predictors have effects on the endogenous construct with small effect sizes.

The results of the SEM confirm our second hypothesis. EE, FC, PE, and SI each had a significant positive effect on students' intention to use the e-learning platform.

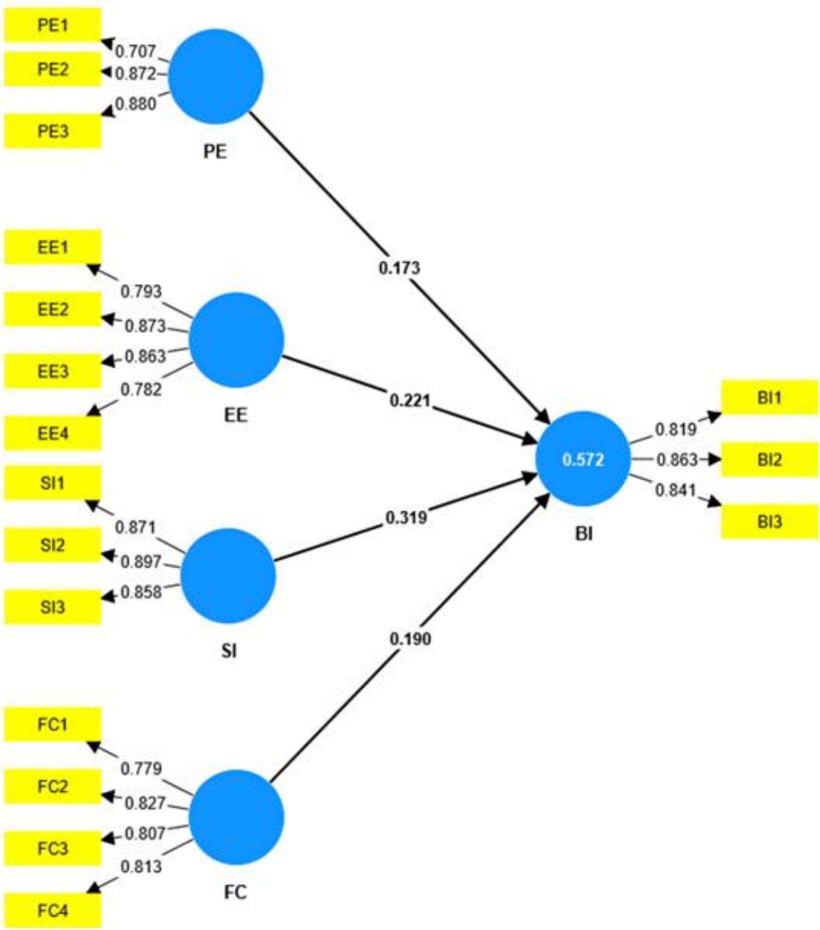

Figure 2. The model and t values (Source: Authors' own elaboration)

Table 9. R^2

	R-square	R-square adjusted	Consideration
BI	0.572	0.559	Moderate

Table 10. f^2 effect size

	f^2	Effect size
EE→ BI	0.047	Small
FC→ BI	0.035	Small
PE→ BI	0.041	Small
SI → BI	0.132	Small

DISCUSSION

This study examined two main hypotheses. First, we hypothesized that the e-learning-based remedial program would significantly improve students' mathematics achievement. The results supported this hypothesis, as evidenced by the significant increase in post-test scores compared to pre-test scores. Second, we hypothesized that EE, FC, PE, and SI would positively influence students' acceptance of the e-learning platform. The SEM analysis confirmed that all four factors had significant positive relationships with BI to use the platform, thus supporting our second hypothesis.

The results of this study show the implementation of an e-learning based remedial program in two senior secondary schools in Indonesia. A difference in program effectiveness emerged between the two schools. In school A, a remarkable 100% of students from targeted classes (class 1, class 3, and class 6) successfully achieved the minimum scores to complete the remedial program. On the other hand, school B witnessed a considerably lower success rate, with fewer than 40% of students across all classes meeting the set score threshold. These findings highlight the essential influence of institutional context and support on the efficacy of e-learning interventions. School A's success can be attributed to factors such as technological infrastructure and teacher commitment. In contrast, the lack of success in school B may be indicative of potential challenges, including limited technological resources and less teacher engagement.

These outcomes are in line with prior research on technology integration in education, where effective implementation is often linked to institutional readiness and support (Almusawi et al., 2021; Gürfidan & Koç, 2016). The different outcomes between the two schools strengthen the necessity for a holistic approach that incorporates stakeholder engagement to ensure successful e-learning adoption, particularly in the context of remedial.

Regarding the factor affecting students' acceptance of e-learning for remedial. The exploration into factors shaping students' acceptance of the e-learning platform for remedial has yielded valuable insights. The results show positive relationships between constructs such as EE, FC, PE, and SI with BI to engage with the e-learning platform. These findings align with the theoretical underpinnings of the UTAUT framework, which highlights the central role of these factors in shaping users' intentions to adopt and utilize technology (Venkatesh et al., 2016)

These identified factors within the UTAUT framework as influential determinants of BI highlight the applicability of established theoretical models in explaining technology acceptance, especially within the context of e-learning for remedial programs. The results contribute to the ongoing discourse on the intricate interplay between user perceptions and technology adoption within the context of e-learning (e.g., Abbad, 2021; Gunasinghe et al., 2020; Osei et al., 2022; Tan, 2013)

The findings of this study are specific to the context of e-learning programs within remedial education and are primarily focused on understanding students' acceptance and use of e-learning platforms for this purpose. The results could potentially inform broader discussions on technology adoption in other educational or non-educational contexts, but any generalization should be approached with caution, as the study's design and focus were tailored specifically to the remedial education setting. Further research is needed to explore the applicability of these findings in other domains.

The findings of this study go beyond e-learning in education. The different results observed in the two schools highlight the importance of using customized approaches that consider the characteristics and preparedness levels of each institution. Educational policymakers and administrators can use these insights to make decisions about integrating technology in schools giving priority to factors that support implementation.

Moreover, the identification of factors influencing students' acceptance holds implications for instructional design and pedagogical practices. Educators can focus on enhancing aspects such as ease of use, FC, and SI to promote the adoption of e-learning tools. Future research could look deeper into the interplay between these factors and potential moderating variables contributing such as gender and student level of digital competency to enhance understanding of technology acceptance in educational contexts.

In conclusion, this study contributes to the understanding of the outcomes of implementing an e-learning based remedial program and identifies critical factors influencing students' acceptance of such platforms. By anchoring the findings within existing literature, this research advances our understanding of the adoption of e-learning and highlights the significance of context-aware strategies in educational technology integration.

CONCLUSION

In conclusion, this research aimed to investigate the outcomes of implementing an e-learning-based remedial program focused on the topic of sequence and series in two senior secondary schools in Indonesia. The study also aimed to identify the factors influencing students' acceptance of the e-learning platform for remedial purposes. The findings of this study reveal insights into the effectiveness of the e-learning remedial program. The results demonstrated that students in school A exhibited good performance in the remedial program, with a remarkable 100% success rate among all classes (class 1, class 3, and class 6). In contrast, the achievement rate in the other school was less promising, with less than 40% of students across all classes meeting the required score. These outcomes highlight the significance of the e-learning intervention in improving student performance. Furthermore, the study employed a SEM analysis within the UTAUT framework, identifying several factors (EE, FC, PE, and SI) that showed a positive and statistically significant relationship with students' BI to accept the e-learning platform for remedial program. This stresses the importance of addressing these factors to facilitate the acceptance and utilization of e-learning tools for remedial purposes.

In essence, this research contributes to the understanding of e-learning's potential in enhancing academic performance and its acceptance among students. The findings provide educators and policymakers with insights into tailoring effective e-learning interventions and addressing key factors to foster students' engagement and success. As technology continues to play an increasingly crucial role in education, further research in e-learning implementation hold promising prospects for improving educational outcomes and addressing learning gap. It is hoped that this study will lay a foundation for future research in integrating e-learning for effective remedial programs.

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