Journal of Engineering Education Transformations,
Volume No. 37, January 2024 Special Issue, eISSN 2394-1707

Development of Inquiry-based Active Learning Pedagogy Approach to Heightening Learners' Critical Thinking Skills in Data Visualization for Analytics Course

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***Abstract*— Data visualization is a powerful tool for communicating complex and multidimensional information in an effective and engaging way. However, creating effective data visualizations requires not only technical skills, but also critical thinking skills to select, analyze, and interpret data. In this paper, we propose an inquiry-based active learning pedagogy approach to heighten learners' critical thinking skills for the course Data Visualization Analytics. We describe the design and implementation of a series of learning activities that involve learners in posing questions, collecting and exploring data, creating and presenting visualizations, and reflecting on their learning outcomes by collecting survey questions from 76 students. We also present the results of a mixed-methods evaluation of the approach, which involved all 76 undergraduate students from Kalasalingam Academy of Research and Education (Deemed to be University) in Tamilnadu, India. The evaluation showed that the approach improved learners' critical thinking skills, as measured by a pre-and post-test, and enhanced their engagement and satisfaction with the course, as indicated by a survey and interviews with four input parameters and one output parameter. We discuss the implications of our findings for the data visualization analytics course and suggest directions for students' efficacy by applying regression and correlation analysis.**

***Keywords*—Active Learning, Inquiry Learning, Pedagogy, Critical Thinking, Data Visualization, Data Analytics.**

I. INTRODUCTION

In the rapidly evolving landscape of data analytics and visualization, the ability to not only comprehend data but also to extract meaningful insights from it has become a critical skill. As industries across the board increasingly rely on data-driven decision-making, the demand for individuals who possess a nuanced understanding of data visualization techniques and can think critically about the information presented has surged. This shift has posed a significant challenge to educators: how to cultivate learners' critical thinking skills within the realm of data visualization effectively (Thaiposri and Wannapiroon, 2015).

Traditionally, education has often relied on passive learning methods, where students passively receive information through lectures and textbooks. However, this approach falls short in cultivating the analytical and problem-solving skills demanded by modern data analysis and visualization. To bridge this gap, there is a growing recognition of the need to implement pedagogical methods that actively engage learners in the learning process and foster critical thinking (Jansson et al., 2021). In response, this paper introduces an innovative pedagogical approach that combines inquiry-based learning and active engagement strategies to heighten learners' critical thinking skills within the context of the course "Data Visualization for Analytics."

The core premise of this paper is rooted in the transformative potential of pedagogical methods that emphasize active inquiry and collaborative problem-solving. Traditional lecture-centric approaches often focus on transmitting information, leaving students with limited opportunities to engage with the material in depth and apply their learning in practical scenarios. In contrast, an inquiry-based active learning approach empowers students to take a central role in their education, encouraging them to explore, question, and analyze data on their own terms (Wertz, 2022; Aldahmash and Omar, 2021).

The specific context of data visualization for analytics provides an ideal setting to test the efficacy of this approach. Data visualization is not only a technical skill but also an art of storytelling, where learners must comprehend the underlying data, choose appropriate visualization techniques, and effectively communicate insights to diverse audiences. Achieving these multifaceted goals requires more than rote memorization; it necessitates the cultivation of critical thinking abilities (Lotzin et al., 2019).

Throughout this paper, we will delve into the process of designing and implementing the inquiry-based active learning pedagogy for the "Data Visualization for Analytics" course. We will outline the key components of the approach, including interactive learning modules, collaborative projects, and

This paper was submitted for review on August 31, 2023. It was accepted on November 15, 2023.
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authentic data analysis tasks. Additionally, we will discuss the assessment methods used to measure the development of learners' critical thinking skills before and after exposure to the pedagogical intervention (Odekerken et al., 2022).

In an era where the ability to interpret and visualize data is integral to success in numerous professional fields, the significance of effective data visualization education cannot be overstated. This paper aims to contribute to the ongoing dialogue on innovative pedagogical strategies that enhance critical thinking skills in data-driven domains. By presenting the development and outcomes of the inquiry-based active learning approach, we seek to provide educators with valuable insights into fostering the next generation of analytical thinkers and communicators (Wang, 2012).

This paper presents the design, implementation, and assessment of an innovative inquiry-based active learning pedagogy approach aimed at enhancing learners' critical thinking skills in the context of the course "Data Visualization for Analytics." As the demand for individuals with proficient data visualization and analytical abilities continues to grow, educators face the challenge of fostering higher-order thinking skills in students. The traditional lecture-based approach often falls short in promoting critical thinking and real-world problem-solving capabilities (Jiang et al., 2018).

To address these challenges, the major contributions of the work is,

- we developed and deployed an inquiry-based active learning pedagogy for teaching data visualization. This approach encourages learners to take an active role in their learning by engaging in hands-on explorations, collaborative activities, and self-directed inquiries.
- Drawing inspiration from constructivist theories, the pedagogy scaffolds the learning process through progressive stages of inquiry, allowing students to gradually build their skills and knowledge.
- The implementation of the pedagogical approach involved the creation of interactive learning modules, group projects, and real-world data analysis tasks.
- Assessment tools were designed to measure learners' critical thinking skills through various dimensions, including analysis, interpretation, evaluation of visualizations, and effective communication of insights.
- These tools were applied before and after the pedagogical intervention to evaluate the approach's impact on learners' skill development.

II. LITERATURE REVIEW

For the benefit of the research community who wish to advance in the field of inquiry-based learning, the research activities that have been eminently collaborated and proposed by several researchers for more than a decade are listed below in tabular form in Table 1.

Table 1. Identifying the cutting-edge methods that have been used in Inquiry-Based Learning

Ref.	Sample Size	Type of Education	Inputs Attributes	Methodology	Output	Findings
Costes-Onishi and Kwek, 2023)	138	10 government schools, 6 government-aided schools, and 4 autonomous or independent schools were chosen in accordance with an arrangement of school types, making the schools chosen representative of the school types in Singapore.	• In order to assist the Ministry of Education's curriculum planning and review cycles, a study was conducted to gather and analyse information on classroom practises in Singaporean schools. • The paper reports on the frequency and occurrence of specific codes in phases (5-min intervals) across all the units observed	• Diverse-methods approach • The study collected and analyzed data using video observations, interviews, and surveys • The authors used the SCS3-MAPC (Singapore Creative Science Schools - Multiple Assessments of Pupil Creativity) frameworks to analyze the data • The SCS3-MAPC is a validated assessment tool that measures creativity in multiple domains, including visual arts.	• Understand the differences between what teachers reported they do in the classrooms and what was observed using the coding scheme • focused on identifying and analyzing specific codes related to pedagogical reasoning and inquiry-based	• The findings of the paper indicate that whole class discussion is more apparent in S1 (secondary level) and is strongly correlated with making connections either by topics or local/global knowledge • Whole class discussion is also strongly correlated with Reframing Talk (S1) and Justification Talk (P5), suggesting that focused discussions on specific topics could lead to deeper forms of meaning-making and inquiry. • In terms of lesson observations, the study found that teachers spent a

				• The authors also used Microsoft Excel and SPSS for statistical analyses • The study is a video-based research project focusing on an extraction modality, using video to record specific interactions so that they can be studied in greater depth by the researcher	practices in the visual arts	significant amount of time on whole-class exposition in both primary (P5) and secondary (S1) levels. • This indicates that teachers relied heavily on whole-class instruction rather than individual or small-group activities. • The study also notes that the findings in the visual arts align with similar findings in music, suggesting that the arts as taught in schools often prioritize practical skills over meaning-making
Nzomo et al., 2023	357	secondary school education in Kenya	• Teachers' ratings on IBL use • Observed use of IBL	• Concurrent triangulation mixed methods research design • Collection of both quantitative and qualitative data to ensure a good understanding of a phenomenon based on IBL and Inquiry	Correlation between inquiry-based learning students' self-efficacy	• In practice lessons, teachers use inquiry-based learning (IBL) once a week, according to the study, and when asked to rate their use of IBL, they tend to overreport it. The study's findings revealed that students had a high level of self-efficacy in chemistry. • The study also found a connection between IBL and students' views of their own efficacy in Chemistry. Inquiry-based learning and students' self-efficacy in Chemistry are significantly positively correlated, according to Pearson's correlation coefficient findings, in secondary schools.
Kor., 2022	155	Nursing Students, hong kong polytechnic university, China	• Student satisfaction • Self-confidence • Students' attitudes toward older people	Self-regulated online inquiry-based learning	Enhanced peer, self-directed learning. Cognitive and critical thinking skills	The impact of an online self-regulated experiential learning program on nursing students' attitudes toward older people
Van der Graaf et al., 2020	78	Secondary school for pre-vocational education in	• Electrical Circuits Lab • Go-Lab Ecosystem	Inquiry-based learning space (ILS)	Pretest and post-test domain knowledge	Learning was impacted by experimentation and the incorporation of the virtual lab and informational text.

		the Netherlands				
Chau et al., 2021	192	Senior-year pre-registration nursing students,	• Self-administrated paper-based questionary • Study process questionary	Pre-test/ post-test mixed-Inquiry methods	Experience of Learning Scale with a learning resource	A technology-enhanced, inquiry-based learning program that increases their understanding of neonatal extravasation injury options to learning experiences and academic study.

III. RESEARCH METHODOLOGY

3.1 Research Design

Inquiry-based active learning pedagogy is a learner-centered approach that starts with an essential question and engages learners in investigating the topic to find answers, developing language and skills throughout the inquiry. It is based on constructivist learning theories, such as the work of Piaget, Dewey, Vygotsky, and Freire, and aims to foster curiosity, creativity, and critical thinking skills in learners.

Data visualization is the graphical representation of information and data, using visual elements like charts, graphs, and maps. Data visualization tools help to make data more accessible and understandable, as well as to communicate data-driven insights and stories. Data visualization is an important part of business intelligence and advanced analytics, as it helps to analyze massive amounts of information and make data-driven decisions.

Some examples of inquiry-based active learning pedagogy for data visualization for analytics are:

Asking learners to formulate their own questions or problems related to a given topic or dataset, and then guiding them to explore different sources of data, visualize the data in various ways, and present their findings and conclusions.

Using real-world scenarios or case studies that require learners to apply data visualization techniques and tools to solve a problem or answer a question.

Encouraging learners to collaborate and share their data visualizations with peers or experts, and to provide and receive feedback on their work. This can help learners to improve their communication skills, as well as to learn from different perspectives and approaches.

3.2 Data Collection

This research investigates the effects of using inquiry-based learning (IBL) as a pedagogical approach for teaching data visualization for analytics to third-year computer science students at Kalasalingam Academy of Research and Education in Tamil Nadu, India. It adopts a mixed-methods design, using both quantitative and qualitative data collection and analysis methods. The quantitative data consists of pre- and post-tests of critical thinking skills. It reports that the students who participated in the internal and external assessment approach showed significant improvement in their critical thinking skills, as well as their engagement, motivation, and confidence in learning data visualization for analytics. The internal assessments are Sessional Examination, Open Book Test, Mini Project Evaluation, Experimental Evaluation, and Industry evaluation (Students are solving Industry Problems). The external assessments are the End Semester Theory Examination and End Semester Practical Examination. This made a representative sample of 60 students from the 4 teachers' classes possible with different academic year and semester. In order to lessen sampling errors, the researcher used a larger sample size because some students might not complete the questionnaires.

3.3 Design Methods

A total of (n=76) III-year engineering (Computer Science and Engineering) students participated in the Inquiry-based collaborative teamwork activities inside the classroom, with (n=56) male students accounting for 73.68 % and (n=15) female students accounting for 19.73 %. They were randomly assigned to teams of one female and the remaining male students. Additionally, it was ensured that the team had at least one advanced learner. The students took individual quizzes before and after the group activity, and the results were compared to gauge how well they did. Student-Professor Interaction (SPI), Student-Team Interaction (STI), Learning Tools (LT), and Assessment (AT) were the attributes used for the survey. Each of these attributes was further subdivided into sub-attributes, which were then represented in the questionnaires via surveys. Google Forms was used to deliver the surveys online. The survey links were distributed to student groups. The students were expected to respond with a total of 76 responses. Each question was presented to the students on a 5-point Likert scale, with 5 representing Strongly Agree, 4 representing Agree, 3 representing Neutral, 2 representing Slightly Disagree, and 1 representing Strongly Disagree. There were a total of 17 sub-attributes in the survey. Table 2 lists the sub-attributes that students were asked about in the survey.

Table 2. Attribute and sub-attribute details of the survey.

I / O	Attribute No.	Attributes	No.	Sub Attributes (Likert Scale 5) 5 = Strongly Agree, 4 = Agree, 3 = Neutral, 2 = Slightly disagree, 1 = Strongly Disagree
Inputs	SPI	Student – Professor Interaction	SPI-1	The professor guided me to develop teamwork skills that enabled me to work in a team effectively
			SPI-2	The professor allowed individual team members to express his / her opinions
			SPI-3	The professor guided team members to form collaborative groups
	STI	Student – Team Interaction	STI-1	There was effective team management and organization within the team
			STI-2	The interaction among the team members favoured the development of teamwork skills
			STI-3	I can develop new skills and knowledge from other members of my group
			STI-4	I can develop problem-solving skills through peer collaboration
			STI-5	I actively exchange ideas with my group members regarding my research articles
	LT	Learning tools	LT-1	The learning materials provided by the professor helped me in applying the skills during the team activity
			LT-2	The hands-on laboratory session allotted for this course helped me to apply problem-solving skills during the team activity
			LT-3	The professor provided relevant links and resources to the books for learning this concept.
	AT	Assessment	AT-1	The quiz questions correctly assessed my problem-solving knowledge learned during the collaborative activity
			AT-2	I can apply the knowledge gained through the group activity in answering the quiz questions
Output	SLE	Student – Learning Experience	SLE-1	Collaborative learning is fun
			SLE-2	I enjoyed working out the problem with my team members
			SLE-3	I am satisfied with this style of group collaboration learning for analytic problem-solving.
			SLE-4	Writing research articles favoured me to develop good relationships with my professor and peers

Table 3 and 4 describes the descriptive statistical information about all the Input and Output Parameters respectively.

Table 3 Descriptive Measures for input attributes used in the survey.

Descriptive Measures / Attributes	SPI1	SPI2	SPI3	STI1	STI2	STI3	STI4	STI5	LT1	LT2	LT3	AT1	AT2
Mean	4.6710	4.6447	4.592	4.526	4.513	4.473	4.434	4.460	4.539	4.460	4.539	4.565	4.526
Standard Error	0.0632	0.0612	0.072	0.071	0.060	0.063	0.077	0.075	0.075	0.088	0.073	0.065	0.068
Median	5	5	5	5	5	4.5	5	5	5	5	5	5	5
Mode	5	5	5	5	5	5	5	5	5	5	5	5	5
Standard Deviation	0.55107	0.53426	0.636	0.621	0.528	0.553	0.679	0.662	0.662	0.773	0.641	0.573	0.599
Sample Variance	0.3036	0.2854	0.404	0.385	0.279	0.30	0.462	0.438	0.438	0.598	0.411	0.328	0.359
Kurtosis	1.2423	0.3193	2.9168	2.3086	-1.295	-0.939	1.0282	8.3610	2.0013	5.070	0.0933	-0.129	-0.207
Skewness	-1.4579	-1.1472	-1.632	-1.301	-0.331	-0.379	-1.062	-1.974	-1.422	-1.90	-1.083	-0.917	-0.866
Range	2	2	3	3	2	2	3	4	3	4	2	2	2
Minimum	3	3	2	2	3	3	2	1	2	1	3	3	3
Maximum	5	5	5	5	5	5	5	5	5	5	5	5	5
Sum	355	353	349	344	343	340	337	339	345	339	345	347	344
Count	76	76	76	76	76	76	76	76	76	76	76	76	76

Table 4 Descriptive Measures for Output Attributes used in the survey.

Descriptive Measures / Attributes	SLE1	SLE2	SLE3	SLE4

Mean	4.526316	4.526316	4.526316	4.473684
Standard Error	0.071263	0.071263	0.071263	0.073684
Median	5	5	5	5
Mode	5	5	5	5
Standard Deviation	0.621261	0.621261	0.621261	0.642364
Sample Variance	0.385965	0.385965	0.385965	0.412632
Kurtosis	-0.07962	-0.07962	-0.07962	1.65222
Skewness	-0.95866	-0.95866	-0.95866	-1.13944
Range	2	2	2	3
Minimum	3	3	3	2
Maximum	5	5	5	5
Sum	344	344	344	340
Count	76	76	76	76

3.4 Data Analysis

Using the Excel Data Analytical Tool, the data was coded and analyzed. Inferential statistics were used to establish the relationship between Learners' and Educators, while descriptive statistics were used to assess all assessments. After performing the regression analysis and correlation analysis residual plot, Line fitted plot, and probability plot are computed to test various hypotheses.

IV. RESULTS AND DISCUSSION

Table 5 describes the regression statistics of all inputs to the respective output and provide R, R^2, Adjusted R^2, Error, Number of observations of the particular output

Table 5. Estimating the Regression Statistics relationship between all Input Parameters SPI, STI, LT, AT with Output Parameter SLE1, SLE2, SLE3, SLE4

Regression Statistics	SLE1	SLE2	SLE3	SLE4
Multiple R	0.86559	0.9039	0.8392	0.8938
R Square	0.7492	0.81713	0.70430	0.79899
Adjusted R Square	0.6966	0.7787	0.6423	0.7568
Standard Error	0.3421	0.27154	0.3584	0.3167
Observations	76	76	76	76

Tables 6, 7, 8 and 9 analyze ANOVA of the data to know the relationship between input terms to the output terms

ANOVA: Helps to analyze differences between means
Degrees of freedom(DF): Independent values present in the data
Sum of squares(SS): ss is the sum of squares of data and the mean
Mean square(MS): Check whether factors are significant (ms=ss/df)
F: Variance analysis

Table 6. Estimating the ANOVA Statistics relationship between all input parameters and SLE1

ANOVA Statistics	*DF*	*SS*	*MS*	*F*	Significance F
Regression	13	21.689	1.6683	14.2512	4.90763E-14
Residual	63	7.2583	0.1170		
Total	76	28.947			

Table 7. Estimating the ANOVA Statistics relationship between all input parameters and SLE2

ANOVA Statistics	DF	SS	MS	F	Significance F
Regression	13	20.428	1.571	21.310	4.36E-18
Residual	63	4.571	0.073		
Total	76	25			

Table 8. Estimating the ANOVA Statistics relationship between all input parameters and SLE3

ANOVA Statistics	DF	SS	MS	F	Significance F
Regression	13	18.97	1.459	11.3598	5.88E-12
Residual	63	7.968	0.128		
Total	76	26.94			

Table 9. Estimating the ANOVA Statistics relationship between all input parameters and SLE4

ANOVA *Statistics*	*DF*	*SS*	*MS*	*F*	*Significance F*
Regression	13	24.72	1.902059	18.9576	7.27E-17
Residual	63	6.22	0.1003		
Total	76	30.9			

Tables 10 estimate regression variable values between the input values to the output values of parameters like coefficients, t statistics, and p value.

Table 10. Regression Variable Values between input parameters and SLE1

Parameters	*SLE1*			*SLE2*			*SLE3*			*SLE4*		
	Coefficients	*t Stat*	*P-value*	*Coefficients*	*t Stat*	*P-value*	*Coefficients*	*t Stat*	*P-value*	*Coefficients*	*t Stat*	*P-value*
Intercept	0.1331	0.31738	0.7520	0.3780	1.1353	0.2606	0.6093	1.3859	0.1707	0.1174	0.30237	0.7633
SPI-1	0.5737	4.6749	1.6334	0.2759	2.8331	0.0062	0.1477	1.1489	0.2549	0.2451	2.15750	0.0348
SPI-2	-0.3559	-1.9939	0.0505	-0.4294	-3.031	0.0035	-0.0608	-0.3253	0.7460	-0.1398	-0.8466	0.4004
SPI-3	-0.0446	-0.4058	0.6862	0.1466	1.6785	0.0982	-0.0849	-0.7360	0.4644	0.1205	1.1824	0.2415
STI-1	0.04986	0.4191	0.6765	0.0233	0.2471	0.8056	0.1894	1.5197	0.1336	-0.1853	-1.6833	0.0973
STI-2	0.5800	3.4964	0.0008	0.4200	3.1903	0.0022	-0.1733	-0.9972	0.3225	-0.2094	-1.3634	0.1776
STI-3	-0.3098	-1.5063	0.1370	0.0989	0.6060	0.5467	0.0464	0.2154	0.8301	0.3009	1.5801	0.1191
STI-4	0.1774	1.5053	0.1373	0.0422	0.4516	0.6530	0.0784	0.6354	0.5274	0.1399	1.2828	0.2043
STI-5	-0.0723	-0.5233	0.6026	-0.1492	-1.359	0.1788	0.4111	2.8373	0.0061	0.4352	3.3995	0.0011
LT-1	-0.0928	-0.7389	0.4627	-0.0439	-0.441	0.6607	0.0545	0.4141	0.6801	0.1943	1.6701	0.0999
LT-2	0.2233	1.9288	0.0583	0.1690	1.8402	0.0705	0.2139	1.7637	0.0827	0.0460	0.4293	0.6691
LT-3	-0.0786	-0.4566	0.6495	-0.1297	-0.949	0.3462	-0.3405	-1.8872	0.0638	-0.3171	-1.9891	0.0510
AT-1	0.1903	0.67867	0.4998	-0.3167	-1.422	0.1598	0.1240	0.4222	0.6743	-0.0403	-0.1554	0.8769
AT-2	0.1244	0.5147	0.6085	0.8106	4.2241	0.0008	0.2561	1.0111	0.3158	0.3799	1.6972	0.0946

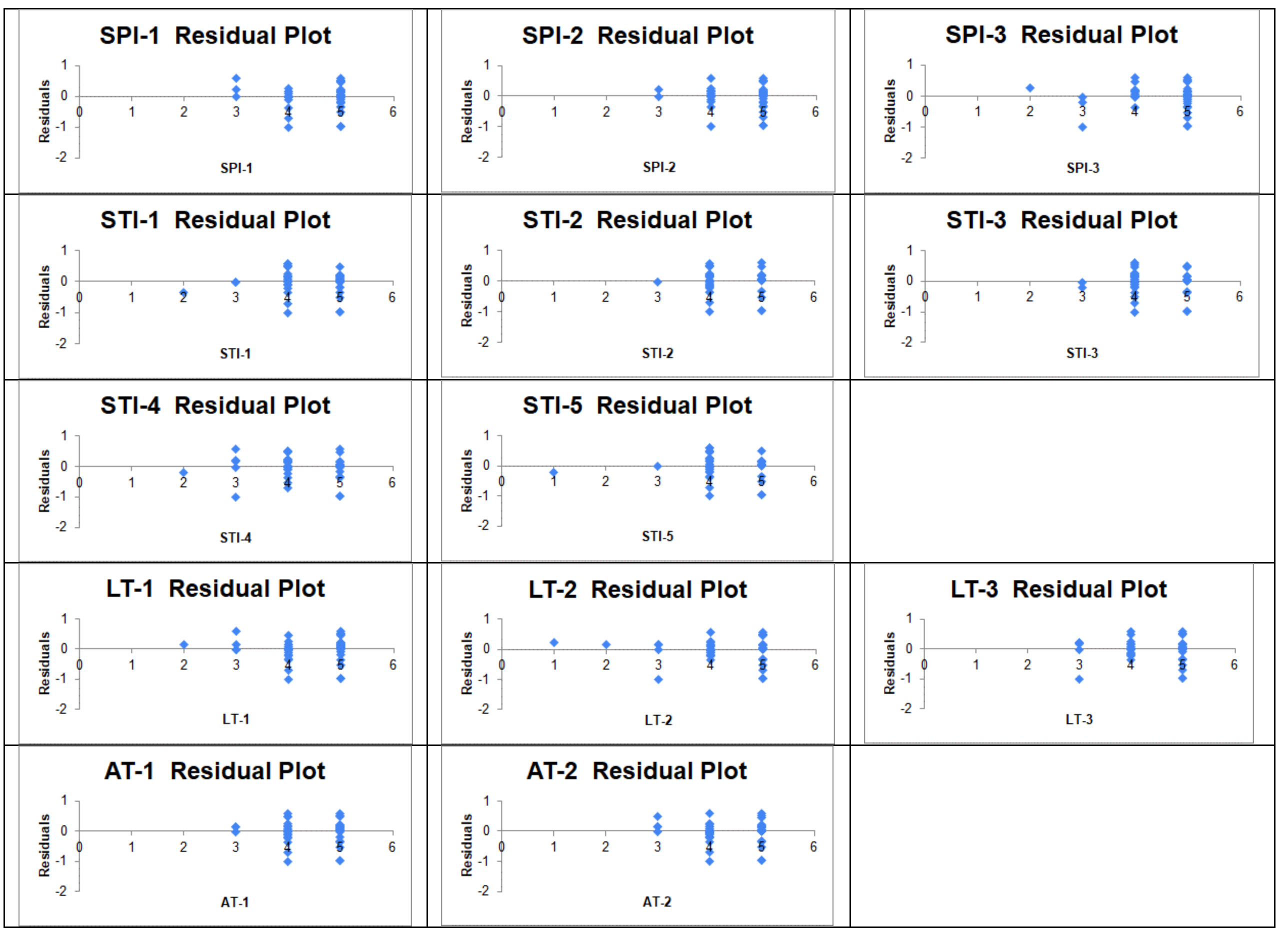

Fig. 1. Residual Plot between all Input Parameters with SLE4 (Residuals)

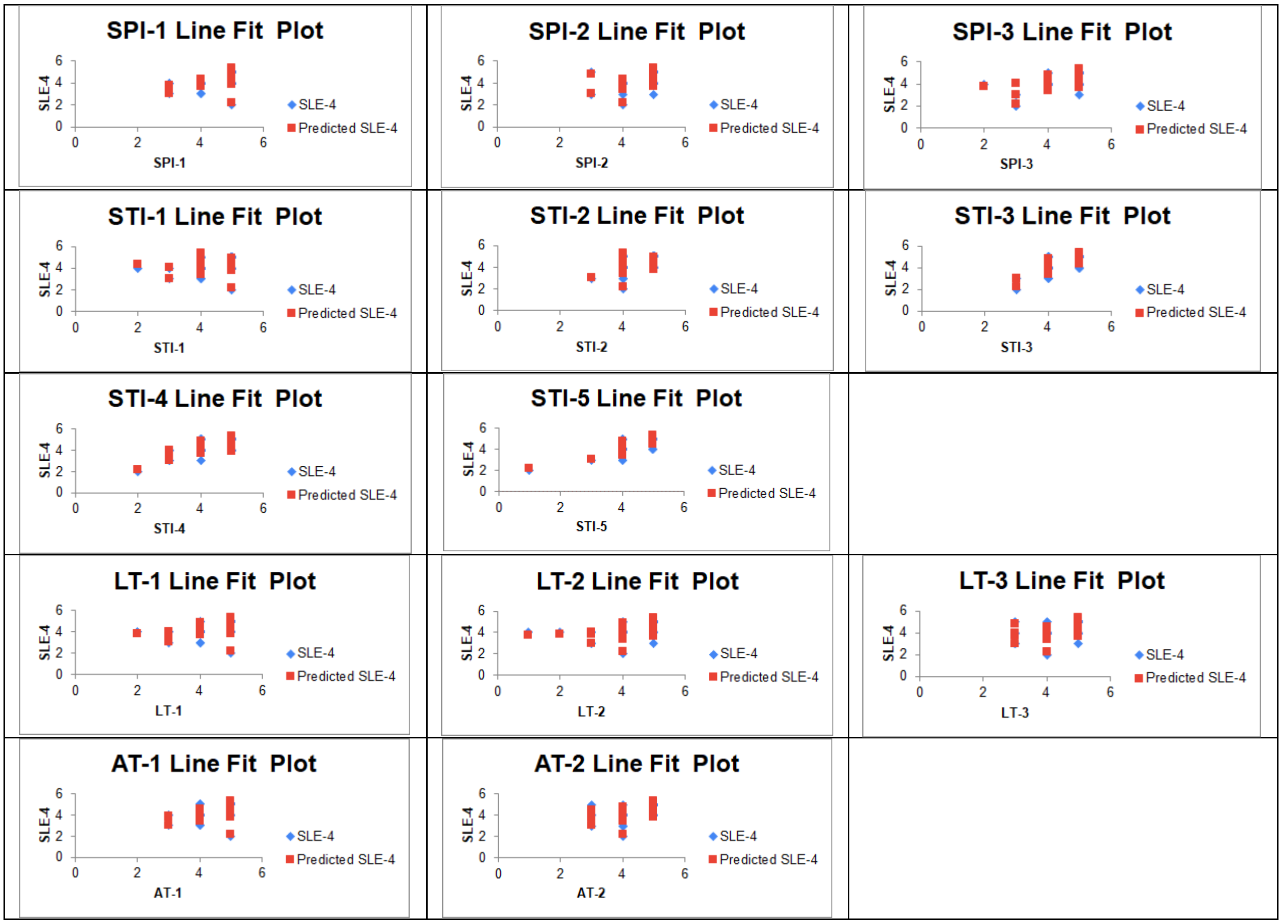

Fig. 2. Line Fit Plot between all Input Parameters with SLE4

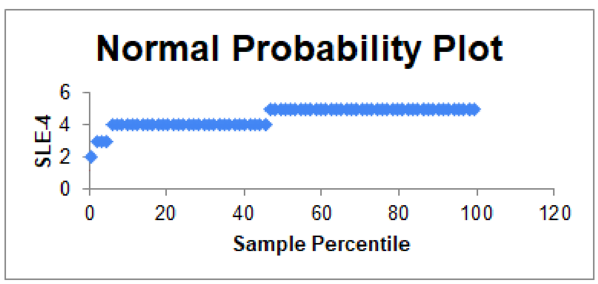

Fig. 3. Normal Probability Plot Sample Percentile with SLE4

Fig. 1 to 3 represents the Residual Plot, Line Fit Plot, and Normal Probability Plot for sample percentile values (Input Parameter values SPI, STI, LT, AT) with all Output parameters for SLE4. The research design focused on writing research article by students to develop good relationship with professor and student for making efficient active learning pedagogy initiatives. So, we consider only SLE4 for analysis and all analysis are described in fig 1-3.

A residual plot is a type of visualization plot that displays the values of a predictor variable (SLE4) in a regression model along the x-axis and the values of the residuals along the y-axis. From this residual plot, we can assess whether or not the residuals in a regression model are normally distributed and whether or not they exhibit heteroscedasticity. Residuals are the differences between the observed values and the predicted values of the dependent variable in a regression model. It can help to identify patterns or trends in the residuals that may indicate problems with the regression model, such as non-linearity, outliers, or unequal variance. A residual plot should ideally show a random scatter of points around the horizontal axis, which means that the regression model is appropriate for the data. If the residual plot shows a curved pattern, a linear model may not fit the data well. If the residual plot shows a fanning or cone-shaped pattern, the residuals may have unequal variance, which violates one of the assumptions of linear regression. Here is an example of a residual plot for a simple linear regression model which is described in Fig. 1.

A line fit plot is a type of visualization plot that shows the relationship between a response variable and a predictor variable using a scatter plot and a fitted line. The fitted line is usually obtained by using a method called least squares, which minimizes the sum of the squared distances between the data points and the line. It can help to assess how well the linear model fits the data and whether there are any outliers or patterns in the residuals. Here is an example of a line fit plot for the head length and total length of 104 brushtails from the collected data seta are highlighted in Fig 2. This plot shows that there is a positive linear association between head length and total length, meaning that possums with longer total lengths tend to have longer head lengths. The line fit plot also shows that most of the data points are close to the fitted line, indicating that the linear model is appropriate for these data. However, there are a few outliers that deviate from the line, such as the points highlighted in Fig 2.

A normal probability plot is a data visualization technique to identify substantive departures from normality. It helps to check whether the data follows a normal distribution or not. A normal distribution is a common statistical model that describes how many natural phenomena behave, such as heights, weights, IQ scores, etc. A normal distribution has a bell-shaped curve that is symmetric around the mean and has a standard deviation that measures how spread out the data are. To make a normal probability plot, need to plot the sorted data values on the vertical axis and the corresponding theoretical quantiles of the normal distribution on the horizontal axis. The theoretical quantiles are values that divide the normal distribution into equal intervals with the same probability. For example, the median of the normal distribution is the 50th percentile or the 0.5 quantile, which means that half of the data values are below it and half are above it. If data follows a normal distribution, then the points on the normal probability plot should form a straight line. This means that data values match well with the theoretical quantiles of the normal distribution. If data does not follow a normal distribution, then the points on the normal probability plot will deviate from a straight line which are described in Fig 3. The data values do not match well with the theoretical quantiles of the normal distribution. For example, if the data is skewed to the right, then the points on the normal probability plot will curve upwards at the right end. If your data is skewed to the left, then the points on the normal probability plot will curve downwards at the left end. A normal probability plot helps to identify outliers, skewness, kurtosis, a need for transformations, and mixtures in data. Outliers are extreme values that are far away from the rest of the data. Skewness is a measure of how asymmetric data is plotted and Kurtosis is a measure of how peaked or flat your data is plotted. Transformations are mathematical operations that change the shape of data to make it more normal. Mixtures are situations where the data comes from more than one population or distribution.

Table 11 Estimating the correlation between all Input Parameters SPI, STI, LT, AT with Output Parameter SLE1, SLE2, SLE3, SLE4

Index	*SPI-1*	*SPI-2*	*SPI-3*	*STI-1*	*STI-2*	*STI-3*	*STI-4*	*STI-5*	*LT-1*	*LT-2*	*LT-3*	*AT-1*	*AT-2*	*SLE-1*	*SLE-2*	*SLE-3*	*SLE-4*
SPI-1	1																
SPI-2	0.639	1															
SPI-3	0.677	0.70558	1														
STI-1	0.590	0.61101	0.51667	1													
STI-2	0.495	0.70084	0.55102	0.70893	1												
STI-3	0.605	0.71238	0.67004	0.66163	0.7986	1											
STI-4	0.599	0.61384	0.66151	0.55654	0.70680	0.79302	1										
STI-5	0.493	0.65711	0.67344	0.50496	0.64864	0.85263	0.7641	1									
LT-1	0.602	0.66207	0.52934	0.66190	0.68370	0.60355	0.5685	0.52060	1								
LT-2	0.672	0.626	0.630	0.487	0.555	0.698	0.704	0.595	0.627	1							
LT-3	0.697	0.7609	0.7095	0.5157	0.6269	0.7354	0.7394	0.6627	0.6866	0.8627	1						
AT-1	0.596	0.6647	0.6043	0.7621	0.7442	0.6989	0.6267	0.5686	0.8005	0.6370	0.7174	1					
AT-2	0.531	0.7581	0.6054	0.6784	0.7768	0.7259	0.6749	0.6577	0.6860	0.6492	0.7078	0.9063	1				
SLE-1	0.707	0.4905	0.5166	0.62	0.6683	0.5840	0.6512	0.4401	0.5970	0.6541	0.6161	0.6873	0.6425	1			
SLE-2	0.607	0.5835	0.5989	0.6319	0.7640	0.7097	0.6963	0.5754	0.5754	0.6717	0.6298	0.7449	0.8090	0.8178	1		
SLE-3	0.558	0.5741	0.5483	0.6463	0.61083	0.7217	0.6663	0.7196	0.5905	0.6159	0.5747	0.6838	0.7070	0.6463	0.7320	1	
SLE-4	0.596	0.61343	0.67485	0.50291	0.60923	0.78605	0.7439	0.82825	0.58241	0.62843	0.63332	0.63809	0.69438	0.56973	0.75498	0.7	1

The results of Table 11 indicate the correlation coefficient between all input and output parameters between the respective parameters. From this Table 11, we analyzed and concluded that the relations are positively correlated. A correlation coefficient is a number that measures how closely two variables are related to each other. It can range from -1 to 1, where -1 means a perfect negative correlation, 0 means no correlation, and 1 means a perfect positive correlation. A negative correlation means that as one variable increases, the other decreases, while a positive correlation means that as one variable increases, the other also increases. A correlation coefficient close to 0 means that there is a weak or no linear relationship between the variables.

There are different types of correlation coefficients, depending on the nature and distribution of the data. The most common one is Pearson's correlation coefficient, which is used for continuous and normally distributed data. It is calculated by dividing the covariance of the two variables by the product of their standard deviations. Another type is Spearman's rank correlation coefficient, which is used for ordinal or non-normal data. It is calculated by finding the ranks of the data values and then applying Pearson's formula to the ranks.

V. CONCLUSIONS

This analytics research work has presented the development and implementation of an inquiry-based active learning pedagogy approach for teaching data visualization analytics to undergraduate students. This approach was to heighten learners' critical thinking skills by engaging them in authentic and meaningful tasks that require them to ask questions, design investigations, interpret data, form explanations and arguments, and communicate findings. It described the theoretical basis, the design principles, the learning activities, and the assessment methods of this approach. This work has also reported the results of a mixed-methods evaluation study that examined the effectiveness of this approach in terms of learners' outcomes, perceptions, and experiences. The findings of the study indicated that the inquiry-based active learning pedagogy approach was successful in enhancing learners' critical thinking skills, as well as their motivation, interest, confidence, and satisfaction with learning data visualization analytics. The study also revealed some challenges and limitations of this approach, such as the need for more guidance and feedback from the instructor, the difficulty of managing time and workload, and the variability of learners' prior knowledge and skills. The paper has discussed the implications of these findings for future research and practice in data visualization analytics education. The paper has concluded that inquiry-based active learning pedagogy is a promising and innovative way of teaching data visualization analytics that can foster learners' critical thinking skills and prepare them for the real-world challenges of data-driven decision-making.

ACKNOWLEDGMENT

The administration of the Kalasalingam Academy of Research and Education, Krishnankoil, is acknowledged by the authors for providing all of the supplies needed and computing resources for the study. The researchers thanked the students who participated in the study with enthusiasm and provided feedback on the survey questions.

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