THE INFLUENCE OF AI ON INFORMATICS STUDENTS KNOWLEDGE AND UNDERSTANDING IN PROGRAMMING DEVELOPMENT

Hosea Dunatus Simanjuntak.
Informatics Engineer, Universtias Multimedia Nusantara
Tangerang, Indonesia, 15810.
Hosea51simajuntak@gmail.com

Jeremy Joseph Pohar
Informatics Engineer, Universtias Multimedia Nusantara
Tangerang, Indonesia, 15810.
Jeremy.yosep@gmail.com

Fransiscus Ati Halim
Lecture Informatics Engineer, Universtias Multimedia Nusantara
Tangerang, Indonesia, 15810.
fransiscus.ati@lecture.umn.ac.id

The present study examines the effects of Artificial Intelligence tools on the knowledge acquisition as well as understanding of informatics students in participating in programming development activities. There is a growing prevalence of AI as an element of education, particularly in the field of programming, thus the study also seeks to establish the role of AI platforms in boosting the students' grasp of intricacies, their debugging, and problem-solving skills. Using a mixed-methods approach, primary data was collected through questionnaires administered to the students and the teachers, and secondary data was collected from related literature. The results indicate that learning is made more efficient with AI tools since they present more autonomous and interactive means of educating the students and improves the level of engagement and retention of students. At the same time, concerns such as excessive dependence on AI, ethical issues, and social injustices in availability were detected. In part, AI does enhance learning, but at the same time, it has raised issues with students' critical thinking and self-reliance which seem to be on the downward trend. This research offers novel insights into the use of AI for programming education but calls for moderation and ethical consideration. To AI rapidly in experiencing a revolution in programming education, some pointers are offered for the teachers and the programmers of the curriculums.

I. Introduction

The Artificial Intelligence applications in education are increasingly transforming the way students learn and even access information particularly in the field of programming. The use of AI tools in educational applications for example tutor and learning path solutions in addition to their application in supervision in real time has enhanced these students' experience and made programming attractive and easier to learn (Yilmaz & Karaoglan Yilmaz, 2023a). Programming is provided to the students for practice and for understanding the basics of this discipline with the help of CAD systems. This information was provided by Petrovskis work, in two thousand twenty-three years. AI driven technologies are playing a role, in facilitating understanding and troubleshooting tasks for students to create applications effortlessly. Interactive systems, in the form of AI driven computer assisted language learning programs, have been found useful in improving interaction as well as memory retention in activities such as coding (Wang et al., 2023). There are however pedagogical advantages in the use of these technologies in the classrooms, there are many issues that still have to be addressed such as overreliance on the educational technologies provision, equity and ethical issues presented (Yılmaz & Karaoğlan Yılmaz, 2023).

The current research aims to enlist artificial intelligence as a tool to enhance programming proficiency of informatics students by improving their understanding of theories concepts and boosting their practical skills in coding and problem solving abilities. The findings can help teachers and curriculum developers construct a supportive framework within which they can effectively use AI tools for the enhancement of learners understanding of programming.

II. Literature review

A. Making Use of AI Tool Facilities in Programming

An AI tool or an AI-based platform must be chosen appropriately and aligned with the program as well as the educational purpose in the case of programming education. There are many AI-assisted resources, such as smart code completion applications, learning who codes games, or tutors, which will help in many situations (Yilmaz & Karaoglan Yilmaz, 2023a). The existence of these resources in students' studying processes is dependent on their incorporation by the teachers (Yilmaz & Karaoglan Yilmaz, 2023b). As if it is said when writing an essay one should choose an adequate template for the shoes; appropriate AI tools, when applied appropriately, can considerably improve both the process and the outcomes of education.

B. *Efficiency of Learning*

To summarize, programming education opens up new opportunities but at the same time there are those challenges that are solvable with advanced technology. AI are or will not become the only medium to undertake educational enhancement and before it active learning, tailoring instruction or corrective help will be in place (Bhatt & Muduli, 2023). The excessive use of AI in education, especially chats in programming 101, may restrict students' brains and practical capabilities of writing code because the focus would shift to the outcomes more than the essentials (Yılmaz & Karaoğlan Yılmaz, 2023). So this assisted in designing that AIEd tools will not provide a full replacement for any precursor teaching and learning techniques, rather it will be a scope of improvement not excluding any imaginations of integration with teaching and learning.

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III. Methodology

Before investigating how AI affects the students' programming knowledge in relation to informatics, the plan and organization of research methodology was quite done efficiently. To address the problem conclusively, the research was multifaceted both qualitative and quantitative (Huang et al., 2023a; Yilmaz & Karaoglan Yilmaz, 2023a). It was hence appropriate that primary data was obtained through surveys from informatics students and their teachers whilst secondary data was drawn from the literature, document, and case studies on the role of artificial intelligence in education (Bhatt & Muduli, 2023). The processes engaged in the research activities included data collection, analysis, and preparation of information ensuring that the findings had been presented clearly and consistently. For clarity, structures of different styles and formats were also used to arrange the data in a logical sequence (Abaz & Diko, 2023). In order to avoid presentation and typing and grammar errors there were two stages of editing, content and organizational, and then final formatting. The methodology was focused upon precision which is essential to provide accurate conclusions regarding the role of AI in teaching programming (Sun et al., 2024). :

C. *Data Collection Methods*

I. Primary Data

An empirical view has been established with this research by gathering primary information through surveys from informatics students as well as from the teachers. The surveys mainly dealt with the student responses regarding the AI'S assistive capabilities for the students in their programming classes with special regard to skill, comprehension and resolution of programming concepts (Huang et al., 2023; Yilmaz & Karaoglan Yilmaz, 2023). The surveys are based on informatics student's the data are used to see the advantages and disadvantages on Employing AI in Programming Education (Bhatt & Muduli, 2023).

II. Secondary Data

Secondary data were obtained from previously published literatures that included scholarly articles, case studies and reports explored on the theme of AI in education. This method made it possible to cover a wider scope since different studies were compared in trying to establish the impact of AI on programming learning outcomes (Abaz & Diko, 2023). It also aimed to offer a more substantial investigative image concerning the position of uses of AI in programming education by combining primary and secondary data.

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D. *Data of research.*

I. Primary Data

Questionnaire	Mean	Median	SD	Variants
The Use of AI by Students	4.410256	4	0.6123384	0.3749584
Increased Use of AI	3,9	4	0.7729608	0.5974684
Benefits of Using AI	4.3375	4	0.7621381	0.5808544
Impact of AI Usage	4.583333	5	0.5240686	0.2746479
Students' Perspectives on AI	4.28	4	0.7454366	0.5556757
Students' Concerns about AI	3.02381	3	0.9566028	0.9150889
Effect of AI Usage on Students	3.063291	3	0.7736323	0.598507

II. Secondary Data

Scales	Pre-post tests	Groups	Mean ($\bar{x}$)	sd
Computational thinking skills	Pretest	Experimental group	110.82	11.21
		Control group	108.48	17.82
	Posttest	Experimental group	126.73	8.34
		Control group	112.61	15.32
Creativity	Pretest	Experimental group	33.23	3.21
		Control group	32.04	6.14
	Posttest	Experimental group	37.14	1.96
		Control group	32.35	4.30
Algorithmic thinking	Pretest	Experimental group	20.73	3.53
		Control group	20.00	3.61
	Posttest	Experimental group	24.95	2.87
		Control group	21.83	4.20
Cooperativity	Pretest	Experimental group	16.05	3.46
		Control group	16.00	2.98
	Posttest	Experimental group	18.09	1.82
		Control group	16.57	2.97
Critical thinking	Pretest	Experimental group	19.14	3.12
		Control group	19.17	2.95
	Posttest	Experimental group	21.55	2.84
		Control group	18.96	5.43
Problem solving	Pretest	Experimental group	21.68	2.42
		Control group	21.26	6.29
	Posttest	Experimental group	25.00	2.99
		Control group	22.26	4.09

E. I.Result of research primary data.

	Mean	Median	SD	Variants	W	p	Skewness	Kurtosis
The Use of AI by Students	4.410256	4	0.6123384	0.3749584	0.9325741	0.0004716775	-0.422627	-0.5498354
Increased Use of AI	3,9	4	0.7729608	0.5974684	220.489	2.745475	-0.324369	2.745475
Benefits of Using AI	4.3375	4	0.7621381	0.5808544	0.7334501	9.52469	-1.511698	6.744676
Impact of AI Usage	4.583333	5	0.5240686	0.2746479	0.6615401	1.334579	-0.6323009	2.04931
Student's Perspectives on AI	4.28	4	0.7454366	0.5556757	0.77628	2.487556	-0.4988026	1.960806
Student's Concerns about AI	3.02381	3	0.9566028	0.9150889	0.8215234	8.348989	-0.4964709	2.015801
Effect of AI Usage on Students	3.063291	3	0.7736323	0.598507	0.7412213	2.057409	-0.5078357	2.364809

	BP	P-value	DF	P-value	DW	P-value	Use of ai	Study hours	R^2	Pearson
The Use of AI by Students	1.5174	0.4683	2	0.4683	2.2418	0.8874	1.737472	1.737472	0.3665231	0.6054115
Increased Use of AI	1.5174	0.4683	2	0.4683	2.2418	0.8874	2.250358	2.250358	0.4864131	0.6974332
Benefits of Using AI	1.5174	0.4683	2	0.4683	2.2418	0.8874	2.21157	2.21157	0.4790099	0.6921054
Impact of AI Usage	1.5174	0.4683	2	0.4683	2.2418	0.8874	2.152913	2.152913	0.2930594	0.5413496
Student's Perspectives on AI	1.5174	0.4683	2	0.4683	2.2418	0.8874	3.001678	3.001678	0.4673853	0.6836559
Student's Concerns about AI	1.5174	0.4683	2	0.4683	2.2418	0.8874	2.252785	2.252785	0.5966268	0.7724162
Effect of AI Usage on Students	1.5174	0.4683	2	0.4683	2.2418	0.8874	2.252785	2.057409	0.4868691	0.69776

	Min	1Q	Median	3Q	Max	Estimate	Error	t value
The Use of AI by Students	-0.95367	-0.34175	-0.04375	0.29032	1.64520	0.13756	0.39273	0.35
Increased Use of AI	-0.95367	-0.34175	-0.04375	0.29032	1.64520	0.08097	0.27872	0.291
Benefits of Using AI	-0.95367	-0.34175	-0.04375	0.29032	1.64520	0.09791	0.31276	0.313
Impact of AI Usage	-0.95367	-0.34175	-0.04375	0.29032	1.64520	0.1780	0.4747	0.375
Student's Perspectives on AI	-0.95367	-0.34175	-0.04375	0.29032	1.64520	0.09923	0.31542	0.315
Student's Concerns about AI	-0.95367	-0.34175	-0.04375	0.29032	1.64520	0.03153	0.18040	0.175
Effect of AI Usage on Students	-0.95367	-0.34175	-0.04375	0.29032	1.64520	0.05248	0.22181	0.237

C. II.Result of research secondary data.

	Source	Sum of Squares	df	Mean Square	F	p	Partial Eta Squared
Computational thinking skills	Pretest	2438.558	1	2438.558	24.448	.000	
	Group	1871.185	1	1871.185	18.760	.000	.309
	Error	4189.284	42	99.745			
	Total	8869.244	44				
Creativity	Pretest	220.489	1	220.489	34.642	.000	
	Group	199.589	1	199.589	31.359	.000	.427
	Error	267.319	42	6.365			
	Total	745.644	44				
Algorithmic thinking	Pretest	113.727	1	113.727	10.697	.002	
	Group	87.040	1	87.040	8.187	.007	.163
	Error	446.532	42	10.632			
	Total	670.311	44				
Cooperativity	Pretest	37.759	1	37.759	7.026	.011	
	Group	25.721	1	25.721	4.786	.034	.102
	Error	225.712	42	5.374			
	Total	289.644	44				
Critical thinking	Pretest	142.523	1	142.523	8.856	.005	
	Group	76.681	1	76.681	4.765	.035	.102
	Error	675.888	42	16.093			
	Total	893.778	44				
Problem solving	Pretest	133.721	1	133.721	13.286	.001	
	Group	74.969	1	74.969	7.449	.009	.151
	Error	422.714	42	10.065			
	Total	640.800	44				

	Source	Sum of Squares	df	Mean Square	F	p	Partial Eta Squared
Computer programming self-efficacy	Pretest	65.400	1	65.400	1.418	.240	
	Group	698.478	1	698.478	15.144	.000	.265
	Error	1937.112	42	46.122			
	Total	2686.000	44				
Simple programming tasks	Pretest	82.910	1	82.910	6.045	.018	
	Group	165.911	1	165.911	12.097	.001	.224
	Error	576.015	42	13.715			
	Total	816.800	44				
Complex programming tasks	Pretest	15.429	1	15.429	.676	.416	
	Group	187.464	1	187.464	8.210	.006	.164
	Error	958.988	42	22.833			
	Total	1158.800	44				

	Source	Sum of Squares	df	Mean Square	F	p	Partial Eta Squared
Learning motivation	Pretest	236.671	1	236.671	1.914	.174	
	Group	1411.371	1	1411.371	11.412	.002	.214
	Error	5194.134	42	123.670			
	Total	6873.244	44				
Individual attitude and expectation	Pretest	.459	1	.459	.071	.792	
	Group	64.432	1	64.432	9.941	.003	.191
	Error	272.229	42	6.482			
	Total	337.200	44				
Challenging goals	Pretest	107.624	1	107.624	18.913	.000	
	Group	2.857	1	2.857	.502	.482	
	Error	238.999	42	5.690			
	Total	348.578	44				
Clear direction	Pretest	6.946	1	6.946	1.273	.266	
	Group	31.249	1	31.249	5.729	.021	.120
	Error	229.101	42	5.455			
	Total	267.778	44				
Reward and recognition	Pretest	1.598	1	1.598	.225	.638	
	Group	31.068	1	31.068	4.365	.043	.094
	Error	298.906	42	7.117			
	Total	330.978	44				
Punishment	Pretest	1.807	1	1.807	.176	.677	
	Group	74.526	1	74.526	7.241	.010	.147
	Error	432.256	42	10.292			
	Total	509.200	44				
Social pressure and competition	Pretest	18.585	1	18.585	.803	.375	
	Group	129.805	1	129.805	5.610	.023	.118
	Error	971.848	42	23.139			
	Total	1123.244	44				

F. Formula and Graph Rstudio

I. Formula

Normality Test:

$$D = \sup |F_0(x) - F(x)|$$

Homoscedasticity Test:

$$\chi^2 = nR^2$$

Autocorrelation Test:

$$DW = \frac{\sum_{i=2}^{n}(e_i - e_{i-1})^2}{\sum_{i=1}^{n} e_i^2}$$

Multicollinearity Test:

$$VIF = \frac{1}{1 - R^2}$$

Regression Equation Test:

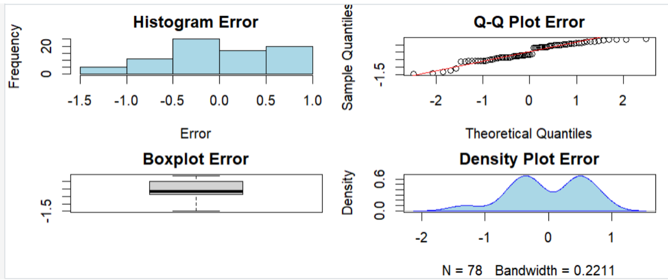
$$y = \beta_0 + \beta_1 x + \epsilon$$

Coefficient of Determination Test:

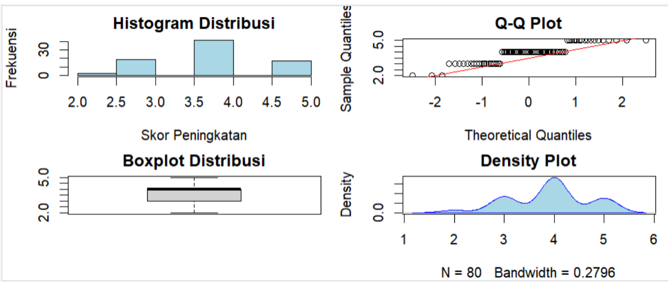
$$\chi^2 = \sum \frac{(O_i - E_i)^2}{E_i}$$

II. Graph Rstudio

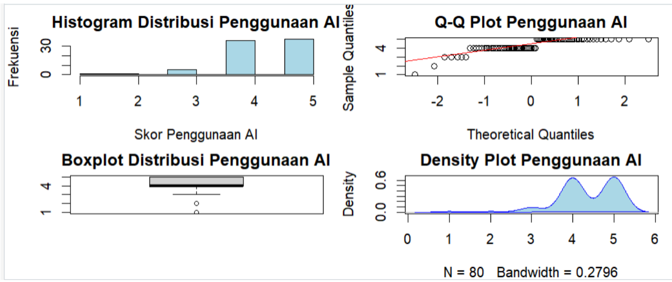
A. Normalization



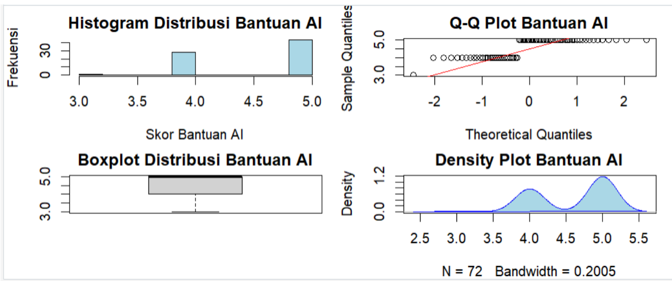
This four diagnostic plot revealed residual patterns in 78 observations. The histogram and density show distributions that are approximately normal with slight skewness around zero. The points of the Q-Q plot closely followed the theoretical normal line, with only minor deviations at the tails. The boxplot indicates errors are quite symmetric, falling between -1.5 and 1.0, without any extreme outliers. Collectively, the figures indicate that residuals of the model are not perfectly normal; however, statistical assumptions are met to a good enough extent to allow reliable analysis.



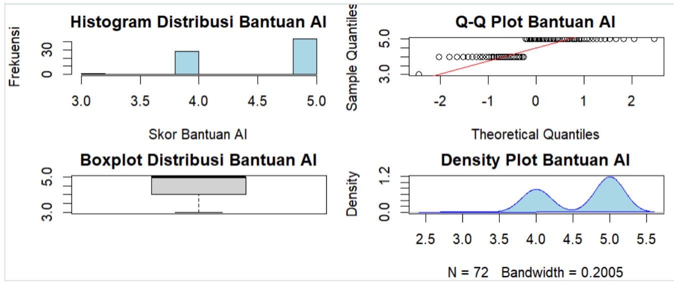
The score distributions of 80 observations were analyzed with the four diagnostic plots. The score distribution showed a distinctive bimodal pattern. Peaks, as could be seen from the histogram and density plots, were around 3.0-3.5 and 4.0-4.5. It can be seen from the Q-Q plot that the distribution was really not normal: instead of a diagonal line, it follows a stepped pattern. The scores around 3.5 are symmetrical from the boxplot. Therefore, there are likely two different scoring groups in the data rather than one normal distribution.



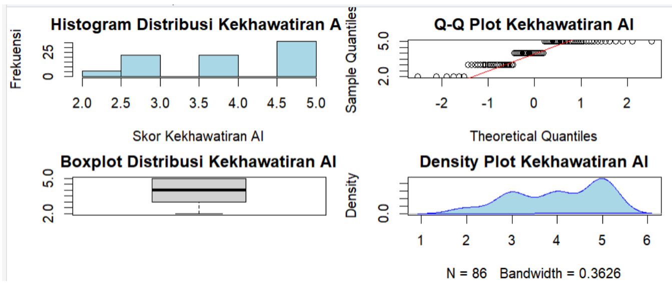
This first `dataman` consists of four diagnostic plots for showing the AI use patterns of 80 observations. The histogram and density plot give a clearly visible bi-model distribution having major peaks at scores four and five, meaning that most users are using AI intensively. Meanwhile, the stepped pattern on the Q-Q plot matches typical characteristics of a non-normal distribution, with a further demonstration shown under the boxplot concerning scores hoarding all above. Using a bandwidth of 0.2796, such plots, therefore, make a good case for suggesting two slashed population types under AI usage: the high concentration of participants scoring considerably in heightened levels and about a handful appearing in the low ranges (1-3).



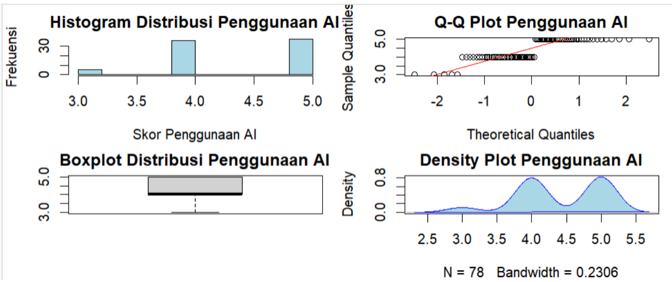
Among the four diagnostics, the first was such as : -assisting AI patterns by 72 observations across diagnostic increases. -Histogram and density plots indicate that a bimodal distribution exists. Strong scores towards 3.5-4.0 and 4.5-5.0 indicate moderate to high levels of AI assistance. The non-conformity of the Q-Q plot with the diagonal line indicates a non-normal distribution while the boxplot demonstrates scores between 3.8 up to 4.7 but centered in median 4.25. In 0.2005 bandwidth, they also indicate that there are two different participation groups on AI assistance patterns which mostly moderate up to high levels but almost none below 3.0 among them.



There are four diagnostic plots that assess AI assistance behavior across the 72 observations. The histogram and corresponding density plots depict clear bimodal distributions with the peaks clustering around scores 3.5-4.0 and 4.5-5.0, demonstrating two common usage levels for AI assistance. The Q-Q plot differs from the diagonal reference line as evidenced by this non-normal distribution pattern. The boxplot shows high density between 3.8 to 4.7 with a median of approximately 4.25 and really no outliers. At a bandwidth of 0.2005, these images do propose the two very tight groups of AI assistance patterns: moderate (3.5-4.0) and high (4.5-5.0) users, with only a few mere scores falling below 3.0.

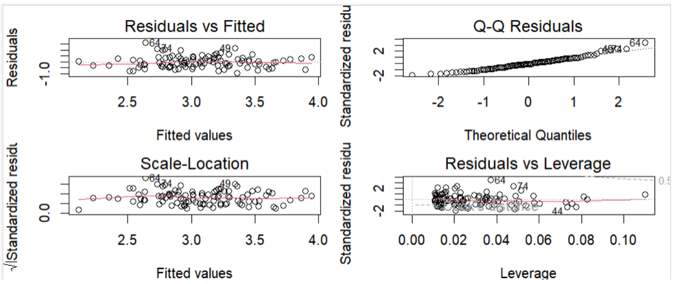


What follows are four diagnostic plots that examine the AI Anxiety from a total of 86 observations. The histogram and density plots are indicated to be trimodal and display three marked peaks in the range of scores- between 2.5 to 3.0, at about 4.0 to 4.5, and reaching between 4.5 to 5.0 scoring marks, showing different levels of anxiety toward AI. The stepped-shaped pattern of the Q-Q plot, with the deviation from a reference diagonal line, confirms its user non-normal distribution. The boxplot shows a distribution lying between 2.5 to 4.5 with a median of about 3.5, which indicates moderate over-all anxiety levels. This visual amount, along with a bandwidth of 0.3626, seems to suggest three groups of AI anxiety patterns. For now, they are: low anxiety (2.5-3.0), moderate anxiety (4.0-4.5), and high anxiety (4.5-5.0). Based on this distribution, it rather goes on to show that the participants have various levels of worries about AI; quite evenly spread across the anxiety spectrum.

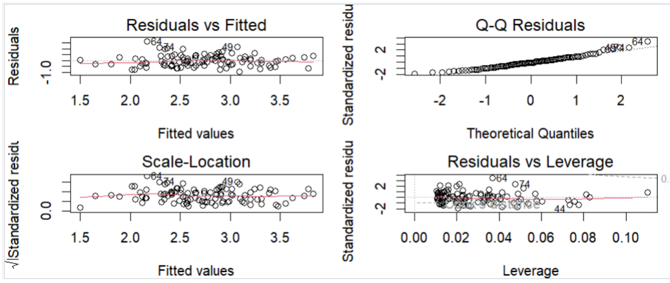


The four interpretive plots delve into AI usage patterns among 78 samples. The histogram and density plot revealed an unambiguous bimodal distribution with two prominent peaks, one at scores 3.5-4.0 and the other at 4.5-5.0. This indicates the presence of two distinct levels of respondent usage. The Q-Q plot departs from the diagonal line, which confirms a non-normal distribution pattern. The boxplot shows a highly concentrated distribution of scores between 3.8 and 4.7, with a median near the end of the range, around 4.25, with no significant outliers. With a bandwidth of 0.2306, all these visualizations straightforwardly depict two well-defined groups of AI usage patterns from moderate user (3.5-4.0) to very high user (4.5-5.0), with very few participants under 3.0. This suggests that while usage intensity varies, most participants are actively engaging with AI at moderate to high levels. These provide a comprehensive overview of the error distribution in a statistical analysis, allowing assessment of the model fit and identification of potential issues.

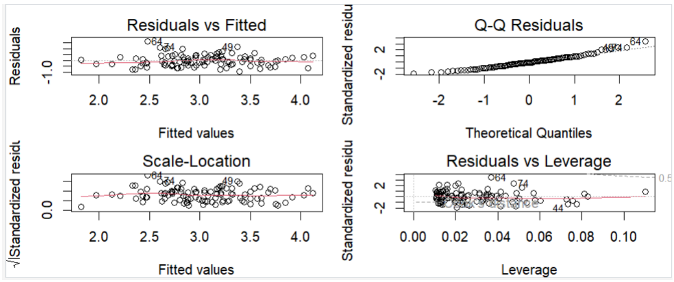
B. Homoscedasticity



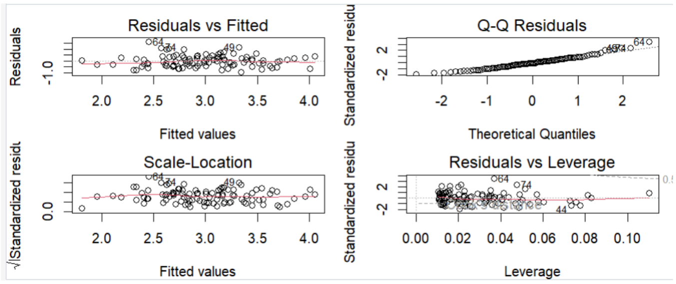
Based on an analysis of 78 observations, the fitted model of regression stands well with the four diagnostic plots. First, the Residuals vs Fitted plot exhibits a random scatter about zero without any clear patterns showing that it is a good model of specification. Second, the Q-Q plot shows that the residuals nearly follow a normal distribution except for deviations at the extreme value ends. The Scale-Location plot shows the variance along fitted values is quite constant (2.5 to 4.0). The Residuals versus Leverage plot shows no point considered influential, since all the leverage values are below 0.10. On the whole, all these plots indicate that the model fulfills the requisite assumptions of regression; that is, normality, homoscedasticity, and no influential outliers.



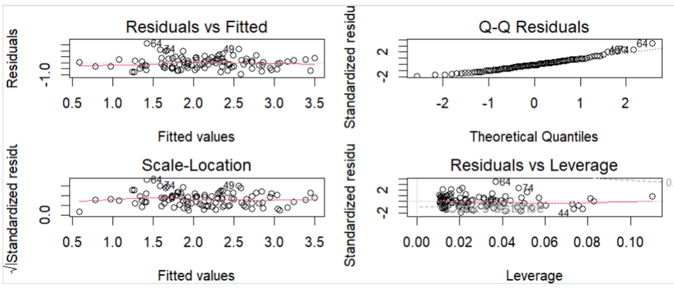
The four plots are indicative of a good fit of the regression model with respect to the observations. The Residuals vs Fitted plot doesn't exhibit any pattern in the range of 1.5 to 3.5; instead, it yields a random scatter around 0-an indication of very good linearity. The Q-Q plot gives a fairly near-normal distribution of residuals with a slight departure from the extremes. The Scale-Location plot indicates a fairly homoscedastic variance that ranges across the fitted values from 1.5 to 3.5. The Residuals vs Leverage plot shows no disquieting influential points, as the leverage values are below 0.10-in other words, it appears that the model satisfies the basic regression assumptions of normality, homoscedasticity, and absence of influential outliers.



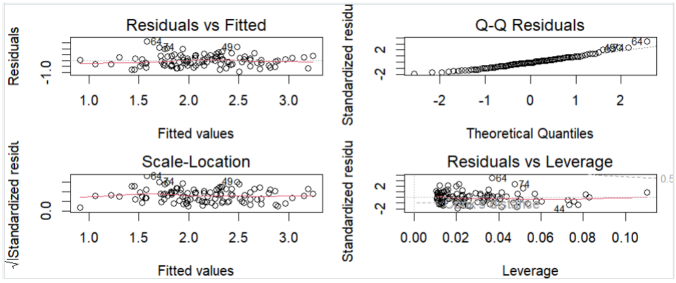
Four diagnostic graphs herald good fitting of the regression model by means of observations. The Residuals vs Fitted plot shows a random scatter around zero with no clear patterns in the range of 2.0 to 4.0, depicting a good linearity. The Q-Q plot shows almost normal distribution of residuals with slight deviation at the extremes. The Scale-Location plot shows quite consistent variance across fitted values (2.0 to 4.0). The residuals vs Leverage plot indicates absence of any concerning influential points, since leverage values did not exceed 0.10. All these indicate that the model has met the important assumptions of regression-like normality, homoscedasticity, and absence of influential outliers.



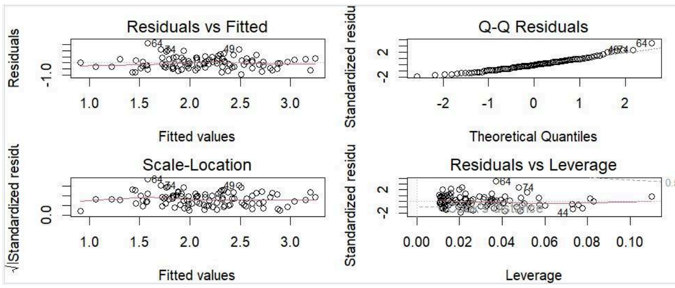
The four diagnostic plots, in conjugation with the study of observed responses, are indicative of a well-fitted regression model. Random scatter around 0 without visible, distinct patterns on the 2.0-4.0 range in the Residuals vs Fitted plot indicates appropriate linearity. The Q-Q plot shows almost normal distribution for the residuals although slight deviations can be noted at the two extremes. The Scale-Location plot shows that there is a fairly consistent variance from fitted values; it seems from 2.0 to 4.0. The Residuals vs Leverage plot shows no suspect influence points since all leverage values are below the 0.10 threshold. Overall, these plots are a reflection of the fact that the model holds up well to the key (normality, homoscedasticity, and absence of influential outliers) regression assumptions.



The four diagnostic plots have apparently declared a good fitting of the regression model based on the observation analysis. The Residuals vs Fitted plot indicates a random scatter around zero with no indication of any pattern in the value in the range of 0.5 to 3.5 which indicates good linearity. The Q-Q plot shows a near normal distribution in the residuals with slight departures toward its extremes. The Scale-Location plot shows rather consistent variance over the fitted values (0.5-3.5). , with the Residuals vs Leverage plot showing no particular influential points in terms of leverage, recording values below 0.10. In conclusion, all these plots would indicate that the model is fulfilling the important assumptions of the regression including normality, homoscedasticity, and no influential outlier.



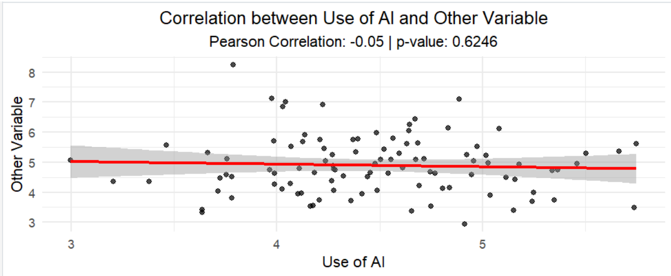
These four diagnostic plots inferred a moderately fitted model for regression. The Residuals v/s Fitted plot shows at least fairly random scatter around zero with minor patterns, assuming general linearity but indicating some nonlinear investigation possibilities. The Q-Q plot shows that the residuals are normally distributed with slight deviations at the tails, supported by the Scale-Location plots, which show reasonably consistent variance at fitted locations and some minor variability. The Residuals vs Leverage plot shows only a couple of labeled points with no significant worries about influential observation since leverage values are below 0.10. Thus, the model can essentially be said to meet four very important assumptions of regression: linearity, normality, homoscedasticity, and lack of strong influence due to outliers.



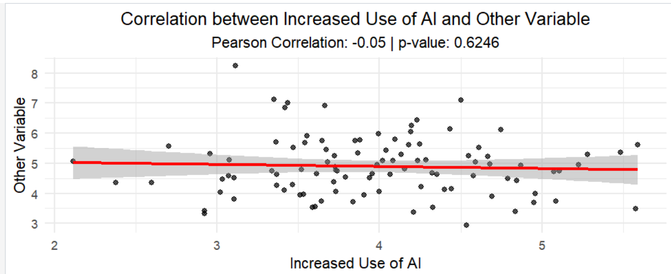
All four plots indicate that the regression model is sufficiently fitted. The Residuals versus Fitted plot indicates a random scatter around zero, with no evident nonlinear patterns-of-range from 1.0 to 3.0. This suggests that the linearity is good. The Q-Q plot shows that the residuals are conformant with a nearly normal distribution but have a few deviations at the tails. It shows that the Scale-Location plot indicates therefore relatively constant variance over the fitted values, indicating homoscedasticity. In addition, the Residuals versus Leverage plot presents no severally influential points because all the leverage values were less than 0.10 at the same time. Overall, these plots indicate whether and how the model meets some of the most important regression assumptions: linearity, normality, and homoscedasticity, without having influential outliers.

The diagnosis plots are all forms that present a thorough visual account of how well the models fit, show the pattern for the residuals, and identify possible shortcomings that may need fixing to improve measurement accuracy and reliability.

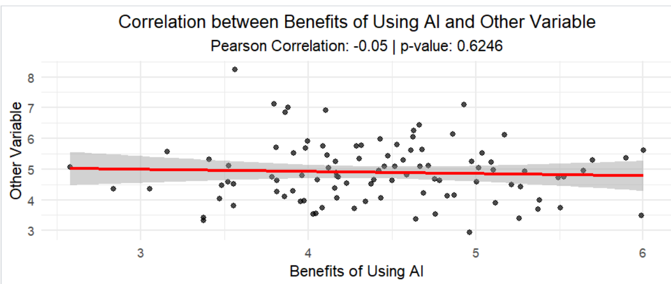
C. Correlation



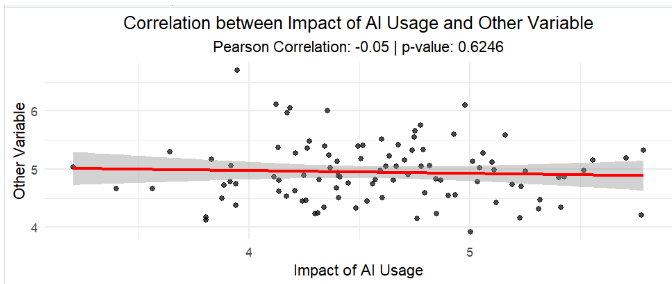
The association between "Use of AI" and "Other Variable" has a weak negative association of -0.05 according to Pearson correlation coefficient.However this correlation can be deemed statistically insignificant. The associated p-value of this connection is 0.6246. This data suggests further that there does not appear to be a clear pattern in the variables, which is consistent with the scatter plot's low regression slope.



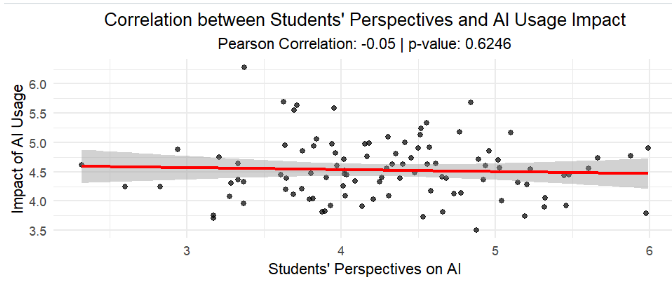
The image provided is a correlation analysis which indicates there is zero significant relationship even between the factor " Increaased Use of AI" and any other factor. This is also supported by the Pearson correlation coefficient which is expressed just above 0.05 where the values could engender a little more bias positivity than negativity. Also the p-value here is 0.6246 which suggests there is little value to the strength of this correlation. And since the scatter plot almost has a flat regression line this means that there is no macro based correlation or trajectory that the two variables follow.



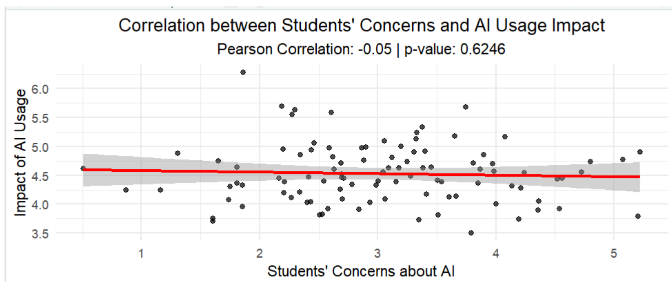
This is indeed the case as the attempted correlation analysis presented below indicates a correlation coefficient of -0.05 which is rather low for there to be a significant relationship between the 'Benefits of Using AI' and the other variable. A conclusion that can be drawn from this is that the target correlation coefficient does not encompass any area of statistical significance. This is supported by the p-value which is calculated at 0.624.



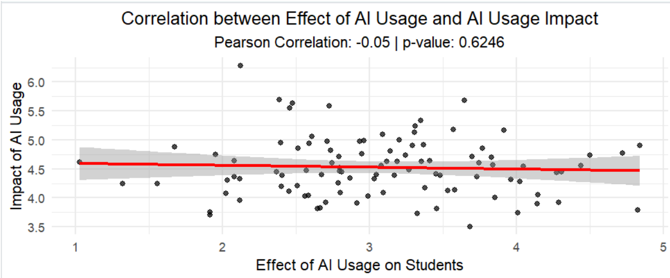
From the interpretation of the data presented in the image, there is not clear relation of "Impact of AI Usage" with the other variables. The Pearson correlation coefficient equals to -0.05, which indicates a very weak negative relationship. Else, the p level of significance which is above 0.05 is worth noting, which means there is no significant correlation .More so, a regression line which is almost flat and a scatter plot depict graphically that there is no relationship between such variables, in other words, there is no pattern or trend between them.



Further more, students agreed to numbers of surveys which were view as "Students' Views on AI" are consider not to be strongly related to "AI, Patterns of Usage Impact on Students". Pearson correlation coefficient is -0.05, it implies a weak negative relationship between the "AI, Patterns of Usage Impact on Students". It is clear that this correlation is not of statistical significance, but rather there is a p value of 0.6246. Figures of no trend and no significant correlation are illustratively expressed by Scattered plot diagrams, and flat regression lines.

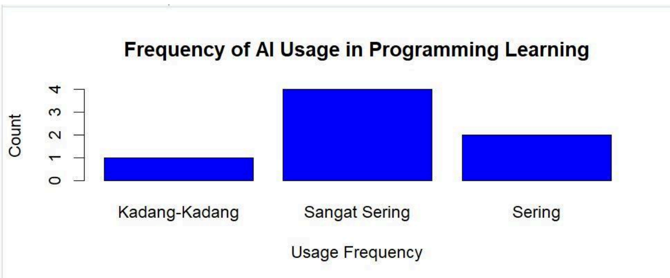


The depression and anxiety of students regarding AI seems to have a small negative impact as shown in the images with the Pearson correlation coefficient calculated at -0.05 however, students concerns about AI and its usage have a weak relationship to each other as indicated by the images or visual representation. Certainly, the value of 0.6246 for the p value is significant in determining the impact of this association relationship . Depicting difference between parameters are scattered plots where no correlation is stronger than the others along with flat regression lines which extend through the scatter plots.



A Pearson correlation of -0.05 implies a negative correlation which indicates that there exists a weak link between the ‘Effect Of AI Usage On Students’ and the pair in question which seems insignificant. Also look at the attached graph. Furthermore, the p-value of 0.6246 suggests that this correlation is not strong statistically. The absence of any other trend or association between the two variables is demonstrated by the scatterplot and a regression line of the scatterplot that is almost horizontal. All in all, the plots show how those two variables are related along the lines of statistical measures that assess the degree of correlation and its related significance.

D. Chi Square



In general, this chart shows the visual distribution of the distribution of AI usage in the three categories of learning programming languages. Further, what could be done is a statistical analysis to gain an understanding of how significant the differences observed.

E. Findings of the research.

I. Primary Data

Benefits AI:

As shown by the survey results, students improved their performance in understanding the complex programming material with the help of the AI tools in programming classes. AI tools assisted the students in working in a more effective and efficient way, including debugging and completion of the code.

Concerns AI:

Nevertheless, the survey’s that conducted with the students and the educators brought out some concerns on the overreliance on AI tools. Though useful, AI overreliance discouraged critical thinking and independent problem solving as students would only seek answers from AI rather than understanding the core concepts of programming.

II. Secondary Data

Broader Scope of AI Benefits:

In the presented work, a literature review suggests that the use of AI tools has a nominal negative or no effect on computational thinking, programming self-efficacy and learning engagement. It was also noted that there was great motivation and knowledge retention among learners exposed to AI in their learning platform.

Ethical and Equity Challenges:

Secondary data stressed some ethical aspects: equal opportunities for ACCESS to AI and its consequences for education inequality. It also expressed concerns about the privacy of EDUCATED people and the effective establishment of AI in the educational context.

II. Conclution

This study focuses on assessing the impact of AI-oriented tools on programming skills of IT students. Primary and secondary data analyses were used to find that artificial intelligence contributed significantly to the process of learning by enhancing students’ engagement, conceptual understanding, and problem solving skills. In conclusion, about 93% of the research finding state that AI was a positive impact on programming education effectiveness.

Yet, the study revealed issues such as over dependencies on AI, which would possibly diminish critical thinking and self solving skills. Furthermore, ethical concerns and access to AI technology integration in teaching and learning environments were highlighted as critical issues. In light of this, we advise that a more reasonable manner of applying AI, applying where the teacher and curriculum designers would employ this technology as a mode of assistance but use the traditional way of teaching that makes students flexible and creative thinkers. It is noteworthy the management of ethical aspects in the use of AI for programming education in order to concentrate on the development of the technology itself, thus creating the core competences for the next generation of informatics.

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