European Journal of Educational Research

Volume 13, Issue 2, 719 - 734.

ISSN: 2165-8714

http://www.eu-jer.com/

Logistic Regression Analysis: Predicting the Effect of Critical Thinking and Experience Active Learning Models on Academic Performance

Hery Sawiji*
Universitas Sebelas Maret, INDONESIA

Sigit Permansah
Universitas Sebelas Maret, INDONESIA

Subroto Rapih
Universitas Sebelas Maret, INDONESIA

Nur Rahmi Akbarini
Universitas Sebelas Maret, INDONESIA

Dede Rusmana
Universitas Negeri Malang, INDONESIA

Yosep Tegar Prameswara
Universitas Sebelas Maret, INDONESIA

Muhammad Irfan Aminudin
Universitas Sebelas Maret, INDONESIA

Received: August 12, 2023 ▪ Revised: September 27, 2023 ▪ Accepted: October 31, 2023

Abstract: This study aims to analyse the relationship between critical thinking and the learning experience provided by instructors through active learning models, specifically Project-based Learning (PjBL) and Simulation-based Learning (SBL), to the potential achievement of academic performance in undergraduate students. The main analysis technique employed in this research was logistic regression, with additional analysis techniques including discriminant validity, EFA, as well as Kendall's and Spearman's correlation, serving as a robustness check. The results of this study indicate significant correlations and effects of critical thinking (CT) on academic performance. Higher levels of CT are associated with a greater likelihood of achieving academic excellence, as indicated by the cum laude distinction, compared to not attaining this distinction. Experiences of receiving PjBL (0.025; 6.816) and SBL (0.014; 14.35) predicted the potential for improving academic performance to reach cum laude recognition, relative to not achieving this distinction. Furthermore, other intercept factors need to be considered to achieve cum laude compared to not achieving cum laude. We recommend that policymakers in higher education, instructors, and others focus on enhancing critical thinking and utilizing both Pub and SBL as learning models to improve students' academic performance.

Keywords: *Academic performance, critical thinking skills, experience with PjBL and SBL, logit analysis.*

To cite this article: Sawiji, H., Permansah, S., Rapih, S., Akbarini, N. R., Rusmana, D., Prameswara, Y. T., & Aminudin, M. I. (2024). Logistic regression analysis: Predicting the effect of critical thinking and experience active learning models on academic performance. *European Journal of Educational Research, 13*(2), 719-734. https://doi.org/10.12973/eu-jer.13.2.719

Introduction

Academic performance is the main objective in fulfilling the quality of learning outcomes. However, academic performance is difficult to determine with a precise measure. There are many factors and circumstances to consider in formulating academic performance. When students' academic performance is determined, the problem of generalization becomes the following problem. The causality of other factors to academic performance may differ when applied to students from diverse backgrounds. Therefore, defining academic performance becomes a multidimensional approach, one facet of which involves competition among universities. Currently, competition within the higher education sector is becoming increasingly intense (Fajnzylber et al., 2019; Gordanier et al., 2019; Helal et al., 2018; Y. Zhang et al., 2010), especially among both public and private universities, among undergraduate students within and outside of universities, and even among universities. They compete to produce high-quality academic performance in undergraduate students. One variable used by them to assess the extent of undergraduate academic performance is the grade point average (GPA) (Fajnzylber et al., 2019; Giunchiglia et al., 2018) which ranges from 1 to 4 (e.g., GPA of 3.2). The higher the grade point, the higher the designation the student will receive, such as cum laude for undergraduate students who graduate with a GPA exceeding 3.50 (>3.50). Such recognition signifies their excellent academic performance and deserving of praise.

Therefore, many universities explicitly instruct their instructors to enhance the academic performance of undergraduate students (Fajnzylber et al., 2019). This instruction encompasses the implementation of active learning models such as project-based learning and simulation-based learning, aiming to enhance the effectiveness and efficiency of learning. It is expected that these approaches will enable undergraduate students to improve their understanding of the learning

* **Corresponding author:**
Hery Sawiji, Universitas Sebelas Maret, Surakarta, Indonesia. ✉ herysawiji@staff.uns.ac.id

materials and positively impact their academic performance as reflected by their GPA. Such policies are in line with previous research findings that indicate the positive impact of project-based learning (PjBL) (Beier et al., 2019; C.-H. Chen & Yang, 2019; Darmuki et al., 2023; Mou, 2020; Parrado-Martínez & Sánchez-Andújar, 2020; Usmeldi & Amini, 2022; Yang et al., 2020) and simulation-based learning (SBL) (Ampountolas et al., 2019; Bakoush, 2022; Banda & Nzabahimana, 2023; Hung et al., 2021; Koparan, 2022; Mishra et al., 2023; Tasantab et al., 2023) on learning motivation, engagement, self-efficacy, and academic performance outcomes.

However, some researchers have found no impact or, in some instances, negative effects from the implementation of these two learning models compared to other models (Aghayani & Hajmohammadi, 2019; Erdogan & Senemoglu, 2017; Kızkapan & Bektaş, 2017; B.-O. Lee et al., 2019; Mai et al., 2019; Pan et al., 2023; Rahmati et al., 2022; Raphael et al., 2021; Suradika et al., 2023). It is similar to previous findings (Asif et al., 2017; Xu et al., 2017) which stated that certain courses do not provide accurate information in measuring academic performance. This could be due to various factors that affect students both internally and externally, such as the teacher factor, instructional factors in education, peer behaviour (Muenks et al., 2018), smartphone use (Giunchiglia et al., 2018; H. Lee et al., 2017; Samaha & Hawi, 2016), stress, boredom (Derakhshan et al., 2021; Samaha & Hawi, 2016) and the use of digital media (Giunchiglia et al., 2018), which can lead to no significant difference in the use of these learning models. These factors should be considered in every study, especially in the application of active learning models, to ensure the collection of unbiased data.

In the past few decades, research on the effect of critical thinking skills has shown positive impacts on students (D'Alessio et al., 2019; Maksum et al., 2021). According to experts (D'Alessio et al., 2019; Ennis, 1993; van Laar et al., 2019), critical thinking involves reasoned and reflective thinking that focuses on making decisions about what to believe and what to do. Therefore, these abilities can be utilized by individuals in the field of education (van Laar et al., 2019).

However, studies on PBL, SBL, and critical thinking have not naturally evolved based on the experiences of undergraduate students. For example, research on PBL and SBL models is often carried out through special treatment in experimental classes and compared with control classes or pre-to-post tests (Banda & Nzabahimana, 2023; Crowl et al., 2022; Darmuki et al., 2023; Koparan, 2022; Sigit et al., 2022; Usmeldi & Amini, 2022). Additionally, in the context of critical thinking, previous researchers (D'Alessio et al., 2019; de Bie et al., 2015; Demirhan et al., 2011; van Laar et al., 2019) have highlighted that these skills enable students to generate arguments, make inductions and deductions, draw conclusions, and render judgments based on gathered information. Under these circumstances, academic performance is frequently regarded as a quantitative parameter that is treated to indicate the success of an educational research product. Therefore, critical thinking needs to be considered in investigating academic performance naturally.

Based on these considerations, this study aims to analyse the experience of undergraduate students in receiving instruction from instructors using active learning models (naturally) limited to the PBL and SBL models, as well as their critical thinking skills, in relation to the potential achievement of their academic performance, as reflected by GPA and categorized GPA. Given the multifaceted nature of academic performance affected by various internal and external factors, the researcher also takes into account variables such as gender, student boredom or dissatisfaction with traditional learning, student choice in using active learning models, smartphone or device usage, risks from digital media, stress levels, instructor evaluations, and digital media opportunities (Derakhshan et al., 2021; Giunchiglia et al., 2018; Muenks et al., 2018; Samaha & Hawi, 2016; Thiele et al., 2016) as independent variables.

Therefore, the main analytical technique employed in this study was logistic regression, as this technique can accurately predict the effect of independent variables on the dependent variable in binary or multinomial data. For example, in this analysis, we will predict the impact of experiencing the PBL model (received or not received) on academic performance (cum laude or non-cum laude). In addition to analysing the general relationship between PBL and academic performance, logistic regression can analyse parameter estimation within this general relationship, such as the effect of students who have received the learning model different in achieving the cum laude designation compared to those who have not. To enhance the robustness of the findings, the researcher also employed discriminant analysis and exploratory factor analysis (EFA) techniques to retest the validity of the prepared instruments, as well as correlation tests (Kendall's and Spearman's correlation) to determine the correlation between variables. These steps are necessary as a robustness check to obtain a strong justification for the results. It is expected that the findings of this study will contribute to the field of education, benefiting policymakers, instructors, and undergraduates in making decisions regarding the use of learning models and other factors that can affect their academic performance. In general, policymakers can design and create strategies for learning to prepare quality graduates in terms of academic performance and competitive job opportunities.

Methodology

Research Design

This study adopted a quantitative approach with logistic regression as the main analytical technique. To enhance the robustness of the research findings, the researcher conducts additional analyses using various techniques. These include discriminant validity and exploratory factor analysis, which serve to validate the instrument measuring critical thinking skills and bolster the justification for instrument validation, as well as Kendall's and Spearman's correlation as a robustness check for the main analysis. As a guide for this study, the researcher organizes the research process into four research phases (see Figure 1).

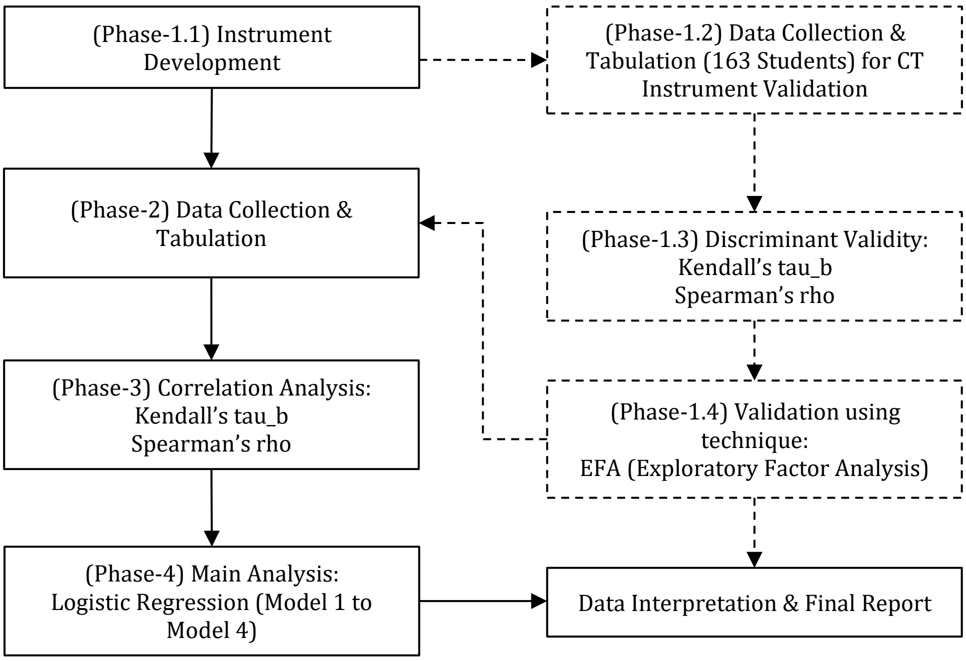

Figure 1. Research Phases

The independent variables in this study are critical thinking skills, the use of project-based learning and simulation-based learning models as the main variables (see Table 1), while the dependent variable is academic performance, reflected through GPA achievement, presented both as a continuous variable and categorized into four models (see Table 1). In addition to these main variables, the study also considers other factors as independent variables that may have an intercept on academic performance, such as gender, students' response to boredom or fatigue in traditional learning, students' choice in using active learning models, smartphones or other device usage, digital media risks, stress levels, instructor evaluation, and opportunities arising from digital media.

Sample and Data Collection

The minimum sample size calculation using the n = 100 + xi method (x is an integer, and i represents the number of independent variables in the final model) is used as the basis of sample size for logistic regression, especially for observational studies where sample size emphasizes statistical accuracy. Consequently, 331 sample data perfectly fulfils the minimum sampling criteria for logistic regression analysis. All samples taken have homogeneous characteristics, ensuring that, based on both the minimum sample size and shared characteristics, the sample effectively represents the population. The participants in this study were 331 randomly selected Indonesian students who voluntarily completed the instruments. The data for this research were collected in two phases. The first phase, Phase 1.2, encompassed the collection of 163 data, which were used to validate the critical thinking (CT) instrument through discriminant validity and exploratory factor analysis (EFA) techniques. The second phase, Phase 2, encompassed the collection of 168 data, which were used for correlation and logistic regression analyses.

Analysing of Data

Data analysis in this study was conducted using SPSS 23 software and started with Phase 1.3, which involved the validation of the data from Phase 1.2 (163 data). Given the considerable diversity in the data, characterized by varying coding types, the normality test in this study relied on Kendall's and Spearman's correlations. Kendall's and Spearman's correlation techniques were employed for this purpose. Following that, in Phase 1.4, a robustness check was performed using the EFA technique to ensure the validity of the CT instrument and identify the underlying components of the statement items used. Other instruments besides CT were not validated as they consisted of direct questions reflecting a single variable analysed with binary (1 & 2) and multinomial (1, 2 & 3) codes.

Next, in Phase 3, correlation analysis employing Kendall's and Spearman's correlation techniques was conducted to examine the relationships between CT, SBL, PjBL, and other intercept-independent variables with academic performance (see Table 1). In Phase 4, the main analysis involved logistic regression to predict the relationships between the predetermined variables and academic performance models (PM1 to PM4). The models were determined by categorizing the GPA, for example, "GPA above 3.51 is categorized as cum laude" (see Table 1).

The interpretation of Kendall's and Spearman's correlations in the study (Phase-1.3 & Phase-3) followed the established guidelines (Akoglu, 2018; Dancey & Reidy, 2007; Puth et al., 2014). Specifically, the correlation coefficient values of (+/-) $.1 <= r <= .399$ indicate a weak correlation, $.4 <= r <= .699$ indicate a moderate correlation, $.7 <= r <= .999$ indicate a strong correlation, and $r = 1$ indicates a perfect correlation. Additionally, the calculated r values are used with degrees of freedom (*df*) of 163/168 ($r > 0.1285/0.1266$), and sig. < .05. As an additional criterion in the Phase-1.3 analysis, when the value of Sig. (2-tailed) < .05 and the correlation is positive, the questionnaire item is declared valid. If the value of Sig. (2-tailed) < .05 and the correlation is negative, the questionnaire item is declared invalid. If the value of Sig. (2-tailed) > .05, the questionnaire item is also declared invalid.

The interpretation of EFA analysis (Phase-1.4) follows several requirements. Firstly, the Kaiser-Meyer-Olkin (KMO)> .50 and sig. $p< .05$. Secondly, the anti-image correlation Measures of Sampling Adequacy (MSA) should be > .50. If MSA < .50, then the corresponding item should be eliminated and retested. Thirdly, the communalities should be > .50. If communalities < .50, then the item should be eliminated and retested. These conditions need to be met before determining the number of factors or dimensions based on the total initial eigenvalues > 1. The items that represent factors or dimensions can be determined through the maximum rotated component matrix value per dimension component, which should have a loading factor of .40 (Hair et al., 2010)

Finally, logistic regression analysis (Phase-4) was conducted following the methodology described in the initial reference for the analysis of the first binary outcome for all available independent variables. In each iteration, the least significant variable was removed (Bürkner & Vuorre, 2018; Healy, 1995; Peng et al., 2002). The criteria and interpretation used for goodness of fit include the person method and deviance sig. $p>0.05$ to determine the "model fit". Model fitting information included sig. $p< .05$ to determine that "in general". Pseudo R-Square value, using methods such as Cox and Snell, Nagelkerke, and McFadden, serves to gauge the degree of effect exerted by the independent variables on the dependent variable. Parameter estimates include sig. $p< .05$ to determine that the "intercept in the category of the independent variable affects the category in the dependent variable." If the criteria for parameter estimates are met, the next step involves observing the value of Exp (B). If Exp (B) < 1.000. It indicates that the dependent variable's "first reference" is affected by the intercept of the independent variable's category. Conversely, if Exp (B) > 1.000, categories other than the "first reference" in the dependent variable is affected by the intercept of the independent variable's category.

Table 1. Research Instruments

Item Code	Question	Option (Intercept Reference/Category Code)
Id_S	Please provide the abbreviation of your name using a maximum of 3 characters, for example: Sigit Permansah, written as SPe or similar!	
Gender	Gender	Female (1); Male (2)
RTL	Have you ever felt bored when lecturers teach using only lecture or presentation techniques?	Yes (1); No (2)
CT	Total of instrument critical thinking skills (Sum(CT1 to CT10))	Sum (CT1, CT2)
SCAL	Among the three active learning models below, which model do you prefer and find easy to adapt to?	Traditional learning (1); Simulation-based learning (2); Project-based learning (3)
SoDU	Among the three options below, which one do you most frequently do with your smartphone or similar device?	Playing online games (1); Using social media (2); Searching for information (3)
RDM	In using digital media (social media, games, e-commerce, etc.), what risks do you frequently face?	Bullying (1); Scams (2); Adult or sexual content (3)
SBL	In the last semester, have you ever been taught by a lecturer using a simulation-based learning model?	Yes, I have received it several times from the same or different lecturers/courses! (1); No, I have never received it (2); Not sure or doubtful, I forgot if I have received it (3)
PjBL	In the last semester, have you ever been taught by a lecturer using a project-based learning model?	
St	How much stress have you experienced due to your studies in the last semester?	High (1); Moderate (2); Low (3)
Mea	In the last semester, did your final grades come from assessments by the lecturers?	Combination of portfolio or assignments, learning process, and mid-term and final exams (1); Only mid-term and final exams (2); Can't remember (3)
OPD	Have you ever received opportunities from digital media?	Non-Financial (1); Financial (2); Any more (3)
P_GPA	What is your latest GPA?	Scale Index (0 up to 4; with two decimals)
PM1	*Categorized by researchers based on GPA, with the cum laude category (GPA>=3.51) and non-cum laude category (GPA<=3.50).	non-cum laude (1); cum laude (2)
PM2	*Categorized by researchers based on GPA with the following categories: Suma Cum Laude (GPA>=3.71), Cum Laude (GPA>=3.51, <=3.70), Very Satisfactory (GPA>=3.01, <=3.50), Satisfactory (GPA>=2.71, <=3.00), Sufficient (GPA<=2.70).	Sufficient (1); Satisfactory (2); Very Satisfactory (3); Cum Laude (4); Suma Cum Laude (5)
PM3	*Categorized by researchers based on GPA with the following categories: Cum Laude (GPA>=3.51), Very Satisfactory (GPA>=3.01), and Otherwise (GPA>=3.00).	Sufficient (1); Very Satisfactory (2); Cum Laude (3)
PM4	*Categorized by researchers based on GPA with the following categories: Obtaining Higher Grades (GPA>=3.81), Acceptable Administration (GPA>=3.00, <=3.80), and Non-Acceptable Administration (GPA>=2.99).	Non-Acceptable Administration (1); Acceptable Administration (2); Obtaining Higher Grades (3)

Table 1. Continued

Item Code	Question	Option (Intercept Reference/Category Code)
CT1	An individual with a special interest in algorithmic activities, thinking to solve problems in the fastest and best way possible.	Very reflecting or describing myself (1); Possibly reflecting or describing myself (2); Not reflecting myself (3)
CT2	An individual with the ability to analyse problems and analyse their solutions.	
CT3	An individual who easily identifies the core issues of a problem and finds the right solutions.	
CT4	An individual who can determine systematic methods to make the right decisions in any condition.	
CT5	An individual who can create new systems to solve problems.	
CT6	An individual who sees a problem as a unique challenge and can solve it in a unique yet effective way.	
CT7	An individual who can distinguish between right and wrong, good and bad, correct and incorrect.	
CT8	An individual who can draw accurate conclusions based on existing conditions.	
CT9	An individual who can connect ideas from various sources for personal and public interests.	
CT10	An individual who can develop ideas from multiple sources and ultimately discover new ideas for personal and public interests.	

Id_S is Id Sample; Gender is Gender; RTL is Response to Traditional Learning; CT is Critical Thinking Skills; SCAL is Student's choice in using active learning models; SoDU is Smartphone or Any More Device Usage; RDM is Risks from Digital Media; SBL is Simulation Based Learning; PjBL is Project Based Learning; St is Stress; Mea is Measurement; OPD is Opportunities from Digital Media; P_GPA is GPA; PM1 is Performance Academic Model 1; PMI2 is Performance Academic Model 2; PM3 is Performance Academic Model 3; PM4 is Performance Academic Model 4; CT1 is Clarification_1; CT2 is Clarification_2; CT3 is Judgment_1; CT4 is Judgment_2; CT5 is Novelty_1; CT6 is Novelty_2; CT7 is Justification_1; CT8 is Justification_2; CT9 is Connecting Ideas_1; CT10 is Connecting Ideas_1.

Findings/Results

Phase-1.1 Instrument Development

The instrument was developed based on credible references, starting with the independent variables in the form of developing the CT instrument by considering CT indicators (see Table 1: CT_1 to CT_10), including clarification, judgment, novelty, justification, and connecting ideas (Indrawati, 2021; Loeneto et al., 2020; Saad & Zainudin, 2022; van Laar et al., 2019). Furthermore, project-based learning (PjBL) and simulation-based learning (SBL) were developed based on previous considerations such as experiments, pre-post tests, cluster randomized trials, and similar studies that compared the use of these models without using other variables (both traditional learning (TL) and other learning models). Therefore, instruments were devised to assess participants' experience with PjBL and SBL, inquiring whether they had engaged in learning using these models during the preceding semester. Participants were expected to respond with either "yes" or "no." Nonetheless, the study also accommodated responses of "do not remember" to account for the possibility that participants might not recall their experiences precisely due to the number of courses or lectures attended, among other factors that could lead to uncertainty. The dependent variable was academic performance reflected using GPA in several models (see Table 1).

In addition to the three main independent variables mentioned, the researchers considered other factors in this study that could potentially predict their effect on academic performance. These factors included students' responses to traditional learning, their choices regarding the utilization of active learning models, smartphone or device usage, digital media risks, stress levels, measurement, and opportunities from digital media. Regarding the question addressing students' response to traditional learning (see Table 1: RTL), the researchers considered previous findings that revealed students' experiences of boredom when instructors heavily relied on presentation-based teaching without incorporating various techniques or other learning models (Derakhshan et al., 2021; Tvedt et al., 2021).

The question on student's choice in using active learning models (see Table 1: SCAL) was developed based on the consideration that each student has unique characteristics and interests, including their preferences and inclinations toward specific learning models (Gallagher, 2023). The question on smartphone or device usage (see Table 1: SoDU) was also developed considering previous research that highlighted the impact of smartphone or similar device usage on online gaming (Evans et al., 2015), social media (Wu & Cheng, 2019) and information seeking (Samaha & Hawi, 2016) on learning and student outcomes. Similar considerations guided the formulation of questions on risks associated with digital media, stress level, measurement, and opportunities from digital media, as these factors can affect the learning process and student outcomes (Du Plessis & McDonagh, 2021; Greenstein, 2012; Klapper & Fayolle, 2023; Liao et al., 2021; Purnama et al., 2021; Samper et al., 2022; Z. Zhang, 2022).

(Phase-1.2) Data Collection for CT Instrument Validation

The data collection process for the validation of the CT instrument in phase 1.2 took place after the students had completed their final exams and were no longer enrolled in any courses (January 2023). However, they remained registered as students at universities in Indonesia. The researchers contacted students who met these criteria to confirm their willingness to participate and answer the instrument through the provided link.

Throughout this process, students were assured that their student ID numbers would be kept confidential. The researchers emphasized that their answers would not affect their final exam grades. Furthermore, after the completion of the study, their student ID numbers would be deleted from the research data and replaced with participant code names.

The inclusion of student ID numbers was necessary for the researchers to ensure the prevention of data duplication and to avoid the participation of the same students in filling out the research instrument again in phase 2. A total of 163 data were successfully obtained by the researchers, and these data were then used for phase 1.3 of the study.

(Phase-1.3) Discriminant Validity Analysis

A total of 163 data points were analysed using Kendall's tau_b and Spearman's rho correlation analysis techniques. The results showed that all questionnaire items met the criterion of sig. $p < .05$, with variations of $p < .01$ and $p < .05$. The threshold value employed was determined based on the number of respondents, utilizing the calculation method for the r table. Furthermore, the required correlation coefficient value ($r > 0.1301$) was also satisfied. The lowest correlation coefficient value was found in Kendall's tau_b for item Q_1 (.115) with the category "low," while the highest correlation coefficient value was observed in Spearman's rho for item Q_3 (.601) with the criteria "moderate." Therefore, all CT questionnaire items were deemed valid (see Table 2).

Table 2. Correlation Validity Report for CT

Correlation	Q_1	Q_2	Q_3	Q_4	Q_5	Q_6	Q_7	Q_8	Q_9	Q_10
Kendall's tau_b	.155	.294	.536	.255	.320	.278	.307	.299	.163	.478
Spearman's rho	.183	.335	.601	.286	.359	.311	.344	.335	.183	.532
Explanation	Valid	Valid	Valid	Valid	Valid	Valid	Valid	Valid	Valid	Valid

(Phase-1.4) Validity Analysis With EFA

After confirming the validity of all CT instrument items in the previous phase, the researchers conducted an Exploratory Factor Analysis (EFA) to examine the item's robustness and ensure that they align with the considered indicators, including clarification, judgment, novelty, justification, and connecting ideas (Indrawati, 2021; Loeneto et al., 2020; Saad & Zainudin, 2022; van Laar et al., 2019) by examining the components formed. The requirements of KMO > .5, anti-image correlation MSA > .5, and communalities > .5 were met (see Table 4), indicating that all items have good and valid robustness. Subsequently, the questionnaire items were grouped and assigned item codes based on the results of the Rotated Component Matrix (Component), demonstrating that the items were grouped according to the considered indicators.

Table 4. EFA Validity Report

Questions	KMO	Anti-image Correlation	Communalities	Rotated Component Matrix (Component)	Declaration
Q_1	.557	.529	.740	.788 (5)	Valid
Q_2		.556	.674	.713 (5)	Valid
Q_3		.540	.645	.621 (4)	Valid
Q_4		.503	.612	.721 (3)	Valid
Q_5		.561	.768	.857 (1)	Valid
Q_6		.568	.748	.835 (1)	Valid
Q_7		.574	.731	.698 (2)	Valid
Q_8		.543	.693	.769 (2)	Valid
Q_9		.616	.598	.734 (3)	Valid
Q_10		.525	.742	.834 (4)	Valid

***KMO is Kaiser-Meyer-Olkin**

(Phase-2) Final Data Collection

The final data collection was conducted after Phase 1.4 (from late January to February 2023) following the validation of the instrument. The categories and data collection requirements in this phase were the same as in Phase 1.2, but the entire designed instrument was employed. The key difference in this phase was the researchers' request or confirmation of the student ID numbers. Upon identifying that a participant had previously completed the instrument based on their ID number, the data collection process for that participant was cancelled to prevent data duplication or participants from filling out the instrument, particularly the CT section, more than once. During the data tabulation process, if any duplicate student ID numbers were found, the researchers deleted and disregarded the participant's answer data for this phase of data collection. These duplicate responses were not included in the total of 168 data points collected and analysed in this study. Therefore, the 168 data points collected and analysed in this study were carefully isolated from any data duplication. After ensuring proper isolation of the data, the researchers removed the student ID numbers and replaced them with participant code names (see Table 1: Id_S)

(Phase-3) Correlation Analysis

The analysis of the 168 data points revealed that the CT1 to CT10 statements can reflect critical thinking (CT) based on the correlations observed in both Kendall's tau_b and Spearman's rho. The lowest correlation value was found for CT5 (.354; $p < .01$), categorized as "low," while the highest correlation value was observed for CT7 (.842; $p < .01$), categorized as "strong."

The correlation analysis between CT and P_GPA (actual GPA) yielded positive and significant results, with $p < .01$ for both Kendall's tau_b (.174) and Spearman's rho (.244). The correlation was categorized as "low" (see Table 5). Specifically, the CT items that showed positive and significant correlations with P_GPA were CT1, CT5, CT6, CT7, CT9, and CT10, with $p < .05$ and categorized as "low" correlation for each item.

Table 5. Report Correlation CT & P_GPA

Correlation	Code	CT	CT1	CT2	CT3	CT4	CT5
Kendall's tau_b	CT	1	.637**	.584**	.531**	.532**	.290**
	P_GPA	.174**	.238**	0.099	0.045	0.121	.127*
Spearman's rho	CT	1	.743**	.681**	.627**	.628**	.354**
	P_GPA	.244**	.294**	0.12	0.054	0.146	.158*
			CT6	CT7	CT8	CT9	CT10
Kendall's tau_b	CT		.667**	.729**	.491**	.489**	.507**
	P_GPA		.137*	.123*	0.083	.135*	.130*
Spearman's rho	CT		.786**	.842**	.594**	.594**	.743**
	P_GPA		.173*	.158*	0.107	.168*	.161*

*$p< .01$, **$p< .05$

Furthermore, the variables PjBL to gender showed correlation values with $p > .05$, indicating no significant correlation between PjBL, RTL, SoDU, RDM, St, Mea, OPD, and gender with P_GPA. However, a significant correlation was found between the SBL variable (.175; $p < .05$) and the P_GPA variable (see Table 6), categorized as a "low" correlation coefficient. In this phase, the researchers did not eliminate any questionnaire items, factors, indicators, or variables. Using the same data, further analysis was conducted in phase 4.

Table 6. Report Correlation

Correlation		SBL	PjBL	RTL	SoDU	RDM	St	Mea	OPD	Gender
P_GPA	Kendall's tau_b	.143	.057	.115	.034	.007	.014	.012	.109	.152
P_GPA	Spearman's rho	.175*	.070	.139	.042	.008	.017	.016	.131	.183

*$p< .01$, **$p< .05$

(Phase-4) Logistic Regression Analysis

The first step involved assessing the goodness of fit, which showed the significance values for Pearson and Deviance in the following models: PM1 (.258; .066), PM2 (1.000; 1.000), PM3 (.882; .999), and PM4 (1.000; 1.000) with $p > .050$. These values indicate that the model is considered adequate based on model fit. Further analysis of the model fit revealed significant values for PM1 (.000), PM2 (.003), PM3 (.001), and PM4 (.000) with $p < .05$, suggesting that, in general, the independent variables have an impact on the dependent variable (refer to Table 7).

Moreover, the overall percentage of the independent variables' effect on the dependent variable, represented by the pseudo R-square values using the Cox and Snell, Nagelkerke, and McFadden methods, were as follows: PM1 (.235 or 23.5%; .321 or 32.1%; .204 or 20.4%), PM2 (.479 or 47.9%; .515 or 51.5%; .244 or 24.4%), PM3 (.342 or 34.2%; .413 or 41.3%; .239 or 23.9%), PM4 (.267 or 26.7%; .390 or 39%; .269 or 26.9%). The smallest percentage was observed in PM1 using the McFadden method at 20.4%, while the largest percentage was found in PM2 using the Nagelkerke method at 51.5%. Since the percentages did not reach 100%, there may be other factors or independent variables that were not analysed in this study that could affect the dependent variable.

Table 7 Model Fitting Information, Goodness of Fit, and Pseudo R-Square values.

	PM 1		PM 2		PM 3		PM 4	
	χ^2	Sig.	χ^2	Sig.	χ^2	Sig.	χ^2	Sig.
Model Fitting Information								
LTR	44.929	.000	109.56	.003	70.199	.000	52.232	.040
Goodness of fit								
Pearson	155.64	.258	424.19	1.000	261.73	.880	185.36	1.000
Deviance	171.39	.066	336.07	1.000	220.13	1.000	142.3	1.000
Pseudo R-Square								
Cox and Snell	.235		.479		.342		.267	
Nagelkerke	.321		.515		.413		.39	
McFadden	.204		.244		.239		.269	

LTR stands for Likelihood Ratio Tests. In this context, PM1 represents academic performance categorized into non-cum laude (1) and cum laude (2) based on GPA. PM2 represents academic performance categorized into Sufficient (1), Satisfactory (2), Very Satisfactory (3), Cum Laude (4), and Suma Cum Laude (5) based on GPA. PM3 represents academic performance categorized into Otherwise (1), Very Satisfactory (2), and Cum Laude (3) based on GPA. PM4 represents academic performance categorized into Non-Acceptable Administration (1), Acceptable Administration (2), and Obtaining Higher Grades (3) based on GPA. For more specific information, please refer to Table 1.

The parameter estimates analysis with the first reference in PM1 indicates that the intercept variables CT, SBL, PjBL, RTL, SCAL, SoDU, and RDM ($p < .05$) have a significant effect on academic performance according to the intercept model (see Table 8). A higher CT value increases the likelihood of achieving "cum laude [=2]" by 1.165 times compared to "not cum laude [=1]". Furthermore, students who have experienced SBL and PjBL have a potential of achieving cum laude 14.353 and 6.816 times higher, respectively, compared to not cum laude. Consistent with the higher impact of SBL compared to PjBL, students (SCAL=2) who choose simulation-based learning have a potential of achieving cum laude 3.230 times higher than not cum laude. Students who feel bored with traditional learning (RTL=1), use smartphones for online gaming (SoDU=2), and have experienced bullying (RDM=1) are more likely to obtain not cum laude rather than achieving cum laude.

Table 8. Result of Parameter Estimates.

Model	Cat. Code		CT	SBL	PjBL	RTL	SCAL	SoDU
		Int	CT	[=1]	[=1]	[=1]	[=2]	[=1]
PM1	[=2]	Sig.	**.004**	**.014**	**.025**	**.000**	**.017**	**.004**
		Exp (B)	**1.165**	**14.35**	**6.816**	**0.177**	**3.230**	**.080**
PM2	[=2]	Sig.	.883	.998	.990	.961	.956	.991
		Exp (B)	0.009	0.021	1.111	7.628	1.338	6.000
PM2	[=3]	Sig.	.885	.998	.998	.961	.952	.991
		Exp (B)	0.010	0.003	7.151	6.298	9.441	4.348
PM2	[=4]	Sig.	.887	.999	.997	.964	.950	.990
		Exp (B)	0.011	0.110	29.699	9.834	3.178	2.534
PM2	[=5]	Sig.	.891	.999	.996	.964	.952	.991
		Exp (B)	0.013	0.121	42.88	1.031	1.203	3.211
PM3	[=2]	Sig.	.759	.382	**.000**	.824	.138	.997
		Exp (B)	1.030	.192	**1.839**	1.183	7.075	1.007
PM3	[=3]	Sig.	.059	.266	.	**.021**	.033	.112
		Exp (B)	1.188	5.146	7.772	**0.195**	15.62	0.066
PM4	[=2]	Sig.	.311	.562	.998	.877	**.000**	1.000
		Exp (B)	1.215	0.289	8.424	0.818	**1.132**	0.151
PM4	[=3]	Sig.	**.023**	.819	.998	.707	.	1.000
		Exp (B)	**1.592**	1.686	4.449	0.593	1.483	0.019

Model	Cat. Code		RDM	St	Mea	OPD	Gender
		Int	[=1]	[=2]	[=2]	[=1]	[=1]
PM1	[=2]	Sig.	**.014**	.315	.060	.155	.712
		Exp (B)	**0.084**	1.923	0.322	2.929	0.847
PM2	[=2]	Sig.	.976	.999	.997	**.000**	.985
		Exp (B)	1.819	0.398	28.61	**3.121**	0.000
PM2	[=3]	Sig.	.983	.998	.996	**.000**	.984
		Exp (B)	1.969	0.142	43.289	**7.718**	0.000
PM2	[=4]	Sig.	.981	.998	.998	**.000**	.984
		Exp (B)	6.125	0.297	6.553	**2.960**	0.000
PM2	[=5]	Sig.	.981	.999	.997	.	.984
		Exp (B)	1.776	0.595	22.425	6.578	0.000
PM3	[=2]	Sig.	**.000**	.368	.563	.324	.632
		Exp (B)	**3.988**	0.391	1.762	0.249	0.695
PM3	[=3]	Sig.	.	.986	.493	.757	.534
		Exp (B)	2.034	1.016	0.524	1.373	0.643
PM4	[=2]	Sig.	1.000	**.000**	.968	**.000**	.706
		Exp (B)	0.013	**4.630**	1.092	**1.039**	0.554
PM4	[=3]	Sig.	.999	.	.906	.	.741
		Exp (B)	0.005	1.691	0.764	9.201	0.572

PM2 shows that the intercept OPD ($p < .05$) significantly affects academic performance according to the intercept model in the categories "Sufficient [=1], Satisfactory [=2], Very Satisfactory [=3], Cum Laude [=4], Suma Cum Laude [=5]" (see Table 8). The utilization of technology (opportunity digital) in the non-financial field (OPD=1) has a significant effect on the categories "satisfactory, very satisfactory, cum laude" compared to "sufficient". The highest potential impact of non-financial OPD on the "very satisfactory" category is 7.718 times higher than satisfactory and cum laude.

PM3 shows that the intercept PjBL and RDM ($p < .05$) significantly affect academic performance according to the intercept model in the categories "sufficient [=1], very satisfactory [=2], and cum laude [=3]". Students who have experienced PjBL=1 have the potential to achieve very satisfactory performance 1.188 times higher than sufficient. Those who experience the risk of bullying (RDM=1) have a significant impact on the "very satisfactory" category, with a likelihood 3.988 times higher than cum laude.

PM4 shows that the intercept SCAL, stress, and OPD have a significant effect on academic performance according to the intercept model in the categories of non-acceptable "administration [=1], acceptable administration [=2], and obtaining higher grades [=3]". Students who choose simulation-based learning (SCAL=2), have moderate stress (Stress=2), and utilize technology in the non-financial field (OPD=1) have the potential to achieve acceptable administration performance 1.839 and 1.309 times higher than non-acceptable administration.

Discussion

In this study, critical thinking is positioned as an independent variable aimed at analysing the correlation relationship as its predictive interpretation on students' academic performance, categorised based on GPA. The CT instrument is developed based on considerations of indicators such as clarification, judgment, novelty, justification, and connecting ideas (Indrawati, 2021; Loeneto et al., 2020; Saad & Zainudin, 2022; van Laar et al., 2019). The analysis results show that the CT instrument is valid based on the validity and reliability tests conducted using discriminant analysis and EFA. In addition, five components were found to be aligned with the considered indicators, indicating that the questionnaire items clearly show the correlation of CT through the considered indicators.

Furthermore, in the correlation analysis, a significant positive correlation was found between CT and the "low" category of GPA. In the logistic regression analysis, a significant effect ($p< .05$) of CT on the academic performance of undergraduate students, in terms of achieving the non-cum laude or cum laude predicate was identified (PM1). This model indicates that CT tends to be associated with the cum laude category, as evidenced by the exp (B) value of 1.165. Although the correlation analysis with the "low" category and the logistic analysis only shows a prediction increase of 1.165 times, the results still indicate a significant positive correlation and effect. Additionally, using the first reference technique, it is evident that higher levels of CT have the potential to achieve the cum laude predicate or a GPA above 3.51, which is higher compared to not achieving cum laude or a GPA below 3.50. These findings are consistent with previous research indicating a correlation and effect of critical thinking on academic performance (D'Alessio et al., 2019; Maksum et al., 2021).

The variables SBL (Simulation-Based Learning) and PjBL (Project-Based Learning) were designated as independent variables using the questions "In the last semester, have you ever been taught by a lecturer using simulation-based learning model?" and "In the last semester, have you ever been taught by a lecturer using project-based learning model?". The aim was to determine whether students had experienced education using simulation-based learning or project-based learning models in the past semester. Additionally, these questions indicate that the study did not involve any specific experiments or treatments using these models. The experiences of obtaining these models were solely based on the natural experiences of the students. However, the researchers only ensured whether they had received such experiences or not and did not confirm any modifications to the models applied by their respective lecturers. Contradictory findings emerged from the correlation and logistic regression analyses, where the correlation analysis showed that SBL and PjBL were not correlated with academic performance as measured by GPA, without categorization. These findings are consistent with previous studies that found no differences in learning outcomes between SBL and PjBL classes (Aghayani & Hajmohammadi, 2019; Frengley et al., 2011; Kızkapan & Bektaş, 2017; B.-O. Lee et al., 2019; Pan et al., 2023; Rahmati et al., 2022; Smelt et al., 2015; Suradika et al., 2023), Self-regulation (Erdogan & Senemoglu, 2017) was found to have a significant effect on academic performance in the logistic regression analysis. The analysis includes four models, PM1 to PM4, which categorize GPA. Parameter estimates show that receiving education through SBL has a significant correlation with achieving cum laude predicate (PM1), while PjBL has a significant effect on achieving the cum laude predicate (PM2) and very satisfactory performance (PM3). The probability of achieving cum laude with the experience of undergraduate students using simulation-based learning is 14.35 times greater than the probability of not achieving cum laude. Similarly, the likelihood of achieving the cum laude predicate with the experience of undergraduate students using project-based learning is 6.816 times greater compared to the likelihood of not achieving the cum laude predicate (PM1). Furthermore, the experience of learning using PjBL has a potential of 1.839 times greater in achieving a very satisfactory performance compared to a sufficient performance (PM3). These findings support the opinions of previous experts (Ampountolas et al., 2019; Bakoush, 2022; Banda & Nzabahimana, 2023; Hung et al., 2021; Koparan, 2022; Mishra et al., 2023; Tasantab et al., 2023) dan PjBL (Beier et al., 2019; C.-H. Chen & Yang, 2019; Darmuki et al., 2023; Mou, 2020; Parrado-Martínez & Sánchez-Andújar, 2020; Usmeldi & Amini, 2022; Yang et al., 2020) that SBL can enhance student outcomes or academic performance. Regarding undergraduate students' learning model preferences (SCAL), those who choose SBL have a greater likelihood of achieving better academic performance compared to other choices such as traditional learning or problem-based learning.

Another notable finding of this study is that students who experience boredom with lecture-based learning (RTL) techniques, such as presentations or lectures, tend to have a higher likelihood of achieving academic performance with a non-cum laude predicate compared to cum laude. Boredom with specific teaching techniques, especially traditional learning, can hinder the learning process (Derakhshan et al., 2021; Samaha & Hawi, 2016). Undergraduate students may struggle to absorb the learning material and lose interest in specific subjects, resulting in a lack of understanding and an increased likelihood of poorer performance. In terms of digital media risk (RDM), students who have experienced cyberbullying are likely to have lower academic performance compared to those who have not experienced bullying. This finding should be carefully considered by academic stakeholders, including educators, students, staff, university officials, and student leaders, as it demonstrates that being a victim of bullying can negatively impact academic performance (Lacey & Cornell, 2013; Rusteholz et al., 2021; Yu & Zhao, 2021).

In contrast to the RDM finding, when students utilize technology or digital media for non-financial gains (OPD), there is a potential for improved academic performance with satisfactory, very satisfactory, or cum laude predicates (GPA>3.00) compared to a sufficient predicate, with the likelihood of achievement being at least twice as high as for a sufficient predicate (GPA<3.00). This indicates that with these capabilities, the likelihood of avoiding poor academic performance is significantly higher (Beer & Mulder, 2020; M.-R. A. Chen et al., 2019; Pagani et al., 2016; Sailer et al., 2021). Additionally, maintaining a moderate level of stress in academia is also crucial. The stress levels resulting from the academic workload, including the number of courses and meetings, can vary. Our final finding indicates that moderate levels of stress are associated with better academic performance.

Conclusion

Based on the analysis and interpretation of the data, several important conclusions can be drawn. First, the validity test, along with robustness checks on the CT instrument, resulted in a CT instrument with a multinomial scale consisting of three points. Second, the CT variable exhibits a significant positive correlation with academic performance as assessed through non-categorized GPA. CT also has a general effect on cum laude academic performance compared to non-cum laude. The higher the CT, the greater the likelihood for students to achieve a cum laude designation. Third, the experience of receiving SBL and PjBL teaching models does not exhibit a significant correlation with academic performance through non-categorized GPA. This may be attributed to the limitations of the correlation technique in identifying other intercepts and binary factors. This is supported by the results of the logistic analysis, which generally indicate that the experience of receiving SBL and PjBL teaching models has a positive effect on academic performance. Specifically, students who have experienced or have the experience of receiving both teaching models have a higher likelihood of achieving a cum laude predicate compared to non-cum laude. Fourth, other factors such as Response to Traditional Learning, students' choice in using active learning models, smartphones or any more device usage, digital media risks, and opportunities from digital media also have a higher potential to achieve better academic performance.

Recommendations

Based on the analysis, data interpretation, and conclusions, the researchers have several recommendations. Firstly, there is a need to enhance critical thinking skills to increase students' chances of achieving higher academic performance. Secondly, we recommend instructors and educators implement PjBL and SBL teaching models in their lectures. Thirdly, external factors, particularly digital risks such as bullying, need to be addressed by various educational stakeholders, including policymakers, universities, faculty members, students, and parents. This is because such factors can negatively impact academic performance and may lead to other negative consequences beyond the scope of this study. Additionally, the role of factors such as traditional learning, student's choice in using active learning models, smartphone or other device usage, and opportunities from digital media should also be considered. Lastly, we recommend researchers in the field of education conduct more detailed investigations on the factors naturally affecting academic performance. Previous studies have extensively explored the effects of various teaching models, yielding varied results. However, research specifically focusing on the natural implementation of these models is still limited.

Limitations

The researchers are aware of the limitations of this study. Firstly, the study did not investigate the frequency of student meetings in receiving the teaching models, nor did it explore the modifications used by the instructors. Additionally, other possible factors could affect the intercept of the academic performance variable, which were not extensively examined. However, this research serves as an initial step for the research team to address these limitations by conducting further studies, the findings of which will be reported in future articles.

Ethics Statements

The studies involving human participants were reviewed and this research obtained approval from several state universities in Indonesia to randomly select students to participate in the study, with the condition that the researchers will maintain the confidentiality of the university identities due to the sensitive nature of the topic. Participants provided their informed consent to participate in this study, with the understanding that the researchers would uphold the confidentiality and privacy of their data.

Authorship Contribution Statement

Sawiji: Conceptualization, editing/reviewing, securing funding, final approval. Permasah: Data analysis / interpretation, design, writing, critical revision of manuscript. Rapih: Data analysis / interpretation, editing/reviewing, final approval.

Akbarini: Admin, critical revision of manuscript, supervision. Rusmana: Critical revision of manuscript, data acquisition. Prameswara: Data acquisition, admin. Aminudin: Data acquisition, technical or material support

References

Aghayani, B., & Hajmohammadi, E. (2019). Project-based learning: Promoting EFL learners' writing skills. *LLT Journal: A Journal on Language and Language Teaching*, *22*(1), 78–85. https://doi.org/10.24071/llt.v22i1.1727

Akoglu, H. (2018). User's guide to correlation coefficients. *Turkish Journal of Emergency Medicine*, *18*(3), 91–93. https://doi.org/10.1016/j.tjem.2018.08.001

Ampountolas, A., Shaw, G., & James, S. (2019). Active learning to improve self-confidence and decision-making skills through the use of hotel simulation. *Journal of Hospitality and Tourism Education*, *31*(3), 125–138. https://doi.org/10.1080/10963758.2018.1487786

Asif, R., Merceron, A., Ali, S. A., & Haider, N. G. (2017). Analyzing undergraduate students' performance using educational data mining. *Computers and Education*, *113*, 177–194. https://doi.org/10.1016/j.compedu.2017.05.007

Bakoush, M. (2022). Evaluating the role of simulation-based experiential learning in improving the satisfaction of finance students. *International Journal of Management Education*, *20*(3). Article 100690. https://doi.org/10.1016/j.ijme.2022.100690

Banda, H. J., & Nzabahimana, J. (2023). The impact of physics education technology (phet) interactive simulation-based learning on motivation and academic achievement among malawian physics students. *Journal of Science Education and Technology*, *32*, 127–141. https://doi.org/10.1007/s10956-022-10010-3

Beer, P., & Mulder, R. H. (2020). The effects of technological developments on work and their implications for continuous vocational education and training: A systematic review. *Frontiers in Psychology*, *11*, Article 918. https://doi.org/10.3389/fpsyg.2020.00918

Beier, M. E., Kim, M. H., Saterbak, A., Leautaud, V., Bishnoi, S., & Gilberto, J. M. (2019). The effect of authentic project-based learning on attitudes and career aspirations in STEM. *Journal of Research in Science Teaching*, *56*(1), 3–23. https://doi.org/10.1002/tea.21465

Bürkner, P.-C., & Vuorre, M. (2018). Ordinal regression models in psychological research: A tutorial. *Advances in Methods and Practices in Psychological Science, 2*(1), 77-101. https://doi.org/10.1177/2515245918823199

Chen, C.-H., & Yang, Y.-C. (2019). Revisiting the effects of project-based learning on students' academic achievement: A meta-analysis investigating moderators. *Educational Research Review*, *26*, 71–81. https://doi.org/10.1016/j.edurev.2018.11.001

Chen, M.-R. A., Hwang, G.-J., & Chang, Y.-Y. (2019). A reflective thinking-promoting approach to enhancing graduate students' flipped learning engagement, participation behaviors, reflective thinking and project learning outcomes. *British Journal of Educational Technology*, *50*(5), 2288–2307. https://doi.org/10.1111/bjet.12823

Crowl, A., Robertson, A., Go, S., Barnes, J., & Shrader, S. (2022). Evaluation of a simulation-based learning activity for communicating about at-risk opioid behaviors in a community pharmacy setting. *Currents in Pharmacy Teaching and Learning*, *14*(12), 1512–1517. https://doi.org/10.1016/j.cptl.2022.10.008

D'Alessio, F. A., Avolio, B. E., & Charles, V. (2019). Studying the impact of critical thinking on the academic performance of executive MBA students. *Thinking Skills and Creativity*, *31*, 275–283. https://doi.org/10.1016/j.tsc.2019.02.002

Dancey, C. P., & Reidy, J. (2007). *Statistics without maths for psychology*. Pearson Education.

Darmuki, A., Nugrahani, F., Fathurohman, I., Kanzunnudin, M., & Hidayati, N. A. (2023). The impact of inquiry collaboration project-based learning model of indonesian language course achievement. *International Journal of Instruction*, *16*(2), 247–266. https://doi.org/10.29333/iji.2023.16215a

de Bie, H., Wilhelm, P., & van der Meij, H. (2015). The Halpern Critical Thinking Assessment: Toward a Dutch appraisal of critical thinking. *Thinking Skills and Creativity*, *17*, 33–44. https://doi.org/10.1016/j.tsc.2015.04.001

Demirhan, E., Besoluk, Ş., & Onder, İ. (2011). The change in academic achievement and critical thinking disposition scores of pre-service science teachers over time. *Western Anatolia Journal of Educational Sciences*, (Spec.Iss.), 403-406. http://surl.li/jpqed

Derakhshan, A., Kruk, M., Mehdizadeh, M., & Pawlak, M. (2021). Boredom in online classes in the Iranian EFL context: Sources and solutions. *System*, *101*, Article 102556. https://doi.org/10.1016/j.system.2021.102556

Du Plessis, A., & McDonagh, K. (2021). The out-of-field phenomenon and leadership for wellbeing: Understanding concerns for teachers, students and education partnerships. *International Journal of Educational Research*, *106*, Article 101724. https://doi.org/10.1016/j.ijer.2020.101724

Ennis, R. H. (1993). Critical thinking assessment. *Theory Into Practice*, *32*(3), 179–186. https://doi.org/10.1080/00405849309543594

Erdogan, T., & Senemoglu, N. (2017). PBL in teacher education: Its effects on achievement and self-regulation. *Higher Education Research & Development*, *36*(6), 1152–1165. https://doi.org/10.1080/07294360.2017.1303458

Evans, K. H., Daines, W., Tsui, J., Strehlow, M., Maggio, P., & Shieh, L. (2015). Septris: A novel, mobile, online, simulation game that improves sepsis recognition and management. *Academic Medicine*, *90*(2), 180–184. https://doi.org/10.1097/ACM.0000000000000611

Fajnzylber, E., Lara, B., & León, T. (2019). Increased learning or GPA inflation? Evidence from GPA-based university admission in Chile. *Economics of Education Review*, *72*, 147–165. https://doi.org/10.1016/j.econedurev.2019.05.009

Frengley, R. W., Weller, J. M., Torrie, J., Dzendrowskyj, P., Yee, B., Paul, A. M., Shulruf, B., & Henderson, K. M. (2011). The effect of a simulation-based training intervention on the performance of established critical care unit teams. *Critical Care Medicine*, *39*(12), 2605-2611. https://doi.org/10.1097/ccm.0b013e3182282a98

Gallagher, K. (2023). Transnational teacher educators in internationalised higher education in the Arabian Gulf. *Journal of Further and Higher Education*, *47*(8), 1074-1086 . https://doi.org/10.1080/0309877X.2023.2212244

Giunchiglia, F., Zeni, M., Gobbi, E., Bignotti, E., & Bison, I. (2018). Mobile social media usage and academic performance. *Computers in Human Behavior*, *82*, 177–185. https://doi.org/10.1016/j.chb.2017.12.041

Gordanier, J., Hauk, W., & Sankaran, C. (2019). Early intervention in college classes and improved student outcomes. *Economics of Education Review*, *72*, 23–29. https://doi.org/10.1016/j.econedurev.2019.05.003

Greenstein, L. (2012). *Assessing 21st century skills: A Guide to evaluating mastery and authentic* (1st ed.). Corwin.

Hair, J. F., Black, W., Babin, F. J., & Anderson, R. E. (2010). *Multivariate data analysis: A global perspective* (7th ed.). Pearson.

Healy, M. J. R. (1995). Statistics from the inside. 16. Multiple regression (2). *Archives of Disease in Childhood*, *73*(3), 270–274. https://doi.org/10.1136/adc.73.3.270

Helal, S., Li, J., Liu, L., Ebrahimie, E., Dawson, S., Murray, D. J., & Long, Q. (2018). Predicting academic performance by considering student heterogeneity. *Knowledge-Based Systems*, *161*, 134–146. https://doi.org/10.1016/j.knosys.2018.07.042

Hung, C.-C., Kao, H.-F. S., Liu, H.-C., Liang, H.-F., Chu, T.-P., & Lee, B.-O. (2021). Effects of simulation-based learning on nursing students' perceived competence, self-efficacy, and learning satisfaction: A repeat measurement method. *Nurse Education Today*, *97*, Article 104725. https://doi.org/10.1016/j.nedt.2020.104725

Indrawati, C. D. S. (2021). The effectiveness of archiving videos and online learning on student's learning and innovation skills. *International Journal of Instruction*, *14*(4), 135–154. https://doi.org/10.29333/iji.2021.1449a

Kızkapan, O., & Bektaş, O. (2017). The effect of project based learning on seventh grade students academic achievement. *International Journal of Instruction*, *10*(1), 37–54. https://doi.org/10.12973/iji.2017.1013a

Klapper, R. G., & Fayolle, A. (2023). A transformational learning framework for sustainable entrepreneurship education: The power of Paulo Freire's educational model. *International Journal of Management Education*, *21*(1), Article 100729. https://doi.org/10.1016/j.ijme.2022.100729

Koparan, T. (2022). The impact of a game and simulation-based probability learning environment on the achievement and attitudes of prospective teachers. *International Journal of Mathematical Education in Science and Technology*, *53*(9), 2319–2337. https://doi.org/10.1080/0020739X.2020.1868592

Lacey, A., & Cornell, D. (2013). The impact of teasing and bullying on schoolwide academic performance. *Journal of Applied School Psychology*, *29*(3), 262–283. https://doi.org/10.1080/15377903.2013.806883

Lee, B.-O., Liang, H.-F., Chu, T.-P., & Hung, C.-C. (2019). Effects of simulation-based learning on nursing student competences and clinical performance. *Nurse Education in Practice*, *41*, Article 102646. https://doi.org/10.1016/j.nepr.2019.102646

Lee, H., Ahn, H., Nguyen, T. G., Choi, S.-W., & Kim, D. J. (2017). Comparing the self-report and measured smartphone usage of college students: A pilot study. *Psychiatry Investigation*, *14*(2), 198-204. https://doi.org/10.4306/pi.2017.14.2.198

Liao, S.-H., Hu, D.-C., Chung, Y.-C., & Huang, A.-P. (2021). Risk and opportunity for online purchase intention – A moderated mediation model investigation. *Telematics and Informatics*, *62*, Article 101621. https://doi.org/10.1016/j.tele.2021.101621

Loeneto, B. A., Ernalida, E., Eryansyah, E., Alwi, Z., & Oktarina, S. (2020). In-service teacher training and education in indonesia. *Creative Education*, *11*(3), 328–342. https://doi.org/10.4236/ce.2020.113026

Mai, C.-W., Lee, E.-L., Wong, P.-S., & Er, H.-M. (2019). Evaluation of computer-based simulation learning on knowledge, learning approaches and motivation among pharmacy students. *Indian Journal of Pharmaceutical Education and Research*, *53*(4), 595–602. https://doi.org/10.5530/ijper.53.4.120

Maksum, A., Widiana, I. W., & Marini, A. (2021). Path analysis of self-regulation, social skills, critical thinking and problem-solving ability on social studies learning outcomes. *International Journal of Instruction*, *14*(3), 613–628. https://doi.org/10.29333/iji.2021.14336a

Mishra, R., Hemlata, & Trivedi, D. (2023). Simulation-based learning in nursing curriculum- time to prepare quality nurses: A systematic review and meta-analysis. *Heliyon*, *9*(5), Article e16014. https://doi.org/10.1016/j.heliyon.2023.e16014

Mou, T.-Y. (2020). Students' evaluation of their experiences with project-based learning in a 3D design class. *The Asia-Pacific Education Researcher*, *29*, 159–170. https://doi.org/10.1007/s40299-019-00462-4

Muenks, K., Wigfield, A., & Eccles, J. S. (2018). I can do this! The development and calibration of children's expectations for success and competence beliefs. *Developmental Review*, *48*, 24–39. https://doi.org/10.1016/j.dr.2018.04.001

Pagani, L., Argentin, G., Gui, M., & Stanca, L. (2016). The impact of digital skills on educational outcomes: Evidence from performance tests. *Educational Studies*, *42*(2), 137–162. https://doi.org/10.1080/03055698.2016.1148588

Pan, A.-J., Lai, C.-F., & Kuo, H.-C. (2023). Investigating the impact of a possibility-thinking integrated project-based learning history course on high school students' creativity, learning motivation, and history knowledge. *Thinking Skills and Creativity*, *47*, Article 101214. https://doi.org/10.1016/j.tsc.2022.101214

Parrado-Martínez, P., & Sánchez-Andújar, S. (2020). Development of competences in postgraduate studies of finance: A project-based learning (PBL) case study. *International Review of Economics Education*, *35*, Article 100192. https://doi.org/10.1016/j.iree.2020.100192

Peng, C.-Y. J., Lee, K. L., & Ingersoll, G. M. (2002). An introduction to logistic regression analysis and reporting. *The Journal of Education Research*, *96*(1), 3-14. https://doi.org/10.1080/00220670209598786

Purnama, S., Ulfah, M., Machali, I., Wibowo, A., & Narmaditya, B. S. (2021). Does digital literacy influence students' online risk? Evidence from Covid-19. *Heliyon*, *7*(6), Article e07406. https://doi.org/10.1016/j.heliyon.2021.e07406

Puth, M.-T., Neuhäuser, M., & Ruxton, G. D. (2014). Effective use of Pearson's product–moment correlation coefficient. *Animal Behaviour*, *93*, 183–189. https://doi.org/10.1016/j.anbehav.2014.05.003

Rahmati, R., Halim, A., & Yusrizal, Y. (2022). Impact of problem solving exercises with Minnesota strategy on learning outcomes and critical thinking skills. *AIP Conference Proceedings*, *2600*(1), Article 070010. https://doi.org/10.1063/5.0113571

Raphael, B. P., Takvorian-Bené, M., Gallotto, M., Tascione, C., McClelland, J., Rosa, C., Dinan, J., O'Connell, B., & Weinstock, P. (2021). Learning gaps and family experience, nurse-facilitated home parenteral nutrition simulation-based discharge training: Proof-of-concept study. *Nutrition in Clinical Practice*, *36*(2), 489–496. https://doi.org/10.1002/ncp.10421

Rusteholz, G., Mediavilla, M., & Pires Jiménez, L. (2021). *Impact of bullying on academic performance: A case study for the community of madrid* (EB Working Paper No. 2021/01). SSRN. https://doi.org/10.2139/ssrn.3785919

Saad, A., & Zainudin, S. (2022). A review of Project-Based Learning (PBL) and Computational Thinking (CT) in teaching and learning. *Learning and Motivation*, *78*, Article 101802. https://doi.org/10.1016/j.lmot.2022.101802

Sailer, M., Schultz-Pernice, F., & Fischer, F. (2021). Contextual facilitators for learning activities involving technology in higher education: The C♭-model. *Computers in Human Behavior*, *121*, Article 106794. https://doi.org/10.1016/j.chb.2021.106794

Samaha, M., & Hawi, N. S. (2016). Relationships among smartphone addiction, stress, academic performance, and satisfaction with life. *Computers in Human Behavior*, *57*, 321–325. https://doi.org/10.1016/j.chb.2015.12.045

Samper, M. G., Sukier, H. B., Palencia, D. B., Molina, R. I. R., Alfaro, K. B., Sánchez, Y. S., & Sarmiento, A. C. F. (2022). Digital transformation of business models: Influence of operation and trade variables. *Procedia Computer Science*, *203*, 565–569. https://doi.org/10.1016/j.procs.2022.07.125

Sigit, D. V., Ristanto, R. H., & Mufida, S. N. (2022). Integration of project-based e-learning with steam : An innovative solution to learn ecological concept. *International Journal of Instruction*, *15*(3), 23–40. https://doi.org/10.29333/iji.2022.1532a

Smelt, J., Corredor, C., Edsell, M., Fletcher, N., Jahangiri, M., & Sharma, V. (2015). Simulation-based learning of transesophageal echocardiography in cardiothoracic surgical trainees: A prospective, randomized study. *The Journal of Thoracic and Cardiovascular Surgery*, *150*(1), 22–25. https://doi.org/10.1016/j.jtcvs.2015.04.032

Suradika, A., Dewi, H. I., & Nasution, M. I. (2023). Project-based learning and problem-based learning models in critical and creative students. *Jurnal Pendidikan IPA Indonesia*, *12*(1), 153–167. https://doi.org/10.15294/jpii.v12i1.39713

Tasantab, J. C., Gajendran, T., Owi, T., & Raju, E. (2023). Simulation-based learning in tertiary-level disaster risk management education: A class-room experiment. *International Journal of Disaster Resilience in the Built Environment*, *14*(1), 21–39. https://doi.org/10.1108/IJDRBE-04-2021-0045

Thiele, T., Singleton, A., Pope, D., & Stanistreet, D. (2016). Predicting students' academic performance based on school and socio-demographic characteristics. *Studies in Higher Education*, *41*(8), 1424–1446. https://doi.org/10.1080/03075079.2014.974528

Tvedt, M. S., Bru, E., & Idsoe, T. (2021). Perceived teacher support and intentions to quit upper secondary school: Direct, and indirect associations via emotional engagement and boredom. *Scandinavian Journal of Educational Research*, *65*(1), 101–122. https://doi.org/10.1080/00313831.2019.1659401

Usmeldi, U., & Amini, R. (2022). Creative project-based learning model to increase creativity of vocational high school students. *International Journal of Evaluation and Research in Education,* *11*(4), 2155–2164. https://doi.org/10.11591/ijere.v11i4.21214

van Laar, E., van Deursen, A. J. A. M., van Dijk, J. A. G. M., & de Haan, J. (2019). Determinants of 21st-century digital skills: A large-scale survey among working professionals. *Computers in Human Behavior*, *100*, 93–104. https://doi.org/10.1016/j.chb.2019.06.017

Wu, J.-Y., & Cheng, T. (2019). Who is better adapted in learning online within the personal learning environment? Relating gender differences in cognitive attention networks to digital distraction. *Computers and Education*, *128*, 312–329. https://doi.org/10.1016/j.compedu.2018.08.016

Xu, J., Moon, K. H., & Van Der Schaar, M. (2017). A machine learning approach for tracking and predicting student performance in degree programs. *IEEE Journal of Selected Topics in Signal Processing*, *11*(5), 742–753. https://doi.org/10.1109/JSTSP.2017.2692560

Yang, D., Baek, Y., & Swanson, S. (2020). Developing computational thinking through project-based airplane design activities. In *2020 IEEE Frontiers in Education Conference (FIE)* (pp.1–4). IEEE. https://doi.org/10.1109/FIE44824.2020.9274021

Yu, S., & Zhao, X. (2021). The negative impact of bullying victimization on academic literacy and social integration: Evidence from 51 countries in PISA. *Social Sciences and Humanities Open*, *4*(1), Article 100151. https://doi.org/10.1016/j.ssaho.2021.100151

Zhang, Y., Oussena, S., Clark, T., & Kim, H. (2010). Use data mining to improve student retention in higher education-a case study. In *Proceedings of the 12th International Conference on Enterprise Information Systems* (pp. 190–197). SciTePress. https://doi.org/10.5220/0002894101900197

Zhang, Z. (2022). Toward the role of teacher empathy in students' engagement in English language classes. *Frontiers in Psychology*, *13*, Article 880935. https://doi.org/10.3389/fpsyg.2022.880935