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The Role of Motivation and Perceived Response Quality in GPT Usage for Chemistry Learning at University

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ABSTRACT

This study explores how AI is used in chemistry education, one of which is using a Generative Pre-trained Transformer (GPT) as a learning tool. This study analyzes the relationship between student motivation, response quality perspective, and frequency of GPT use in chemistry learning. This study uses a quantitative approach with multiple regression methods to predict the frequency of GPT use based on two predictor variables, namely motivation and response quality evaluation. Data were collected through a survey of 58 students from chemistry and chemistry education study programs at the undergraduate, master's, and doctoral levels. Correlation analysis results showed a significant positive relationship between motivation and response quality evaluation ($r(56) = .59$, $p < .001$) and between response quality evaluation and frequency of GPT use ($r(56) = .49$, $p < .001$). However, the relationship between motivation and frequency of GPT use was weaker ($r(56) = .32$, $p = .015$). Regression analysis showed that evaluation of response quality significantly predicted the frequency of GPT use ($\beta = .57$, $p < .001$), and motivation had a more negligible effect ($\beta = .21$, $p < .01$). The R^2 value of .25 indicated that both predictor variables could explain 25% of the variability in the frequency of GPT use. These findings inform strategies for enhancing GPT integration in chemistry learning.

Keywords: GPT, motivation, response quality, frequency of use, chemistry learning.

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1. INTRODUCTION

Generative Pre-Trained Transformer (GPT) is a generative artificial intelligence (GenAI) category similar to a chatbot. Like any other AI that can perform cognition and decision-making processes, GPT can generate text similar to human responses. GPT use increased significantly after ChatGPT was developed by Open AI in November 2022 (Haleem et al., 2022). This latest generation of GPT can perform various, more complex tasks and respond similarly to human responses. ChatGPT uses natural language processing (NLP) to interact more realistically, recognize errors, provide follow-up questions, and reject false premises (Farazouli et al., 2023). GPT can support students with homework and study assistance, flexible, personalized learning, and help in skill improvement (Karakose & Tülübaş, 2023; Labadze et al., 2023). GPT can provide an accessible and effective learning environment to improve student performance. The increased capability of GPT allows students to utilize it in more complex fields, such as STEM.

ChatGPT is considered to have an important role in supporting the development of human intelligence and contributing to STEM fields (Nam & Bai, 2023). Despite the concerns and risks, STEM teachers also approved using AI in the classroom (Beege et al., 2024). This is undoubtedly related to the ability of GPT to assist learning. A study by Antonio and Vasconcelos (2023) showed that using GPT as an agent to think with can improve problem-solving, critical thinking, and creativity in STEM education. These studies show that GPT has excellent educational potential, especially in chemistry, which contains many abstract concepts and is difficult to understand.

In the context of chemistry learning, GPT can provide students with ease in solving chemistry-related problems. GPT can convert names into structures and know the structure of coordination compounds and water solubility in polymers (Castro Nascimento & Pimentel, 2023). Several similar studies also show the ability and understanding of GPT in learning chemistry (Clark et al., 2023; Fernández et al., 2024; Hallal et al., 2023; Sallam et al., 2024; Scoggin & Smith, 2023). GPT can also write reports that fulfill aspects of chemistry, such as order to symbols, although the language used tends to be repetitive (Emenike & Emenike, 2023; Humphry & Fuller, 2023; West et al., 2023). GPT can also be a learning resource, providing context and data for simulations that help students apply their knowledge (Leite, 2024; Ramos & Condotta, 2024). Applying knowledge in a real context gives students a more authentic and meaningful learning experience (Ardyansyah et al., 2024) (Ardyansyah, 2024). With such a wide application, using GPT in chemistry learning is straightforward (Lolinco & Holme, 2023). However, behind the ability of GPT to improve learning, there are still many issues and challenges in its utilization (Yu, 2023).

Despite the opportunity to assist students in learning, misinformation and plagiarism are important issues in using GPT in education (Joyce, 2023). Previous research on the ethical use of AI has been conducted by Tlili et al. (2023), illustrating that the use of AI is not far from plagiarism, cheating, and laziness tendencies of users and is prone to information bias and false information. Other issues related to GPT also concern the level of trust, user privacy, and manipulation, indicating the need to evaluate security and responsibility in using GPT in learning. As AI in Education (AIEd) research is still in its infancy, the use of AI is not yet fully understood for its potential and risks. This is in line with UNESCO data, which shows that by January 2023, although ChatGPT users had reached 100 million people, only one country had regulations on Generative AI as of July 2023 (UNESCO, 2023). Therefore, to cope with the rapid development of technology, insights from current research and early adopters are valuable in providing insights on how GPT is used in chemistry education (Yuriev et al., 2023). Thus, research on GPT (AI in education) needs to continue.

GPT is like any other technology, so its use can be seen from several theories of technology use, such as UTAUT and TAM. Research related to GPT adoption through the perspective of these theories has been widely conducted (Romero-Rodríguez et al., 2023; Saif et al., 2024; Strzelecki, 2023; Yilmaz et al., 2023). However, the use of GPTs varies in each field and is influenced by the branch of science, including chemistry, so specific understanding in each discipline is still needed. The use of GPT in chemistry learning is influenced by several things, namely motives for use, assessment of response quality, and constraints. These three things can affect usage intention behavior (Ardyansyah et al., 2024). However, it is not yet known how much influence each factor has and the relationship between them. Therefore, this research studied the relationship between motivation and GPT quality perspective on frequency of use. The results of this study can show the relationship between the three variables and explain how much influence they have. Through the results of this study, in the future, the frequency of a person's GPT use can be predicted based on motivation and perspective of response quality in the context of chemistry learning. These results can be a consideration in providing interventions that need to be done in learning, which will also impact the formulation of policies related to GPT.

2. RESEARCH METHODS

Design

This research is included in correlational research, aiming to predict or explain the relationship between two or more variables. More specifically, this research uses the multiple regression analysis method because two predictor variables are used to determine the criterion variable (Fraenkel et al., 2012). This quantitative research was conducted using a survey as the main instrument related to the following three variables: motivation, response quality perspective, and frequency of use of GPT. The type of regression used in this study is multiple linear regression. Multiple linear regression is a statistical method to analyze the relationship between one dependent variable and two or more independent variables. In this quantitative research, a survey instrument was used to measure three independent variables: motivation, perspective on response quality, and frequency of use of GPT. Using multiple linear regression allows researchers to understand how much the three variables simultaneously influence the dependent variable under study. This study defines motivation as a person's motivation to use GPT. The response quality perspective is defined as the user's perception of the answer or response provided by GPT. Meanwhile, the frequency of use of GPT is defined as the time described by the level of use of GPT by participants.

Participants

The sampling technique used was convenience sampling (Creswell, 2012). The sample of this study was 58 chemistry students from chemistry and chemistry education programs from three levels, namely undergraduate, master, and doctoral. Questionnaires were distributed through flyers on social media containing links to fill out questionnaires and respondent requirements. Respondent requirements include students majoring in chemistry and using GPT for chemistry learning.

Instrument

This data collection uses a self-assessment questionnaire developed by researchers based on previous research (Ardyansyah et al., 2024). The questionnaire is in the form of a Likert scale totaling eight questions, including one question related to frequency, four questions related to the perspective of the answer assessment, and three questions related to motivation. The following is the content of the items used in the questionnaire. Questions related to frequency of use were asked, "How often do you use GPT in chemistry learning?". Meanwhile, the perspective section related to response quality was asked through the following four questions.

1. How accurate is the GPT in giving the answers?
2. How relevant does GPT answer?
3. The language used by GPT is easy to understand.
4. How confident are you in the answers provided by GPT?

For the motivation variable, the following three questions were asked.

1. The presentation of the GPT answer encouraged my thinking.
2. The existence of GPT increases motivation in learning chemistry.
3. The use of GPT makes it easier for me to do independent learning.

Each Likert scale has 5 rating points (1 = strongly disagree, 5 = strongly agree). For some items consisting of several questions, the average of each pin was calculated to get the final aspect score.

Procedure

Participants voluntarily accessed and filled out the online questionnaire via a provided link. The data collection process ensured anonymity and informed consent from participants.

Data Analysis

The analysis was descriptive statistical analysis to provide an initial overview of the survey results obtained, then continued with correlation and regression analysis to explain the relationship between existing variables. In determining the strength of the relationship between variables, the coefficient of determination (R^2) is obtained by squaring the correlation coefficient value (r) (Pratiwi et al., 2024). We also use Orange Data Mining to visualize our analysis results.

3. RESULTS AND DISCUSSION

Results

Based on the survey results, the demographics of respondents can be categorized based on study program, education level, and year of study. Regarding study programs, 13 respondents were from the Chemistry department, and 43 were from Chemistry Education. Regarding education level, the majority of respondents came from the Bachelor level 38 people, followed by the Master level as many as 17 people, and only one respondent came from the Doctoral level. Based on the year of study, 27 respondents were in the first year, nine respondents in the second year, 12 respondents in the third year, and eight respondents were in the fourth year or more.

The descriptive statistical analysis results show that user motivation in utilizing GPT is relatively high, with a mean value of 3.70 (SD = 0.69) out of a maximum scale of 5.00. This finding indicates a strong internal drive from users to utilize this generative AI technology. This result is also not much different from other studies that show student motivation has a mean value of 3.88 (SD = 0.87) (Munoz et al., 2023) and 3.90 (SD = 0.93) (Ali et al., 2023). Although the mean score in this study is lower than that of the previous studies, the motivation level for using GPT is a valuable tool in AI technology. Meanwhile, the evaluation of GPT response quality showed positive results with an average of 3.40 (SD = 0.62), with a range of values from 1.75 to 4.75. This data reflects a reasonably good level of user satisfaction with the output produced by the GPT language model. This result is similar to research showing that chemistry students tend to be in the middle of both camps, positive and negative (Young et al., 2024). In addition, students tend to be positive towards GPT with an understanding of its limitations (Hamid et al., 2023). This suggests that although users are satisfied, they remain critical and realize that AI is not a perfect solution. This balance between appreciation and caution is important to ensure technology is used wisely and responsibly.

Regarding frequency of use, a moderate pattern was found with a mean value of 2.86 (SD = 0.91). The range of usage varied from a minimum of 1 to a maximum of 5, suggesting considerable variation in the intensity of interaction with GPT among respondents. This result also aligns with another study that showed a mean value of GPT usage of 2.63 (SD = 1.2) (Saranza et al., 2024). Interestingly, while the level of motivation and evaluation of response quality showed relatively high values, the frequency of use did not show a comparable pattern. This indicates that motivation and positive perceptions of GPT output quality do not directly correlate with actual usage levels.

In regression analysis, testing regression assumptions is a crucial step to ensure the validity and reliability of the model used in the study. The three main assumptions that need to be tested are residual normality, multicollinearity, and homoscedasticity (Budi et al., 2024; Osborne & Waters, 2003; Williams et al., 2013). The residual normality test is needed to ensure that the model residuals follow a normal distribution, a prerequisite for unbiased and efficient parameter estimation. Multicollinearity needs to be tested to avoid a relationship that is too strong between the independent variables, which may lead to errors in interpreting the contribution of each variable. Meanwhile, the homoscedasticity test aims to ensure that the residual variance remains constant across the range of predictors so that the model does not suffer from heteroscedasticity problems that can lead to errors in statistical inference.

The residual normality test results using the Jarque-Bera test show a statistic of 0.0194 with a p-value of 0.9903. Because the p-value is much greater than 0.05, there is no evidence that the residuals deviate from the normal distribution, so the assumption of residual normality is met. Furthermore, the multicollinearity test analyzed through the Variance Inflation Factor (VIF) shows that the Motivation variable has a VIF value of 1.56. At the same time, the Response Quality Evaluation also has a VIF of 1.56. Since the VIF value is below 10, it can be concluded that there is no multicollinearity problem in this model, so the two independent variables can be used together without distorting parameter estimation.

Finally, the homoscedasticity test using the Breusch-Pagan test yields a p-value of 0.7577, greater than 0.05. This indicates that there is no evidence of heteroscedasticity in the model, so it can be concluded that the residual variance is constant and the assumption of homoscedasticity is met.

Based on the results of this assumption test, the regression model in this study meets the requirements of a good regression analysis. Regression analysis results can be interpreted more accurately and validly with the assumptions of residual normality, the absence of multicollinearity, and the fulfillment of the assumption of homoscedasticity. This provides a strong basis for understanding the relationship between motivation, response quality evaluation, and frequency of GPT use in chemistry learning. Furthermore, correlation and regression tests were conducted.

Table 1. Results Correlation And Regression Analysis Test

Test Analysis	Results	Description
Correlation		
Motivation with response quality evaluation	$r(58) = 0.59$ $p < .001$	Shows a moderately strong positive relationship
Frequency of GPT use with response quality evaluation	$r(58) = 0.49$ $p < .001$	Shows a moderately strong positive relationship
Frequency of GPT use with motivation	$r(58) = 0.32$ $p < 0.01$	Shows a moderately strong positive relationship
Regression		
Motivation	$\beta = 0.21$ $p < 0.01$	Significant predicts the dependent variable
Response quality evaluation	$\beta = 0.57$ p < p.001	Significant predicts the dependent variable
R^2	0.25	The two predictor variables could explain 25% of the variability in the frequency of GPT use.

Discussion

The results of the correlation test analysis showed a positive relationship between motivation, frequency of GPT use, and evaluation of response quality in Table 1. The correlation between motivation and response quality evaluation showed a moderately strong relationship, $r(58) = .59$, $p < .001$. Meanwhile, frequency of GPT use was also positively correlated with response quality evaluation, $r(58) = .49$, $p < .001$, as well as with motivation, $r(58) = .32$, $p < .01$. Regression analysis showed that motivation ($\beta = .21$, $p < .01$) and evaluation of response quality ($\beta = .57$, $p < .001$) significantly predicted the dependent variable. The R^2 value of .25 indicated that the two predictor variables could explain 25% of the variability in the frequency of GPT use. Response quality evaluation played a greater role than motivation in the frequency of GPT use.

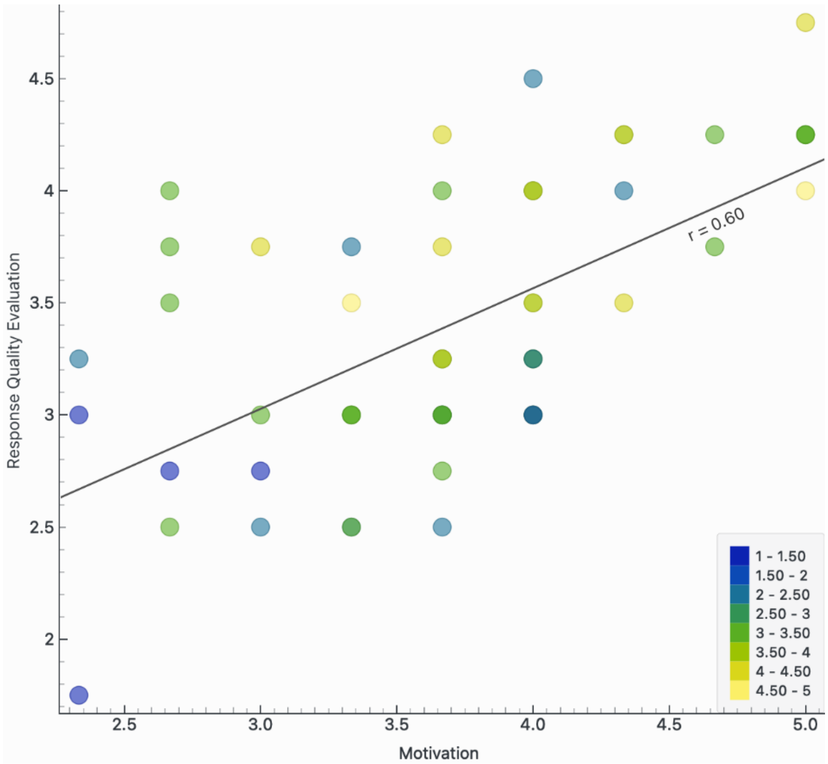

Figure 1. Scatter plot of the relationship between frequency, response quality evaluation, and motivation.

Figure 1 shows the relationship between students' motivation in using GPT in chemistry learning and their response quality evaluation, with the color scale in the diagram indicating the frequency of use on a scale from 1 to 5. Based on the scatter plot, a positive trend indicates that the higher the motivation, the better the evaluation of response quality provided by students. This is supported by the results of the correlation analysis, which showed a significant positive relationship ($r = .59$, $p < .001$). Further analysis showed that motivation explained approximately 34.81% ($R^2 = .35$) of the variability in response quality evaluation. In addition, the colors in the scatter plot represent the frequency of GPT use in learning. Lighter colors indicate a higher frequency of use, while darker colors indicate a lower frequency. From this visualization, it can be seen that students with a higher frequency of use tend to have higher motivation. However, the relationship between motivation and frequency of use is weaker than between motivation and response quality evaluation ($r = .32$, $p = .015$). Frequency of use only explained about 10.24% ($R^2 = .10$) of student motivation variability. Overall, these figures support the finding that college students' motivation plays a role in improving AI response quality assessment. However, it is not necessarily closely related to the frequency of use of GPT.

The results of this study indicate that the higher the response quality perspective of GPT, the more frequently students use it in chemistry learning. However, motivation was not the main factor in determining the frequency of GPT use. This indicates that students are more likely to use GPT if they rate the response quality as high (positive), regardless of their initial motivation level. Another factor influencing interaction with ChatGPT is baseline knowledge or prior knowledge (Dindorf et al., 2024). A person can interact a lot with ChatGPT if he/she understands and can respond to GPT's response, so prior knowledge is essential.

In addition, since the judgment of response quality is also influential, students also need to understand that to produce relevant responses, an understanding of prompt engineering is required (Clark & Tafini, 2024). Other factors may emerge and could be investigated further. These findings are relevant for understanding the factors that can increase the adoption of AI-based technologies in chemistry learning and lead to recommendations for improving the quality of GPT to make it more effectively used by students.

4. CONCLUSION

Correlation analysis results showed a significant positive relationship between motivation and response quality evaluation ($r(56) = .59$, $p < .001$) as well as between response quality evaluation and frequency of GPT use ($r(56) = .49$, $p < .001$). However, the relationship between motivation and frequency of GPT use was weaker ($r(56) = .32$, $p = .015$). Regression analysis showed that evaluation of response quality significantly predicted the frequency of GPT use ($\beta = .57$, $p < .001$). In contrast, motivation had a more negligible effect ($\beta = .21$, $p < .01$). The R^2 value of .25 indicated that both predictor variables could explain 25% of the variability in the frequency of GPT use. GPT performs well in providing answers, and this can help increase user motivation. However, there are still challenges in encouraging users to use the GPT regularly. While there is a positive relationship between motivation and the quality of the answers received, this relationship is not direct, as frequency of use is an influence. Users who use the GPT more frequently tend to give better ratings. However, the variation in ratings suggests other factors, such as user expectations, task difficulty, or understanding of how the system works. Therefore, the development of GPT-based systems should focus on technology and things that can encourage the more active and consistent use of GPT.

In addition, this study has limitations on the gap in results between motivation and frequency of use, using only questionnaires and no interviews. Motivation is one of the important variables in learning. Although not fully developed, motivation contributes to chemistry learning outcomes (Yudanti & Premono, 2021) and interpersonal intelligence (Cahyani, 2020). Scholarly research indicates that students who effectively use GPT are typically highly motivated and recognize its value in improving their work (Hsu & Silalahi, 2024). Future research can expand the study to explore barriers to GPT utilization further.

5. LIMITATION OF THE STUDY

This study is limited by its small sample size (n=56) and the lack of investigation into external factors that may influence usage patterns. Future research should analyze the causal relationships between the studied variables and expand the sample size for a more comprehensive understanding.

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