

# Becoming Literature Students in the Age of AI: First-Year English Literature Students' Challenges and Digital Learning Practices

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**Abstract.** Being a first-year student in the English Literature Department often face challenges in learning literature and therefore; to overcome the challenges, students have to prepare their learning strategy in learning English literature in the era of digital learning. The research objectives tried to reveal students' challenges and the impact of digital learning practices in literature instruction. This study employed a sequential mixed method beginning with quantitative stages and was then followed by qualitative stages. Participants were 41 students consisting of 22 females and 18 males. Data collection was gathered through questionnaires and interviews. Quantitatively, data analysis used Structural Equation Modelling (SEM) through SmartPLS to evaluate validity and reliability and test hypotheses. Qualitatively, thematic analysis was used to analyze the semi-structured interview with the following steps: data recognition, code generation, theme naming, definition phase and writing the report. The result of the quantitative analysis revealed all indicators have a loading factor value greater than 0.60, indicating they are valid, and the Cronbach alpha value was greater than 0.7, which means all variables were categorized as reliable. Based on hypothesis testing, self-regulated learning does not have a significant influence on academic literacy challenges with a P-value of  $0.737 > 0.05$ . On the other side, self-regulated learning has an effect on AI in literary learning with a P-Value value of  $0.000 < 0.05$ . AI in literary learning has a positive and significant effect on academic literary challenges with P-Value value of  $0.000 < 0.05$ . The result of qualitative analysis revealed students burdened to analyse literature that needs understanding of metaphor and cultural context. Students used AI as a dialogue partner and cognitive scaffold to help them understand literature works with strong self-regulated learning. In conclusion, the strong self-regulated learning was effective when mediated by the use of AI in facing academic literary challenges.

**Keywords:** Self-Regulated Learning, Artificial Intelligence, Academic Literary Challenge

**Abbreviations:** AI: Artificial Intelligence ; SEM: Structural Equation Modelling ; PLS: Partial Least Squares ; AVE: Average Variance Extracted (AVE), CR: Composite Reliability ; NFI: Normed Fit Index

## INTRODUCTION

The first-year student in the English Literature Department is a crucial transition phase that demands critical thinking skills, in-depth textual analysis, and creative writing skills[1], [2]. These three abilities are vital for English literature students because they are required to undergo a radical transformation from language users to literary analysts capable of dissecting English texts rich in metaphor, cultural context, and linguistic complexity[3]. These abilities are a key instrument in facing the academic challenges of literature, where new students often experience academic culture shock when having to interpret classic and contemporary texts with high originality of argument.

Several studies in English Literature show that the success of first-year students in overcoming this initial obstacle is highly dependent on the learning independence and strategies they employ. Self-Regulated Learning encompassing the stages of strategic thinking (forethought), performance monitoring, and self-evaluation, serves as a significant predictor of academic success in complex tasks [4], [5]. In the context of literature, metacognitive strategies and time management have a significant positive correlation with student achievement in learning environments that demand high levels of independence[6].

Furthermore, students with strong self-regulation gravitate to be more resilient when faced with difficult texts[7]. This is particularly crucial for first-year English Literature students often find themselves trapped in academic anxiety due to their unpreparedness for the burden of textual analysis[8], [9]. In the current era, this challenge is further exacerbated by the presence of AI in literature learning. The term "efficiency

paradox" indicates students with weak learning strategies tend to use AI as a substitute for thinking processes, while students with strong self-regulated learning use AI as a dialogue partner to deepen their analysis[10]. Furthermore, digital research tools, online databases, collaborative platforms, and AI writing assistants can be used by students to develop reading skills, literary appreciation, and literary text interpretation, which are part of the development of literary literacy[11]. In conclusion, understanding students combine technology to develop literary literacy competency in the first year is one effort to improve analytical and interpretation of literature works.

Although studies on the integration of AI in English literature are beginning to emerge, there is a gap in the literature that empirically explores how academic challenges and self-regulation strategies interact specifically in the context of literary analysis among first-year students. Most previous research has focused on the effectiveness of AI tools in writing, but has not addressed the intellectual aspects of literature students when confronted with canonical texts amidst the use of AI. Previous studies are unclear on how students' self-learning strategies transform to maintain depth in literary analysis when technology offers instant interpretation. This gap is the primary focus of this study.

This study aims to comprehensively investigate various forms of academic challenges faced and the use of digital learning, including AI by first-year students of the English Literature Study Program in adapting to the demands of literary learning in higher education. To answer the research objectives, this study formulates a problem formulation consisting of 1) what are the learning challenges faced by first-year English literature students, 2) what are the patterns and practices of digital learning applied by first-year students and 3) how they integrate the use of AI in their learning activities.

To response the research problem formulation and objectives, this study used the sequential explanatory mixed-method design begins with quantitative data collection and followed by a qualitative phase to deepen the initial findings. In the first phase, a structured questionnaire was distributed to measure learning challenges, academic literacy development, and AI use patterns among respondents. The statistical data obtained were then further developed in the second phase through semi-structured interviews. This qualitative phase served to deeply explore students' perceptions of the challenges they face and the process of developing their literary literacy amidst the massive use of AI, thus providing a more comprehensive and nuanced view of the phenomenon.

## METHODS

This study investigated students' challenges and strategies for developing academic literary understanding in the era of AI during the first year as students of the English Literature Department. Applying a sequential mixed method using quantitative data collection and followed by qualitative data collection [12], [13]. In the first stage, data collection in quantitative was conducted through the distribution of a structured questionnaire to first-semester students in the English Literature Study Program. This questionnaire instrument was specifically designed to map patterns in three main areas: academic literary challenges, strategies for developing literary literacy skills, and the use of AI in literature learning. After analyzing the quantitative data from the first phase, the research proceeded to the qualitative phase through semi-structured interviews. The interview was conducted with selected participants to gain deeper insights into their experiences. The goal was to find the reasons why students drive the strain between the use of AI, challenges in literature courses and the demands of critical thinking in literary studies.

### Participants

Participants were 41 students who were first-semester students who enrolled in introduction to literary studies course at the English Literature Department. The sample consisted of 22 females and 18 males, with ranging from 18 to 20 years. The sample selection was purposive sampling, where the sample had specific criteria that were highly relevant to the research objectives[13]. Students who were in the early first year's students who adapting to the demands of academic literary analysis and the use of digital tools in their learning literature. Ethical standards were implemented, with all participants informed about the stages and objectives of the study. They were then given a consent form, stating that the students agreed to volunteer as research participants and that their identities would be kept confidential.

### Quantitative Data Collection and Analysis

The quantitative phase of this research was conducted through the distribution of an online questionnaire addressed to all participants. This instrument consisted of 13 questions designed using a Likert scale with options ranging from 1 (strongly disagree) to 5 (strongly agree) to capture data on students' perceptions on challenge in learning English literature. The 13 questions were developed based on three main research variables. First, self-regulated learning strategies were measured through 4 questions (SL1–SL4) covering indicators of planning, performance monitoring, and self-evaluation. Furthermore, 4 questions (A1–A4) consists of frequency of digital tool use, utilization of AI as a mediation resource, and perceptions and

confidence in using AI for literary studies. In addition, academic literary challenges were measured through 5 questions (AI1–AI5) covering indicators of interpretive analysis skills, mastery of academic literacy, and understanding of basic concepts in analyzing complex literary texts.

Data analysis used Structural Equation Modelling (SEM) based on Partial Least Squares (PLS) through SmartPLS. The analysis stage began with an evaluation of the measurement model (outer model) to ensure the validity and reliability of the instrument before hypothesis testing. In this phase, convergent validity is determined based on the outer loading value, which must be greater than 0.60, and the Average Variance Extracted (AVE) value exceeding the threshold of 0.50 for each latent variable [14]. Furthermore, discriminant validity is tested through cross-loading analysis, where decision criteria are determined based on the correlation obtained between indicators with their own variables, which must be higher than their correlations with other latent variables[15]. Instrument reliability is also ensured through construct reliability testing, where variables are declared reliable if the Composite Reliability (CR) and Cronbach's alpha values are consistently above 0.70[14]. After the measurement model was declared eligible, the analysis continued with the evaluation of the structural model (inner model) and hypothesis testing to elaborate on the relationship between self-regulated learning strategies (X), the use of AI (Z), and academic literary challenge (Y). The strength of the model in explaining the variation of endogenous variables was evaluated through the coefficient of determination value, while the overall model suitability was measured using the Normed Fit Index (NFI) value approaching one as an indicator of good fit. To make decisions regarding the proposed hypothesis, this study refers to the path coefficients through the T-statistic and P-value tests, where a relationship is declared positive and significant if the T-statistic value is greater than 1.96 with a P-value below 0.05. Finally, the direction of influence is determined through the original sample value (O), where a number between 0 and 1 indicates a positive relationship and a number between 0 and -1 indicates a negative relationship.

Qualitative Data Collection and Analysis

The qualitative phase was used to elaborate on and provide in-depth understanding of the quantitative results. Data collection was semi-structured interviews with selected participants, with each interview session lasting between 20 and 40 minutes. The objective was to know students' challenges and their learning experiences mediated by AI technology in literature course. Data analysis used thematic analysis techniques which began with the data recognition stage through transcribing interview[16]. The code generation stage was carried out to identify meaningful patterns related to academic literary challenge and the use of digital tools in literature learning. The initial code stage was grouping relevant codes and reviewing them to ensure the relevance of the emerging themes to the entire original data set. After the themes were validated, the theme naming and definition stage was carried out to clarify the boundaries of each finding. This series of analyses concluded with a write-up of a report that presented a comprehensive qualitative narrative explaining how students navigated the use of AI in their efforts to achieve in-depth literary analysis.

## RESULTS AND DISCUSSION

The present study adopted a mixed-methods to find the challenges faced by first-year English Literature students and their interaction digital learning tools, with a particular emphasis on the use of AI in literary learning. The study involved 41 first-semester students (22 females, 18 males) from the English Literature Department, combining quantitative structural equation modeling (SEM) with qualitative thematic analysis. The findings showed that in literature instruction, self-regulated learning, AI and academic challenges interact with each other.

Quantitative Data Analysis

### Result of Convergent Validity

The convergent validity of the measurement model with the reflexive indicator can be seen from the correlation between the item/indicator score and the construct score. Indicators that have an individual correlation value greater than 0.7 are considered valid, but at the development stage of research, the indicator values of 0.5 and 0.6 are still acceptable. The results for outer loading indicate that there is an indicator with a loading below 0.60, which is considered insignificant. The following are the results of the outer loading value in the following table:

**Table 1. Outer Loading**

| Indicator                   | Outer Loading               | Status                      |
|-----------------------------|-----------------------------|-----------------------------|
| Self-Regulated Learning (X) | Self-Regulated Learning (X) | Self-Regulated Learning (X) |
| SL1                         | 0.838                       | Valid                       |
| SL2                         | 0.919                       | Valid                       |

| Indicator                       | Outer Loading                   | Status                          |
|---------------------------------|---------------------------------|---------------------------------|
| SL3                             | 0.909                           | Valid                           |
| SL4                             | 0.879                           | Valid                           |
| Academic Literary Challenge (Y) | Academic Literary Challenge (Y) | Academic Literary Challenge (Y) |
| A1                              | 0.857                           | Valid                           |
| A2                              | 0.767                           | Valid                           |
| A3                              | 0.752                           | Valid                           |
| A4                              | 0.719                           | Valid                           |
| AI in Literary Learning (Z)     | AI in Literary Learning (Z)     | AI in Literary Learning (Z)     |
| AI1                             | 0.857                           | Valid                           |
| AI2                             | 0.875                           | Valid                           |
| AI3                             | 0.817                           | Valid                           |
| AI4                             | 0.789                           | Valid                           |
| AI5                             | 0.810                           | Valid                           |
|                                 |                                 |                                 |

Table 1 shows that all indicators have a loading factor value greater than 0.60. All indicators in this study are valid and can be used for further research. The outer model evaluation confirmed the validity and reliability of all research instruments. Convergent validity testing demonstrated that all indicators possessed outer loading values exceeding the 0.60 threshold, with the self-regulated learning construct showing particularly strong loadings (0.838–0.919). The Academic Literary Challenge indicators ranged from 0.719 to 0.857, while AI in Literary Learning indicators demonstrated strong validity (0.789–0.875). These results indicate that each measurement instrument accurately captured its corresponding construct. The shape of the structural model as shown in the following figure:

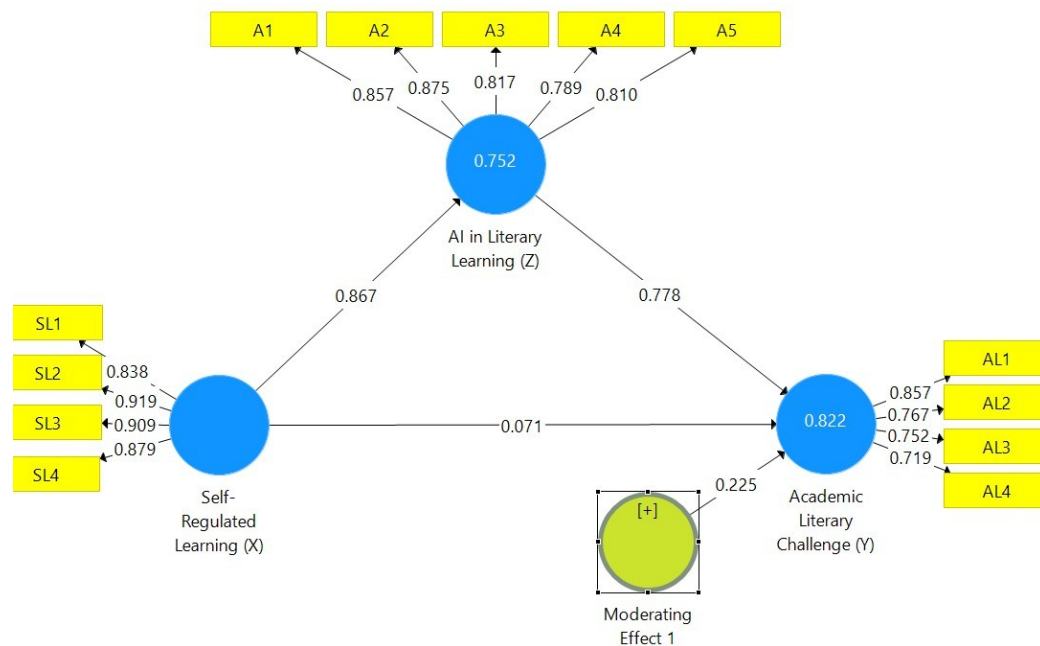


Figure 1. Result of outer model

### Result of Discriminant Validity

The next test is to test the validity of the discriminant; this test aims to determine whether a reflective indicator is a reliable measurement for its contrast based on the principle that the indicator is highly correlated with its contrast. The following are the results of cross-loading from the discriminant validity test as shown in the following table:

Table 2. Discriminant Validity

| Indicator Variables | AI in Literary Learning (Z) | Academic Literary Challenge (Y) | Self-Regulated Learning (X) |
|---------------------|-----------------------------|---------------------------------|-----------------------------|
| A1                  | 0.857                       | 0.735                           | 0.626                       |
| A2                  | 0.875                       | 0.725                           | 0.775                       |
| A3                  | 0.817                       | 0.657                           | 0.785                       |
| A4                  | 0.789                       | 0.709                           | 0.740                       |

| Indicator Variables | AI in Literary Learning (Z) | Academic Literary Challenge (Y) | Self-Regulated Learning (X) |
|---------------------|-----------------------------|---------------------------------|-----------------------------|
| A5                  | 0.810                       | 0.721                           | 0.656                       |
| AL1                 | 0.739                       | 0.857                           | 0.764                       |
| AL2                 | 0.538                       | 0.767                           | 0.501                       |
| AL3                 | 0.596                       | 0.752                           | 0.614                       |
| AL4                 | 0.707                       | 0.719                           | 0.669                       |
| SL1                 | 0.693                       | 0.685                           | 0.838                       |
| SL2                 | 0.865                       | 0.807                           | 0.919                       |
| SL3                 | 0.799                       | 0.739                           | 0.909                       |
| SL4                 | 0.703                       | 0.726                           | 0.879                       |

Based on table 2, it can be seen that the cross-loading value in each indicator and variable is greater than other variables and indicators; the cross-loading of the AI in the literary learning variable shows that the cross-loading of the variable indicator is greater than the cross-loading of other latent variables. Cross-loading of the academic literary challenge variable indicator showed that the value of the cross-loading indicator was greater than other latent variables. Self-regulated learning cross-loading also showed a higher value for the cross-loading indicator than the latent variable cross-loading. Based on this data, it can be stated discriminately that the results of cross-loading are considered valid. Based on these criteria, self-regulated learning, academic literary challenge and AI in literary learning were variables that have a value greater than 0.70, indicating that they meet the reliability requirements for the construct.

### Composite reliability Result

The reliability value was used based on the composite reliability of the indicator block that measures the construct. A construct is considered reliable if the indigo composite reliability exceeds 0.60. In addition to looking at the composite reliability value, the reliability value can be seen in the value of the variable construct with the Cronbach's alpha of the indicator block that measures the construct. A construct is declared reliable if the Cronbach's alpha value is above 0.7. The following is a table of loading values for the construct of research variables resulting from running the Smart PLS program in the following table:

**Table 3. Construct Reliability and Validity**

| Variables                       | Cronbach's Alpha | Composite Reliability | Average Variance Extracted (AVE) |
|---------------------------------|------------------|-----------------------|----------------------------------|
| AI in Literary Learning (Z)     | 0.887            | 0.917                 | 0.689                            |
| Academic Literary Challenge (Y) | 0.779            | 0.857                 | 0.601                            |
| Self-Regulated Learning (X)     | 0.909            | 0.936                 | 0.786                            |

*Note: Output Smart PLS, 2026*

Based on table 3, it can be explained that the AVE value of each variable tested has a value of  $> 0.5$ , which shows that all variables in this study meet the criteria of discriminant validity. To determine the reliability in this study, the composite reliability value was used. The accepted value for the reliability level is  $> 0.7$ . Composite reliability testing yielded values well above the 0.70 threshold: Self-Regulated Learning (CR = 0.936,  $\alpha = 0.909$ ), AI in literary learning (CR = 0.917,  $\alpha = 0.887$ ), and academic literary challenge (CR = 0.857,  $\alpha = 0.779$ ). Additionally, average variance extracted values exceeded 0.50 for all constructs (self-regulated learning = 0.786, AI = 0.689, and ALC = 0.601), satisfying the requirements for construct reliability and convergent validity. This result collectively demonstrated the measurement model was robust and suitable for hypothesis testing.

Evaluation of the structural model (inner model) is carried out to ensure that the structural model is built robust and accurate. The stages of analysis carried out in the evaluation of structural models are seen from several indicators, namely:

### Determination Coefficient Test Results (R<sup>2</sup>)

The determination coefficient test (R<sup>2</sup>) is used to see the influence of certain independent latent variables on the dependent latent variable, whether it has a substantive influence. Based on the data processing that has been carried out using the SmartPLS 3.0 program, the R Square value is obtained as in the following table.

**Table 4. R Square Results**

| Variable                        | R Square | Adjusted R Square |
|---------------------------------|----------|-------------------|
| AI in Literary Learning(Z)      | 0.752    | 0.749             |
| Academic Literary Challenge (Y) | 0.822    | 0.816             |

*Note: Output Smart PLS, 2026*

Based on table 4, it is known that the R-squared adjusted value of the AI in the literary learning variable is 0.749 or 74.90%, which means that the influence of self-regulated learning on AI in literary learning is in the high category. This means that the more self-regulated learning increases, the more AI in literary learning will increase. Meanwhile, the R-squared value in the variable AI in literary learning is 0.752 or 75.20%, which means self-regulated learning to AI in literary learning is 75.20%. The value of R-squared adjusted for the academic literary challenge variable is 0.816 or 81.60% which means that self-regulated learning affects the academic literary challenge by 81.60% or in the very high category, which means that self-regulated learning significantly increases the academic literary challenge. Furthermore, the R-squared value of the academic literary challenge variable was 0.822 or 82.20%, which means that self-regulated learning affected the academic literary challenge by 82.20%, while the remaining 18.80% was influenced by other variables that had not been researched.

### Goodness of Fit Result

The goodness of fit test is a statistical method used to evaluate how well the model or statistical distribution being tested is in accordance with the observed data. The goodness-of-fit test aims to determine the extent to which the observed data corresponds to the theoretical distribution assumed by the model or hypothesis. The goodness-of-fit model test can be seen by looking at the NFI value in the program. If the NFI value > SRMR and is closer to 1, then the better the model (good fit). Based on the data processing that has been carried out using the SmartPLS 3.0 program, the model fit value is obtained as follows.

**Table 5. Model Fit**

|            | Saturated Model | Estimated Model |
|------------|-----------------|-----------------|
| SRMR       | 0.111           | 0.117           |
| d_ULS      | 1.116           | 1.256           |
| d_G        | 1.543           | 1.534           |
| Chi-Square | 482.171         | 498.979         |
| NFI        | 0.608           | 0.594           |

Note: Output Smart PLS, 2026

Based on table 5, it can be seen that the NFI value is  $0.608 > 0.117$  so that it can be stated that the model in this study has sufficient goodness of fit and is suitable to be used to test the research hypothesis

### Hypothesis Testing

Internal model analysis was carried out to evaluate the relationship between latent constructs in order to answer the hypothesis in this study. The hypothesis test in this study was carried out by looking at T-Statistics and P-Values values. The hypothesis is stated to be accepted if the T-Statistics value is  $> 1.96$  and the P-Values  $< 0.05$ . The following are the results of Path Coefficients of direct influence between variables as shown in the following table.

**Tabel 6. Path Coefficients (Direct Effect)**

|                                                                | Original Sample (O) | Sample Mean (M) | Standard Deviation (STDEV) | T Statistics ( O/STDEV ) | P Values |  | Result   |
|----------------------------------------------------------------|---------------------|-----------------|----------------------------|--------------------------|----------|--|----------|
| Self-Regulated Learning (X) -> Academic Literary Challenge (Y) | 0.071               | 0.072           | 0.212                      | 0.337                    | 0.737    |  | Rejected |
| Self-Regulated Learning (X) -> AI in Literary Learning (Z)     | 0.867               | 0.871           | 0.026                      | 32.975                   | 0.000    |  | Accepted |
| AI in Literary Learning (Z) -> Academic Literary Challenge (Y) | 0.778               | 0.732           | 0.157                      | 4.937                    | 0.000    |  | Accepted |

Note: Output Smart PLS, 2026

Table 6 data indicated a positive but insignificant effect of self-regulated learning on academic literary challenges. This can be seen from the T-statistical value of  $0.337 < 1.96$  with a P-value of  $0.737 > 0.05$ . This means that self-regulated learning does not have a significant influence on academic literary challenges. This result answers the first hypothesis in this study, namely that self-regulated employee

learning does not have a positive and significant effect on academic literary challenge in literature instruction. Furthermore, on the effect of self-regulated learning on AI in literary learning, T-Statistics value data was obtained  $32.975 > 1.96$  with a P-Value value of  $0.000 < 0.05$  so that it can be stated that self-regulated learning has an effect on AI in literary learning. This can be interpreted that if self-regulated learning is improved, the use of AI in literary learning will increase. This statement explores the second hypothesis, namely that self-regulated learning has a positive and significant effect on AI in literary learning.

Regarding the influence of AI in literary learning on academic literary challenges, data was obtained that the T-Statistic value was  $4.937 > 1.96$  with a P-Value value of  $0.000 < 0.05$  which means that AI in literary learning has a positive and significant effect on academic literary challenges. This indicates that the use of AI in the context of literary learning significantly helps students in facing or solving student challenges in learning and improving literary literacy.

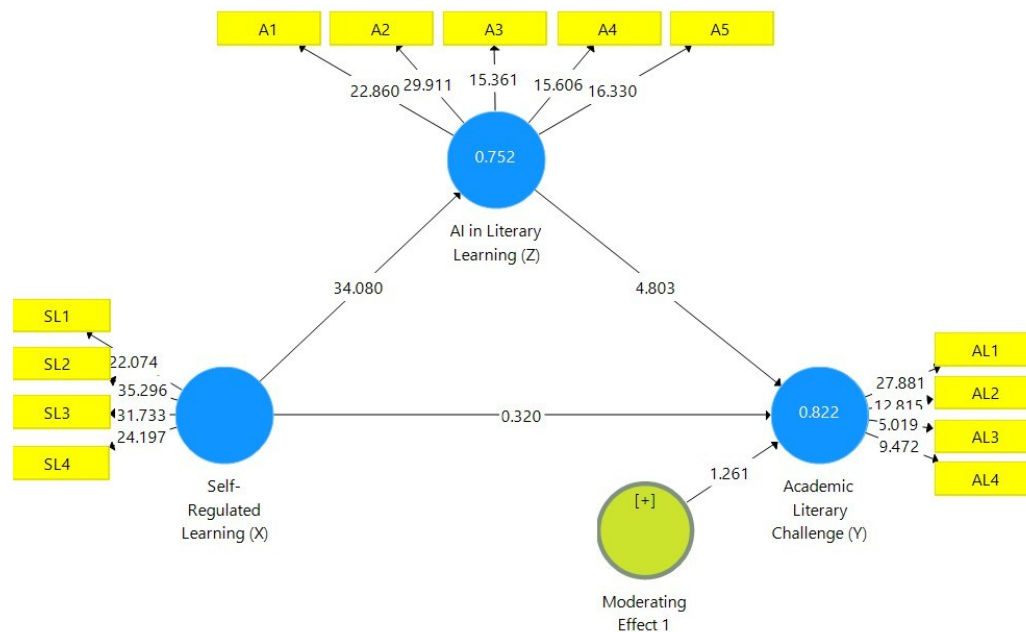


Fig 2. Result of Path Coefficients

Table 7. Indirect Effect

| Variabel                                                                                     | Original Sample (O) | Sample Mean (M) | Standard Deviation (STDEV) | T Statistics ( O/STDEV ) | P Values | Result   |
|----------------------------------------------------------------------------------------------|---------------------|-----------------|----------------------------|--------------------------|----------|----------|
| Self-Regulated Learning (X) -> AI in Literary Learning (Z) -> Academic Literary Challenge(Y) | 0.524               | 0.525           | 0.135                      | 3.884                    | 0.000    | Accepted |

Note: Output Smart PLS, 2026

Based on the results of the analysis of the indirect influence hypothesis testing, it shows that self-regulated learning (X) has a significant influence on academic literary challenges (Y) through the mediation of AI in literary learning (Z). The original sample value of 0.524 indicates a positive and quite strong direction of influence. This means that the involvement of AI in literary learning is able to bridge students' learning independence in facing academic literary challenges effectively. The T-statistic value was recorded at 3.884, which far exceeds the critical threshold of  $T > 1.96$ , reinforced by the significance of the results reinforced by the P-Values value of 0.000 ( $P < 0.005$ ). These findings provide empirical evidence that the indirect influence hypothesis in this study is accepted. Conceptually, these results confirm that the process of transforming students' cognitive capacity does not only depend on independent self-regulation but is strengthened through the integration of AI technology in the literary pedagogical ecosystem. This study's results indicate that the use of targeted AI can help literature students overcome academic challenges in their higher education literature courses.

## Qualitative

## Data

## Collection

In this study, the qualitative phase was conducted to strengthen findings based on the quantitative analysis. Qualitative data were collected through semi-structured interviews with purposively selected participants from a total of 41 first-year English literature students taking the introduction to literary studies course. Interview session conducted between 20 and 40 minutes that focused on students' experiences with AI digital learning practices and literary challenges. Following interview data collection, the analysis phase consisted of interview transcription, grouping relevant codes, and reviewing emerging themes to ensure the relevance of the overall original data set. After the theme was validated, the naming and definition phase were conducted to clarify the boundaries of the findings, and three main themes emerged that illustrate students' journeys in integrating AI to address academic challenges in their first year of college. These themes are presented as follows.

Theme 1: Academic Culture Shock and Text Complexity.

This theme explains why self-regulated learning is insufficient to significantly impact the resolution of challenges without assistance from digital tools. This condition happened because students feel burdened by the demands of shifting from mere language users to literary analysts who must dissect texts rich in metaphor and cultural context.

Honestly, reading classical poetry texts this first semester felt like academic culture shock. I know English, but I felt incredibly anxious because the burden of textual analysis was so heavy. I tried to study independently, but the complexity of the language often made me stuck, while I had to reveal the hidden meanings in the poetry. I felt my usual study strategies were no longer adequate. (Informant 3, Male)

Theme 2: AI as a Dialogue Partner and Cognitive Scaffold

This theme confirms the statistical findings that the use of AI significantly assists students in addressing literature challenges. Students with strong self-regulation use AI as a discussion partner to deepen their analysis, rather than as a substitute for their thinking processes.

"I do not use AI to write my answers. I treat it as a 'dialogue partner'. I ask it for my interpretations, and then we discuss them. Furthermore, AI helps me see patterns in literary works. It acts as a bridge for me to understand the difficult theories taught in 'Introduction to Literary Studies' course. This helps me achieve a depth of analysis that I would have previously found difficult to do on my own".

Theme 3: Transforming Learning Strategies in the Digital Era

This theme explains the relationship between self-regulated learning and how students strategically integrate AI technology. The transformation of student learning is strengthened by combining self-regulated learning with AI technology in literature instruction.

"My learning strategy has changed. I plan which parts I will analyze for myself and which parts need AI assistance to strengthen my perspective. I used to think AI was a shortcut, but it turns out that if we have self-control, AI actually helps us be more independent in evaluating our understanding of literary works. This makes me more confident in facing literary analysis assignments."

The qualitative findings provide an explanation for the quantitative results tested in the previous phase. Student interviews confirmed that the insignificant direct effect of self-regulated learning on academic challenges was due to the high cognitive load and culture shock experienced by first-year students when confronted with literary texts. In these circumstances, independent learning alone is insufficient without the support of tools capable of facilitating the interpretation of complex literary texts. The interviews clarified the correlation between self-regulated learning and AI use was not coincidental, but rather the result of students' adaptation of their learning strategies. Students with high self-regulation transformed AI from a mere efficiency tool into a cognitive dialogue partner that helped them analyze literature more deeply. Thus, these qualitative data successfully demonstrated that the learning transformation process of literature students in the digital age does not occur in isolation. Through the mediation of AI technology integrated into the literature learning ecosystem, students are able to bridge the gap between their initial abilities and the high academic demands of higher education, which include critical analysis, interpretation of complex texts, and effective communication of their insights. These qualitative findings also demonstrate that the involvement of AI is key to students' success in handling the complexities of literature learning in their first year.

## Discussion

This study investigated the students' challenges in learning literature as the first-year students in the English Literature Department. Quantitative findings show students faced significant challenges in analyzing and completing literary works. The results of the hypothesis test indicate that AI serves as a successful mediator between self-regulated learning and academic challenges (T-statistic: 3.884; P-value: 0.000). Self-regulated learning did not have a significant effect on challenge completion but became highly effective when mediated using AI. Qualitative results indicate that students who successfully integrated AI

treated it as a dialogue partner to deepen their analysis of literary texts. This integration enabled students to align their knowledge with the requirements of literary text analysis. In addition, the result was confirmed through validity in A1-A4 indicators that have a loading factor above 0.60. The quantitative result was confirmed with qualitative findings. Students experienced academic culture shock, which was burdensome due to the transition from being language users to analyzing literature that is rich in metaphor and cultural complexity. This lack of preparation triggers academic anxiety for students when producing original arguments in their analysis of literature. Meanwhile, this study found a correlation between self-regulated learning and the use of AI in literary learning. The R-squared value of 0.752 shows that students' self-regulated learning accounts for 75.20% of the differences in how they use AI to learn literature. Qualitative results confirmed the quantitative findings, revealing students' use of AI assistants. Students with strong self-regulation used AI in literary learning to learn about self-performance and self-evaluation, rather than simply seeking shortcuts, which allowed them to enhance their learning outcomes and develop a deeper understanding of the literature.

This study confirmed students' challenge in learning literature and literature literacy in literature instruction. The findings of this study assuming student's difficulties in analyzing literature texts were relevant to previous research revealed that first-year students often fall into a superficial learning approach because they have not yet mastered the academic literacy conventions necessary for reading deeper meaning [17]. The positioning of AI in learning is also highlighted, strengthening AI function as a scaffold. The qualitative results position AI as a dialogue partner in line with the deep learning framework which depicted using generative AI improved cognitive regulation and prevented students from getting shortcuts[18]. The result aligned with findings in this research that students with high self-regulated learning use AI for self-evaluation, not simply for shortcuts. Furthermore, the position of AI as a mediator of self-regulated learning provides a new nuance. The classical theory of self-regulated learning assumes that directly improved students' performance in the learning environment. However, this study provides new empirical evidence that aligns with previous study focused on AI and self-regulated learning that the result found AI-based learning environments, learning engagement acts as a mediating chain that makes self-regulated learning strategies effective [19]. The finding revealed that self-regulated learning is only effective when mediated by AI reinforces the theoretical shift that in the digital age, self-regulation skills must be realized through the ability to interact with AI technology.

Furthermore, the implications of this research demonstrate the urgency for a transformation of the scaffolding model in literary studies. This research showed that the obstacle for first-year students is the cognitive load between linguistic ability and analytical depth in the context of literary analysis. This research reveals that AI is no longer viewed as a threat, but rather as a crucial digital scaffold. AI can be used intensively to help students dissect the complexities of literary texts.

## CONCLUSION

This study concludes that first-year English literature students face a challenging transition that triggers academic culture shock when transforming from language users to literary analysts. Quantitative findings indicated self-regulated learning did not significantly influence academic literary challenge. However, self-regulation becomes highly effective when mediated by the use of AI in literature instruction. Students' self-regulation plays a key role, with variations in AI use determined by the level of learning independence. Qualitatively, students with strong self-regulation do not use AI as a shortcut but rather as a dialogue partner to deepen text analysis and conduct self-evaluation. Finally, targeted AI integration serves as a crucial cognitive scaffolding in helping students overcome academic challenges and strengthen their literary literacy in the digital age.

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