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The Impact of Differentiated Learning, Adversity Intelligence, and Peer Tutoring on Student Learning Outcomes

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ABSTRACT

Objective: Differentiation is a well-recognized strategy that assists teachers in addressing the needs of students with varying abilities in a classroom of students with different characteristics. The research investigates the impact of differentiation learning, adversity intelligence, and peer tutoring on student learning outcomes. **Method:** This research employs a statistical survey approach to guarantee outcome accuracy. The researchers employed a partial least squares-structural equation model (PLS-SEM) to determine the values of latent variables to make predictions. The questionnaire was used as the data-gathering tool in this study. The investigation occurred at a vocational high school in Serang Regency in Banten Province, Indonesia. Were 250 students in the vocational high school in Serang Regency, Indonesia. The sampling procedure was conducted using a random approach. **Results:** The statistical study of the structural model indicates a considerable positive link between differentiated learning and adversity intelligence. Adversity intelligence and peer tutoring were positively correlated. Differentiated learning is positively correlated with learning outcomes. Learning outcomes are positively correlated with peer tutoring. **Novelty:** This research presents novelty research that combines differentiated learning, adversity intelligence, and peer tutoring to examine their impact on student learning outcomes. This research is novel in its attempt to incorporate multiple variables into a single unit for investigation and exploration. This research is intriguing due to variations in emphasis, research participants, and incorporation of research factors compared to earlier studies.

INTRODUCTION

Differentiation is a well-recognized strategy that assists teachers in addressing the needs of students with varying abilities in a classroom composed of students with different characteristics. Additionally, it enables teachers to deliver valuable and purposeful learning experiences to students while fostering the development of 21st-century skills throughout the learning journey (Hassan & Ajmain, 2022). Differentiated learning refers to the implementation of differentiation strategies in the classroom. This involves offering several methods for comprehending information, processing ideas, and creating learning outcomes. These approaches enhance students' learning process effectiveness (Maulida et al., 2024).

Differentiated learning is an increasingly significant pedagogical strategy that acknowledges pupils' varied learning styles and needs. Differentiated learning is an instructional method that caters to the diverse learning requirements of students. Differentiated learning is an educational method where teachers employ various instructional techniques to address the unique requirements of individual students, taking into account their distinct needs (Siringoringo et al., 2023). The requirements encompass preexisting knowledge, cognitive inclinations, personal interests, and

Comprehension of the subject matter. This notion modifies instructional approaches to accommodate individual requirements, acknowledges students' areas of proficiency and limitations, and promotes a more inclusive and tailored educational setting. Multiple prior studies on differentiated learning (Dalila et al., 2022; Haq & Arifin, 2024; Maulida et al., 2024; Putranti & Maksum, 2024) have demonstrated an improvement in students' cognitive learning outcomes following the implementation of differentiated learning.

Teachers need to assess each student's proficiency and intellect in class, including their ability to handle hardship. Adversity Intelligence refers to the abilities and perseverance students acquire when encountering difficulties, fostering a mentality that transforms barriers into chances for personal development—Rahayuningsih & Putra (2018) stated that individuals with high adversity intelligence attribute challenges to external sources and perceive their role as ordinary. This adversity intelligence represents a significant advancement in comprehending the requirements for achieving success (Rini et al., 2023). Individuals with high adversity intelligence may endure hardships and enhance their abilities to overcome difficulties. Individuals with high adversity intelligence tend to exhibit greater optimism when encountering challenges, viewing them as opportunities, as indicated by previous studies (Prahara et al., 2021).

In addition to these methods, the peer tutoring technique is anticipated to help uncover students' abilities in the classroom. Peer tutoring adds a collaborative aspect to the learning process. Peer interactions promote information sharing and enhance a nurturing learning atmosphere. Peer tutoring (PT) is a method that enhances student learning motivation, fosters thinking abilities, and promotes collaborative work with teacher oversight. This technique teaches students to work together, leveraging the expertise of their highly knowledgeable classmates. Peer tutoring involves students taking responsibility for discussing, asking questions, practicing, and evaluating their learning with direct peer input (Alibraheim et al., 2024). Peer tutoring encompasses several tutoring activities, primarily including students studying together in pairs to assist each other. Peer tutoring is most effective when students of varying skill levels collaborate, leading to a deeper comprehension of academic subjects. Peer tutoring is a crucial method employed by teachers to enhance their pupils' confidence and self-assurance. This strategy involves pairing students, one serving as a tutor and the other as a tutee or learner.

Combining differentiated learning, adversity intelligence, and peer tutoring aims to enhance student learning results. Student learning outcomes evaluate the knowledge, understanding, and skills students acquire after involvement in a program or educational endeavor. Evaluation is the process of measuring and assessing the outcomes of student learning. Learning outcomes are achieved after the learning process. When information absorption peaks during the learning process, the learning outcomes will likewise be maximized (Harefa et al., 2023). Learning outcomes are a direct effect of the process of learning and teaching. The teacher's role concludes with the assessment of learning results. Learning outcomes represent the culmination of education as viewed by students at the highest point of the learning journey. Learning outcomes can be seen as a reflection of the effort put into learning (Yani et al., 2023). Higher levels of student learning attempts lead to improved learning results. Learning outcomes can serve as a benchmark for evaluating the effectiveness of students' learning.

This study investigates the intricate relationships among differentiated learning, adversity intelligence, and peer tutoring, analyzing how they collectively influence student learning outcomes. Multiple prior studies on differentiated learning have demonstrated that it can significantly enhance learning outcomes. Prior studies by (Fitrianingtyas et al., 2024 Puspitacandri et al., 2020; Sigit et al., 2019; and Sujana et al., 2019) indicate that diversity intelligence impacts student learning outcomes. Prior studies by Astuti & Sianipar (2023), Chen et al. (2023), Irmawan (2019), Rusmini et al. (2024), and Ycong et al. (2021) have demonstrated that peer tutoring can enhance student learning outcomes. Past studies have shown distinctions between prior research and present research.

This research presents novelty research that combines differentiated learning, adversity intelligence, and peer tutoring to examine their impact on student learning outcomes. This research is novel in its attempt to incorporate multiple variables into a single unit for investigation and exploration. This research is intriguing due to variations in emphasis, research participants, and incorporation of research factors compared to earlier studies. The researcher formulated hypotheses based on the relationship between variables, which aligned with the established objectives.

1. Differentiated learning and adversity intelligence have a positive correlation.
2. Adversity intelligence and peer tutoring have a positive correlation.
3. Differentiated learning and learning outcomes have a positive correlation.
4. Learning outcomes and peer tutoring have a positive correlation.

RESEARCH METHOD

This research uses a statistical survey approach to ensure the accuracy of the results. The researchers used partial least squares structural equation modeling (PLS-SEM) to determine latent variable values and make predictions. This research uses a research model integrated into Smart PLS and Structural Equation Modeling (SEM). The investigation occurred at a vocational high school in Serang Regency, Banten Province, Indonesia. There are 250 students at Serang Regency Vocational School in Indonesia. The sampling procedure was carried out using a random approach. An examination of the data collection process involved a questionnaire survey. Each student received an electronic survey via WhatsApp using Google Forms.

Questionnaires were used as a data collection tool in this research. Researchers conduct surveys to collect information and data. The investigation used data collected from a Likert scale questionnaire. Then, the questionnaire was tested for validity and reliability using convergent validity (table 3). The Likert scale is a survey approach in which participants rate their level of agreement on a scale of one to five. Participants can receive the questionnaire directly via the Google Form link. The research sample consisted of 250 students. The questionnaire includes a list of respondents' names and questions/statements regarding each trait being evaluated.

PLS route modeling is used for data analysis because it can estimate all model parameters simultaneously, differentiating it from regression analysis. This research uses Partial Least Squares Structural Equation Modelling (PLS-SEM) to evaluate construct validity, discriminant validity, convergent validity, and composite reliability. This concept is examined through reliable PLS bootstrapping and Smart PLS multiple regression analysis. Figure 1 displays the flowchart used in this research.

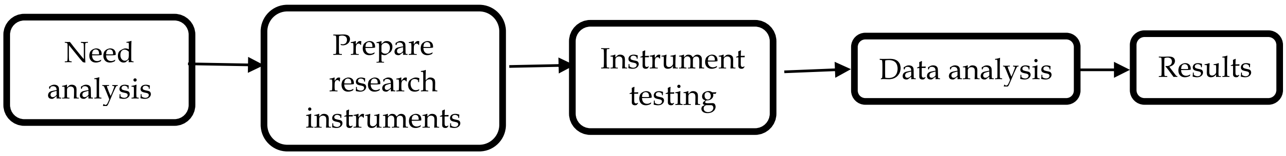

Figure 1. Flowchart of research procedure (Mulyana et al., 2024).

RESULTS AND DISCUSSION

Results

The study sample comprised 250 students. The respondent profile consists of gender, age, and grade. Table 1 presents the demographic characteristics of participants.

Table 1. Respondent profile.

No.	Variable	Total	Percentage
1	**Students**		
	Man	150	60.000%
	Woman	100	40.000%
		250	100.000%
2	**Age**		
	16-17	100	40.000%
	17-18	150	60.000%
		250	100.000%
3	**Classes**		
	X	50	20.000%
	XI	100	40.000%
	XII	100	40.000%
		250	100.000%

Evaluation and Statistical Analysis of Normal Distributions

The inquiries solely present data in the form of numerical values. According to Curran et al. (1996), data follow a regular distribution when the absolute values of the skewness and kurtosis statistics are each below 2 and 7. A series of descriptive statistics and normality metrics, including mean, standard deviation, skewness, and kurtosis, are provided in Table 2 at the item level for each distinct construct. The DL2 variable has the smallest mean value (3.990) and standard deviation (1.227) among the DL variables, according to descriptive statistics. Conversely, the DL1 variable exhibits the highest mean value of 4.440 and a standard deviation of 0.875. A positive correlation has been observed between adversity intelligence and differentiated learning among vocational high school pupils in the Serang district. The range of the AI value is as follows: minimum of 4.250, deviation of 0.921, and mean of 3.960, both exhibiting a deviation of 1.122 (AI1). The results above underscore the significance of adversity intelligence in a learner's capacity. The PT5 dimension exhibits the minimum mean and standard deviation values compared to PT3 (3.980 and 1.039, respectively). The dimension containing the most excellent mean and variability is PT4, with values of 4.060 and 1.047, respectively. Student achievement can be enhanced through the implementation of peer tutoring. Lastly, yet crucial. The minimal values of the mean LO dimensions and standard deviation are 3.960 and 1.122 (LO3, respectively). These dimensions have respective maximal values of 4.440 and 0.875 (LO1). According to these findings, the increase in student learning outcomes is attributable to differentiated learning, adversity intelligence, and peer tutoring.

Table 2. Statistical analysis and assessment of normal distribution.

Statistic Descriptive						Normality Indicator	
Con struct	**Item**	**Mean**	**Min**	**Max**	**Standard Deviation**	**Excess Kurtosis**	**Skewness**
DL	DL1	4.440	1.000	5.000	0.875	2.293	-1.630
	DL2	3.990	1.000	5.000	1.277	-0.389	-0.976
	DL3	4.000	1.000	5.000	1.275	-0.051	-1.074
	DL4	4.050	1.000	5.000	1.203	-0.341	-0.972
	DL5	4.210	1.000	5.000	1.098	0.904	-1.349
AI	AI1	3.960	1.000	5.000	1.122	0.072	-0.913
	AI2	4.250	1.000	5.000	0.921	0.553	-1.069
	AI3	4.020	1.000	5.000	1.157	-0.275	-0.904
	AI4	4.140	1.000	5.000	1.010	0.348	-0.996
	AI5	4.050	1.000	5.000	1.220	-0.405	-0.970
PT	PT1	4.050	1.000	5.000	1.226	0.361	-1.082
	PT2	4.020	1.000	5.000	1.049	-1.098	-0.780
	PT3	3.980	1.000	5.000	1.039	0.196	-0.828
	PT4	4.050	2.000	5.000	1.062	-0.842	-0.712
	PT5	4.060	2.000	5.000	1.047	-0.829	-0.705
LO	LO1	4.440	1.000	5.000	0.875	2.293	-1.630
	LO2	3.990	1.000	5.000	1.277	-0.389	-0.976
	LO3	3.960	1.000	5.000	1.122	0.072	-0.913
	LO4	4.250	1.000	5.000	0.921	0.553	-1.069
	LO5	4.050	1.000	5.000	1.126	0.361	-1.082
	LO6	4.020	1.000	5.000	1.049	-1.098	-0.780
	LO7	4.050	2.000	5.000	1.062	-0.842	-0.712
	LO8	4.060	2.000	5.000	1.047	-0.829	-0.705

Note: DL stands for differentiated Learning, AI for adversity Intelligence, PT for peer Tutoring, and LO for learning Outcomes.

Model of Measurement (External Model): Reliability and Validity

The statistic is used to evaluate convergent and competitive validity. Composite reliability (CR), average variance extracted (AVE), and peripheral loadings are the indicators used to assess convergent validity. Table 3 and Figure 2 show the dependability of the measurement data. All sixteen outside loadings (ranging from 0.705 to 0.955) are statistically significant at the 0.05 level, surpassing the significance threshold 0.50. Seven items were removed from the study because their peripheral loadings were less than 0.50: DL3, DL5, AI3, PT3, LO3, and LO4. Results also showed that, with a range of 0.613 to 0.786, AVE values were higher than the cutoff of 0.500. Cronbach's alpha and composite reliability (CR) should be higher than 0.700. All of the structures' Cronbach's alpha and CR values are higher than the crucial value of 0.70, as shown in Table 3.

Table 3. Convergent validity.

Construct	**Item Code**	**Outer Loading**	**Cronch's Alpha**	**CR**	**AVE**
DL	DL1	0.855	0.725	0.833	0.636
	DL2	0.808			
	DL4	0.704			
AI	AI1	0.822	0.701	0.826	0.613
	AI2	0.755			
	AI4	0.770			
PT	PT1	0.951	0.904	0.935	0.786
	PT2	0.700			

Construct	Item Code	Outer Loading	Cronch's Alpha	CR	AVE
	PT4	0.916			
	PT5	0.955			
LO	LO1	0.722	0.935	0.949	0.760
	LO2	0.942			
	LO5	0.928			
	LO6	0.732			
	LO7	0.934			
	LO8	0.939			

Note: *N = 250. DL: Differentiated Learning; AI: Adversity Intelligence; PT: Peer Tutoring; LO: Learning Outcomes*

The test's ability to distinguish between distinct groups was evaluated using the Fornell-Larcker Criterion. A comparison between the correlation between latent concepts and the square root of the average variance extracted (AVE) is used in this method. Compared to other latent constructs, one should be able to shed more light on differences in expression. Thus, it is reasonable to have square roots of the AVE for each construct greater than the correlations between the AVE of the latent constructs. Therefore, the construct's empirical distinctiveness provides enough discriminant validity. Using convergent and discriminant validity assessments, the research model demonstrates that the construct is sufficiently valid and reliable.

Table 4. Discriminant validity: Fornell-Larcker criterion.

	DL	AI	PT	LO
DL	0.783			
AI	0.764	0.791		
PT	0.617	0.772	0.872	
LO	0.602	0.807	0.887	0.993

Structural Model: Analysis of the Influence of Interaction

The primary purpose of structural model evaluations is to test hypotheses about the relative importance (R2), confidence interval range (CI), and statistical significance (t-values) of endogenous and exogenous variables. The T-values and standard errors were computed using the bootstrap method. Making an average of the results requires creating five thousand random samples.

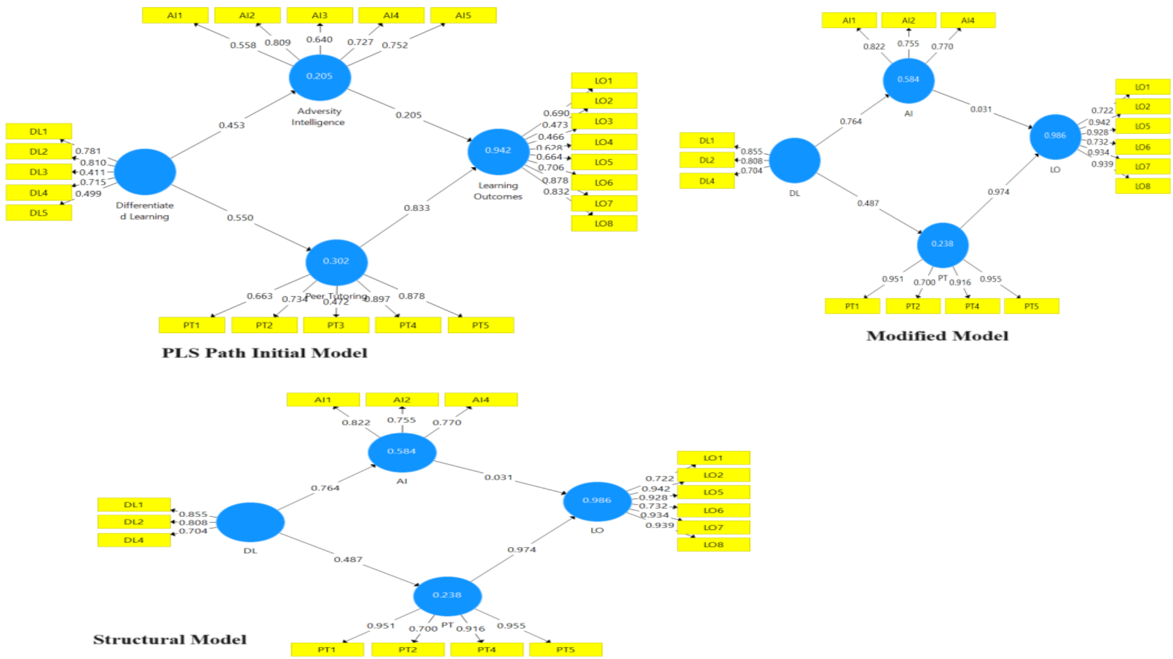

Figure 2. PLS-path initial model, modified model, and structural model.

The correlation between DL and AI is shown by confidence intervals in Figure 2 and Table 5, which range from 0.702 to 0.798. With a beta coefficient (β) of 0.764 and a t-value of 32.077, this relationship has a high level of statistical significance. Based on these results, an increase in AI was associated with a DL of one standard deviation. Consequently, we are unable to reject H1.

Table 5. Hypothesis statistics.

Hypotheses	Path	Std. Beta	Std. Error	t-Value	Bias	Confidence Bias 2.5%	Interval Corrected 97.5%	Decision
H1	DL -> AI	0.471	0.072	6.254	0.018	0.286	0.565	Accepted
H2	AI-> PT	0.556	0.065	8.412	0.016	0.408	0.663	Accepted
H3	DL-> LO	0.208	0.044	4.654	0.003	0.761	0.903	Accepted
H4	LO -> PT	0.831	0.039	21.535	-0.002	0.761	0.903	Accepted

Note: $p < 0.05$ (two-tailed test

Furthermore, the t value 6.254 demonstrates statistical significance, indicating a clear positive connection between DL and AI. The confidence interval for the association ranges from 0.286 to 0.565 in Figure 2 and Table 4. Therefore, a reduction of one standard deviation in DL results in an increase in AI of 0.471. Therefore, the evidence substantiates H2. Moreover, the β coefficient is 0.556, demonstrating a positive association between AI and PT. The association is statistically significant, as indicated by the t-value of 8.412. As shown in Figure 2 and Table 4, the confidence intervals for the linkages range from 0.408 to 0.663. The data suggests a strong positive relationship between the increase in AI and the growth in PT standard deviation, with a value of 0.556. Thus, H3 is statistically validated; The higher the DL, the more exemplary the learning outcomes. Ultimately, the data supports H4, as there is a clear and positive correlation between LO and PT. The correlation coefficient (β) is 0.831, and the t-value is 21.535. The confidence intervals for this correlation range from 0.761 to 0.903. The statistics indicate a positive correlation between a one standard deviation increase in LO and a PT of 0.761. R2 measures the extent to which external factors explain the variability observed in the dependent variable inside the modified PLS path model. Using the standard errors of the structural model, it is possible to ascertain that DL accounts for approximately 58.400% of the potential IA (moderate) variability.

Similarly, deep learning can accurately identify approximately 23.800% of differences in integrated circuits, although its performance in this area is relatively modest. Furthermore, the combination of DL and AI was responsible for 98.600% of the total LO variation, indicating a strong relationship. The blindfold test (Q2) also indicates that the model is sufficiently capable of predicting endogenous variables. The quantitative values of DL, AI, and LO are 0.308, 0.179, and 0.740, respectively. Hair et al. (2017) state that the model has a solid predictive relevance if the Q2 value exceeds 0.

Discussion

The current study investigated the impact of differentiation learning, adversity intelligence, and peer guidance on student learning outcomes. Four research hypotheses are presented in this study. This study has yielded numerous significant findings. To address the initial idea of differentiated learning for adversity intelligence. Table 5 hypothesis findings indicate a favorable association between differentiated learning and adversity intelligence. Differentiated learning involves creating a diverse classroom where students are given opportunities to excel in mastering material, processing ideas, and enhancing their learning outcomes (Faiz et al., 2022; Herwina, 2021; Juliani, 2019; Rini et al., 2023; Wulandari, 2022). This approach aims to facilitate more effective learning, encourage student engagement, and support natural learning opportunities. Efficiency individuals with vital adversity intelligence prefer to attribute challenges to external factors and perceive their part as inherent. Adversity intelligence refers to an individual's capacity to acknowledge and handle challenges in life, such as stress and current issues.

The second study discovered a favorable association between adversity intelligence and peer tutoring. Research has found a significant association between resilience and peer tutoring. This is evident from the values (t=8.412 and p=0.000) in Table 5. The results of this study align with previous research by (Alibraheim et al., 2024). Adversity intelligence promotes positive values, and PT is a method that boosts students' motivation, fosters critical thinking, and improves teamwork in the presence of a teacher. Peer tutor learning allows students to take a more active role in seeking clarification by asking questions about topics they find challenging. Peer tutors, who are students' friends, create a comfortable environment where students feel at ease seeking help without feeling ashamed, reluctant, awkward, or having poor self-esteem, encouraging students to openly discuss their difficulties (Astuti & Sianipar, 2023). This research differs from prior studies by incorporating adversity intelligence and peer tutoring characteristics to examine the favorable link between them.

The third study demonstrates a positive correlation between differentiated learning and learning outcomes. Research has revealed substantial disparities in differentiated learning and learning outcomes. This research aligns with other studies (Jorgensen & Brogaard, 2021; Liou et al., 2023; Sitanggang et al., 2022; Timbola et al., 2023), indicating that differentiated learning effectively enhances student learning outcomes. A differentiated learning technique can enhance learning results (Jayantika & Santhika, 2023). Students' cognitive learning outcomes improve after implementing differentiated learning using the PBL approach (Dalila et al., 2022). Differentiated learning in the instructional design positively influences student learning outcomes. Students are allowed to discover learning styles that are ideal for developing their abilities and potential. The fourth study reveals that the impact of learning outcomes and peer tutoring have a positive link. Empirical evidence suggests that there is an effect on learning outcomes and peer tutoring. This is confirmed by the research findings in Table 5 (t= 21.535 and p=0.000). This research's results align with prior research (Kaharuddin, 2019; Pramika & Putri, 2019; Winarti, 2020), suggesting that adopting peer tutoring learning approaches can increase student learning outcomes.

CONCLUSION

Fundamental Finding: The research revealed four noteworthy and statistically significant conclusions based on previous findings and discussion: Differentiated learning and adversity intelligence are positively correlated. Adversity intelligence and peer tutoring are positively correlated. Differentiated learning is positively correlated with learning outcomes. Learning outcomes and peer tutoring are positively correlated. **Limitation:** Additionally, this topic faces some research hurdles. The research sample was restricted to pupils at senior vocational high school Negeri 1 Kramat Watu in Serang Regency, primarily because of time and money constraints. This research can only encompass some areas in Serang Regency, Indonesia. **Future Research:** Future studies are anticipated to be conducted throughout all educational levels in Indonesia, utilizing various variables and research methodologies.

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