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# Improving Vocational Students' Outlining Skills Through Perplexity AI

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**Abstract**

Outlining is an important part of analytical exposition writing, which enables students to plan and organize their ideas. However, the students' arguments in vocational high schools are not organized well, and research on AI-assisted outlining has been limited in vocational secondary education. This study aimed to investigate the impact of the outlining instruction using Perplexity AI on students' outlining skills for analytical exposition texts. The quasi-experimental pre test – post test design involving 64 vocational high school students in grade 10 was used. Students' outlining performance was assessed using an analytic outlining rubric. Improvements were found in both groups, with the experimental group significantly outperforming the control group. An independent-sample t-test found significant gain scores ($p < .05$), and effect size analysis showed a very large effect (Cohen's $d = 1.05$). The results indicate that the use of Perplexity AI is an effective tool for outlining performance on EFL writing tasks.

**Keywords:** *Perplexity AI, outlining instruction, outlining performance, analytical exposition writing, EFL learners*

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## INTRODUCTION

Education has a significant role in equipping students for future academic, career, and social success in the twenty-first century. A sign of good learning is when pupils can communicate clearly and think critically in their answers to different questions. In English as a Foreign Language (EFL) learning, writing is one of the fundamental skills that underpins these qualities as it enables learners to voice their opinions, form arguments, and convey information in a structured way (Cherry Chan, 2025; Fang, 2021). But writing is a complex skill because students need to think of ideas, organize information, and present ideas in a coherent way. Compared to other types of texts taught in EFL classrooms, analytical exposition writing requires students to have a certain level of organization in order for them to build logical arguments to win the readers' belief (Harefa & Zebua, 2023; Vilar & Tolchinsky, 2022). Thus, it is important to plan and organize ideas in order to create an analytical exposition text that is well structured.

In the process-oriented approach to writing, writing does not end with the finished product, but rather involves a chain of related processes such as planning, drafting, and revising (Nunan, 2003). Of these stages, planning is very important as students must brainstorm, cluster, and plan their thoughts before they can write a full text. A common type of planning is outlining, which enables students to organize main ideas and supporting arguments in a logical way (Damayanti et al., 2025). Students can use outlining to "see" how

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their texts are organized and make clear connections between ideas before writing. But for many students, there are problems in constructing and arranging arguments properly (de Smet et al., 2023), especially when producing analytical exposition texts that require logical thinking and coherent argumentation. Thus, there is a need for instructional support to enhance the students' outlining skills and produce well-structured written texts.

Education is constantly evolving with the changing needs of the learners in a modern-day society. In conjunction with the above developments, the use of technology in learning processes has gained significance in supporting learning and teaching. In English language learning, technology becomes a common use in making students' learning process easier, and also as an additional tool in the process of doing complex learning activities (Rashtchi & Porkar, 2020). In writing instruction, technological tools can help students more effectively brainstorm more ideas, organize information, and plan more and better texts (Siregar et al., 2022). In addition, technology can offer some extra instructional support and learning options in addition to classroom instruction.

Artificial intelligence (AI) has revolutionized the field of education in several ways, such as in language learning and writing teaching. Beyond its role as a text generator, AI has been used more as a teaching aid to help learners control complicated text generation (Kuddus, 2022). AI-powered tools have been shown to help with idea generation, content structure, and planning in the writing process, as of late. AI writing support is especially valuable in EFL environments, where teachers might not have the expertise or resources to deliver the support needed in class (Son et al., 2023). Hence, there is an interest in employing AI in the teaching of writing as a means of helping students in planning their writing.

Outlining is a crucial stage in analytical exposition writing because it enables students to organize ideas, formulate a clear thesis, sequence arguments logically, and establish coherent relationships before drafting a complete text. However, many vocational high school students still experience difficulties in generating, organizing, and developing ideas, resulting in outlines that are incoherent, lack logical progression, and remain incomplete (Asep Saepuloh, 2023). These challenges are exacerbated by limited instructional support during the planning stage, as writing instruction in vocational high schools often emphasizes task completion rather than guiding students through the process of planning and organizing ideas due to practical learning goals and limited instructional time (Sartika et al., 2023). Consequently, students are expected to construct outlines independently with minimal teacher guidance. To address these challenges, AI-assisted writing tools have increasingly been introduced to support writing instruction. Among them, Perplexity AI provides interactive prompts and organizational suggestions that facilitate brainstorming, argument development, and idea organization, making it a promising instructional tool for improving students' outlining performance in analytical exposition writing (Accad et al., 2025).

From a cognitive perspective, outlining is a complex planning activity that requires students to generate, evaluate, and organize ideas into a coherent structure before drafting (Gayed et al., 2022). This process is consistent with Cognitive Load Theory, which posits that learning becomes more effective when instructional support helps learners manage complex cognitive demands and focus on essential learning processes (Sweller et al., 2011). In this context, AI-assisted writing tools function as instructional scaffolds by providing structured prompts, guided questioning, and organizational support that reduce unnecessary cognitive load while enabling students to concentrate on idea development and argument organization (Brünken et al., 2003; Wan et al., 2024). Accordingly, Perplexity AI offers a practical form of such scaffolding by supporting students in exploring, organizing, and refining their own ideas under teacher supervision rather than generating complete texts for them (Krajka & Olszak, 2024). Although previous studies have investigated AI integration in writing instruction (Schmidt & Strassner, 2022; Son et al., 2023; Venugopal & Mamatha, 2023), most have

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focused on writing products rather than outlining as an independent planning process, while vocational high school students and the educational application of Perplexity AI remain underrepresented in the literature.

**Outlining Instruction**

Outlining instruction refers to instructional practices that support students in planning and organizing ideas before drafting by providing systematic guidance to identify key ideas, establish relationships among concepts, and arrange arguments into a coherent structure (Suliman Saeed et al., 2020). Within process-oriented writing instruction, effective outlining instruction incorporates explicit modeling and scaffolding to help learners generate ideas, sequence arguments, and maintain logical coherence, thereby reducing the cognitive demands associated with writing tasks (Siahaan et al., 2025). Previous studies have shown that structured outlining activities contribute to improved organization and coherence in students' writing (Aljafen, 2025). With the growing integration of educational technology, outlining instruction can also be supported through digital tools that provide organizational prompts and structured guidance, enabling students to engage more actively in the planning process before composing their texts.

**Perplexity AI in Writing Instruction**

Perplexity AI is an artificial intelligence-based platform that combines natural language processing with information retrieval to generate synthesized responses supported by references, enabling learners to explore information and alternative perspectives through interactive dialogue rather than conventional keyword-based searching (He et al., 2025). In writing instruction, AI-assisted tools can support the planning stage by facilitating idea generation, content exploration, and organizational development while helping students identify relevant arguments, evaluate relationships among ideas, and develop a clearer conceptual structure before drafting (Koç & Savaş, 2025). Within outlining instruction, Perplexity AI functions as an instructional scaffold by guiding learners to explore arguments, identify supporting evidence, and organize ideas into a coherent outline, thereby fostering more systematic planning and supporting the development of effective analytical exposition texts (Demartini et al., 2024).

**Analytical Exposition Writing**

Analytical exposition writing is an essential genre in EFL instruction because it requires students to present and justify a particular viewpoint through logical reasoning, coherent organization, and persuasive argumentation, distinguishing it from descriptive and narrative writing (Salima & Hidayat, 2020). Its primary purpose is to convince readers that a particular position is reasonable and justifiable (Zuana, 2020), requiring students to evaluate information, determine the relevance of evidence, establish logical relationships among ideas, and organize arguments systematically (Ritonga et al., 2025). These demands involve higher-order thinking skills, including analysis, evaluation, and reasoning, making analytical exposition one of the most cognitively challenging writing genres in EFL contexts (Hardianti et al., 2023). From a genre-based perspective, analytical exposition texts consist of three interconnected components: (1) thesis, (2) arguments, and (3) reiteration, which function to establish the writer's position, support it with logical reasoning and evidence, and reaffirm the central claim; however, maintaining coherence across these components remains challenging for many learners (Yuningsih & Novarita, 2020).

Previous studies have shown that many EFL learners experience difficulties in producing effective analytical exposition texts, particularly in developing arguments, selecting relevant supporting evidence, and maintaining logical progression, resulting in texts that often lack coherence and persuasive power despite containing appropriate language forms (Mertosono, 2023; Nurlatifah & Yusuf, 2022). In many cases, ideas are presented without sufficient justification or are arranged in ways that weaken the coherence of the

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overall argument (Rahman & Ekka, 2024). These challenges indicate that successful analytical exposition writing depends not only on linguistic competence but also on effective planning and organization before drafting, as inadequate preparation frequently leads to fragmented arguments, repetitive ideas, and weak textual organization (de Smet et al., 2023).

## METHOD

### Research Design

This study employed a quantitative approach to investigate the effect of Perplexity AI-assisted outlining instruction on students' outlining performance in analytical exposition writing. Quantitative research is appropriate for examining relationships between variables through numerical data and statistical analysis, allowing researchers to determine whether an instructional intervention produces measurable changes in students' performance (Creswell, 2018). In the present study, quantitative procedures were utilized to compare students' outlining performance before and after the implementation of the instructional treatment.

The study adopted a quasi-experimental design, which is widely used in educational research when random assignment of participants is not feasible. Since the participants were drawn from intact classrooms that had been established before the study, random allocation could not be implemented. Consequently, two existing classes were assigned as the experimental and control groups. Quasi-experimental designs provide an appropriate framework for examining the effectiveness of educational interventions in authentic classroom settings while maintaining comparison between groups (Li et al., 2025).

Table 1. Research Design

| Group | Pre-test | Treatment | Post-test |
|---|---|---|---|
| Experimental Group | $O_1$ | X | $O_2$ |
| Control Group | $O_3$ | — | $O_4$ |

As presented in Table 1, $O_1$ and $O_3$ represent the pre-test administered to the experimental and control groups, respectively, while $O_2$ and $O_4$ represent the post-test. The symbol X refers to the Perplexity AI-assisted outlining instruction implemented in the experimental group. A pretest–posttest control group design was employed. Before the intervention, both groups completed a pre-test to identify their initial outlining performance. The experimental group subsequently received Perplexity AI-assisted outlining instruction, whereas the control group participated in conventional outlining instruction. Following the treatment period, both groups completed a post-test using a comparable outlining task. The comparison of pre-test and post-test scores within and between groups enabled the researcher to examine the extent to which the instructional treatment influenced students' outlining performance in analytical exposition writing.

### Research Setting and Participants

This study was conducted at a vocational high school in Surabaya during the first semester of the 2025/2026 academic year, from August 28 to September 29, 2025, within an English as a Foreign Language (EFL) writing course focusing on analytical exposition writing. The participants consisted of 64 tenth-grade students from two intact classes, with 32 students assigned to the experimental group and 32 to the control group. Tenth-grade students were selected because analytical exposition writing is formally introduced at this level and requires learners to organize and develop arguments systematically, making them an appropriate population for examining outlining performance. Given the quasi-experimental design, purposive sampling was employed since random assignment was not feasible. Accordingly, one existing class received Perplexity AI-assisted outlining instruction, whereas the other received conventional outlining instruction, allowing the intervention to be

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implemented under authentic classroom conditions while preserving the school's existing instructional structure.

**Research Instrument**

Data were collected through an outlining task administered as both the pre-test and post-test. The task required students to develop an outline for an analytical exposition text based on a designated topic. The outlining was therefore selected to capture students' planning abilities and their readiness to construct argumentative texts.

Students' outlining performance was assessed using an analytic scoring rubric adapted from Abeywickrama & Brown. The rubric consisted of four dimensions: (1) organization of ideas, (2) sequencing of arguments, (3) clarity of structure, (4) idea adaptation and student voice (Brown & Abeywickrama, 2019). Organization of ideas referred to the systematic arrangement of relevant content, while sequencing of arguments concerned the logical progression of claims and supporting reasons. Clarity of structure evaluated the coherence and completeness of the outline, whereas idea adaptation and student voice reflected students' ability to develop and express ideas meaningfully within the proposed argument. Collectively, these dimensions represented the key components of effective outlining performance in analytical exposition writing.

To ensure the consistency of scoring, all outlines were evaluated independently by two raters using the same assessment rubric (Rumrill Jr et al., 2020). The first rater was the researcher, while the second was an English teacher with experience in teaching EFL writing. The scores assigned by both raters were subsequently averaged to obtain the final score for each participant. This procedure was employed to enhance scoring reliability and minimize potential bias in the assessment process.

**Validity and Reliability of the Instruments**

Before data collection, the instrument underwent content validation to ensure its alignment with the study objectives and the construct being measured, as content validity reflects the extent to which an instrument adequately represents the intended domain of knowledge and skills (Brown & Abeywickrama, 2019). The outlining task and analytic scoring rubric were reviewed by experts in English language teaching and writing instruction, and their feedback was used to refine the instrument before implementation. Instrument reliability was established through inter-rater reliability because outlining performance was evaluated using an analytic scoring rubric, requiring two independent raters to assess students' outlines using the same rubric and assessment procedures to ensure scoring consistency (Nha, 2021). The degree of agreement between the raters was examined using the Intraclass Correlation Coefficient (ICC).

**Research Procedure**

The procedure consisted of three stages: (1) pre-testing, (2) instructional intervention, (3) post-testing (Creswell, 2018). Both the experimental and control groups participated in the same assessment procedures; however, they received different instructional treatments during the intervention phase. A pre-test was administered to assess students' initial outlining performance by requiring them to produce an outline for an analytical exposition text, which was evaluated using an analytic scoring rubric. Next, the experimental group received Perplexity AI-assisted outlining instruction, while the control group received conventional outlining instruction, with both groups completing the same learning objectives and writing tasks. Finally, a post-test was administered using the same assessment procedures to examine the effectiveness of the instructional treatment in improving students' outlining performance.

**Data Analysis**

The collected data were analyzed using IBM SPSS Statistics. Before conducting parametric statistical analyses, the normality of the data distribution was examined using the Shapiro–Wilk test at a significance level of $\alpha = 0.05$. The Shapiro-Wilk test was selected

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because the number of participants in each group was fewer than 50 (Permatasari et al., 2025). The normality test aimed to determine whether the pre-test and post-test scores were drawn from a normally distributed population. Data were considered normally distributed when the significance value exceeded the alpha level ($p > 0.05$), indicating that the assumption of normality was satisfied. Conversely, when the significance value was lower than the alpha level ($p < 0.05$), the data were considered not normally distributed, indicating that the assumption of normality was violated.

To examine changes in students' outlining performance within each group, paired-sample t-tests were performed on the pre-test and post-test scores. The paired-sample t-test is used to determine whether a statistically significant difference exists between two related measurements obtained from the same participants (Creswell, 2018). A result was considered statistically significant when the probability value was lower than the predetermined alpha level of 0.05 ($p < 0.05$). Furthermore, an independent-sample t-test was conducted to compare the post-test performance of the experimental and control groups and to determine whether the instructional treatment resulted in statistically significant differences between the two groups.

In addition to significance testing, Cohen's *d* was calculated to determine the magnitude of the treatment effect (Cohen et al., 2007). Effect size analysis was included to provide a more comprehensive interpretation of the practical significance of the intervention beyond statistical significance alone. Following Cohen's (2007) guidelines, *d* values ranging from 0.20 to 0.50 indicate a small effect, values between 0.51 and 0.80 indicate a medium effect, and values greater than 0.80 indicate a large effect. The interpretation of Cohen's *d* effect size is presented in Table 2.

Table 2. Interpretation of Cohen's d Effect Size

| **Cohen's d (d)** | **ES Interpretation** |
|---|---|
| 0.20 – 0.50 | Small effect |
| 0.51 – 0.80 | Medium effect |
| > 0.81 | Large effect |

## FINDING AND DISCUSSION

### Finding

Students' outlining performance was initially examined through descriptive statistical analysis of the pre-test and post-test scores. The analysis aimed to provide an overview of students' outlining performance before and after the instructional intervention. The descriptive statistics for both the experimental and control groups are presented in Table 3.

Table 3. Mean Score of Pre-Test and Post-Test

| **Group** | **N** | **Pre-test Mean** | **Pre-test SD** | **Post-test Mean** | **Post-test SD** |
|---|---|---|---|---|---|
| Control | 32 | 66.37 | 3.89 | 68.59 | 3.30 |
| Experimental | 32 | 65.10 | 2.22 | 71.42 | 2.24 |

As shown in Table 3, the mean pre-test scores of the control group and the experimental group were relatively comparable, with mean scores of 66.37 and 65.10, respectively. This finding indicates that the two groups demonstrated similar outlining performance before the implementation of the instructional treatment. The relatively small

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difference between the pre-test means suggests that the participants began the study with comparable levels of outlining ability.

Following the intervention, improvements were observed in both groups. The control group's mean score increased from 66.37 to 68.59, representing a gain of 2.22 points. Meanwhile, the experimental group showed a more substantial increase, with the mean score rising from 65.10 to 71.42, resulting in a gain of 6.31 points. Although both groups demonstrated positive development in outlining performance, the improvement achieved by the experimental group was notably greater than that of the control group. These descriptive findings provide preliminary evidence that the integration of Perplexity AI-assisted outlining instruction may have contributed to stronger improvements in students' outlining performance.

**Reliability Test**

Inter-rater reliability was established to ensure consistency in assessing students' outlining performance. Since outlining quality was evaluated through human judgment, two independent raters, namely the researcher and an experienced EFL teacher, assessed each student's outline using the same analytic outlining rubric adapted from the writing assessment frameworks proposed by Brown & Abeywickrama (2019); Brown & Lee (2015). The use of a shared scoring rubric was intended to minimize subjective judgment and promote consistency across all assessment criteria. The reliability analysis was conducted using the Intraclass Correlation Coefficient (ICC) in IBM SPSS Statistics. The results of the analysis are presented in Table 3.

Table 3. Inter-rater Reliability Test using ICC

| | Intraclass Correlation[b] | 95% Confidence Interval | | F Test with True Value 0 | | | |
|---|---|---|---|---|---|---|---|
| | | Lower Bound | Upper Bound | Value | df1 | df2 | Sig |
| Single Measures | ,527[a] | ,324 | ,683 | 3,210 | 63 | 63 | ,000 |
| Average Measures | ,690[c] | ,490 | ,812 | 3,210 | 63 | 63 | ,000 |

The Average Measures ICC of (0.690) indicates a moderate level of agreement between the two raters based on the classification proposed by Martínez Pérez (2023). The 95% confidence interval (0.490–0.812) suggests that the estimated reliability remained within an acceptable range, while the statistically significant result ($p < .001$) indicates that the observed agreement was unlikely to have occurred by chance. Although the obtained ICC did not reach the threshold for good or excellent reliability, it demonstrates sufficient consistency for educational assessment involving performance-based scoring. Therefore, the averaged scores assigned by the two raters were considered appropriate for subsequent statistical analyses.

**Normality Test**

Before conducting hypothesis testing, the normality assumption was assessed using the Shapiro–Wilk test because each group consisted of fewer than 50 participants (n = 32) (Yap & Sim, 2011). The test was performed on the pre-test and post-test scores of both the experimental and control groups to determine whether the data met the assumptions required for subsequent parametric analyses. The results are presented in Table 4.

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Table 4. Normality Test Output

| | | **Kolmogorov-Smirnov[a]** | | | **Shapiro-Wilk** | | |
|---|---|---|---|---|---|---|---|
| | Group | Statistic | df | Sig. | Statistic | df | Sig. |
| PreTestMeanScore | Control | ,104 | 32 | ,200* | ,965 | 32 | ,372 |
| | Experimental | ,168 | 32 | ,022 | ,967 | 32 | ,422 |
| PostTestMeanScore | Control | ,123 | 32 | ,200* | ,954 | 32 | ,193 |
| | Experimental | ,125 | 32 | ,200* | ,947 | 32 | ,119 |

Since all significance values exceeded the predetermined alpha level (α = .05), the pre-test and post-test scores in both groups were normally distributed. Accordingly, the assumption of normality was satisfied, confirming the suitability of the dataset for subsequent parametric analyses, including the paired-samples t-test and the independent-samples t-test.

**Hypothesis Test**

To examine whether conventional outlining instruction led to significant changes in students' outlining performance, a paired-samples t-test was conducted to compare the pre-test and post-test scores of the control group. Since the assumption of normality had been satisfied, the paired-samples t-test was considered appropriate to determine whether students' outlining performance improved following the instructional treatment (Maciejewski, 2020). The results are presented in Table 5.

Table 5. Paired Sample T-test Control Group

| **Paired Samples Test** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | Paired Differences | | | | | | | Sig. (2-tailed) |
| | | Mean | Std. Deviation | Std. Error Mean | 95% Confidence Interval of the Difference Lower | Upper | t | df | |
| Pair 1 | Pre_Mean - Post_Mean | -2,2188 | 4,2785 | ,7563 | -3,7613 | -,6762 | -2,934 | 31 | ,006 |

As presented in Table 5, students in the control group demonstrated a statistically significant improvement in outlining performance after receiving conventional outlining instruction ($t(31) = -2.934$, $p = .006$). The negative mean difference indicates that the post-test scores were higher than the pre-test scores, reflecting an overall improvement following the instructional treatment. Although the improvement was statistically significant, the magnitude of the mean difference suggests that the gain in outlining performance was relatively modest. These findings indicate that conventional outlining instruction contributed to improving students' outlining performance and provide a basis for comparison with the experimental group that received Perplexity AI-assisted outlining instruction.

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Having established the within-group improvement in the control group, the analysis proceeded to the experimental group to investigate whether the integration of Perplexity AI-assisted outlining instruction produced a similar or greater improvement in students' outlining performance. Accordingly, a paired-samples t-test was performed to compare the pre-test and post-test scores. The results are presented in Table 6.

Table 6. Paired Sample T-test Experimental Group

| **Paired Samples Test** | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Paired Differences | | | | | | | Sig. (2-tailed) |
| | | | | 95% Confidence Interval of the Difference | | | | |
| | Mean | Std. Deviation | Std. Error Mean | Lower | Upper | t | df | |
| Pre_Mean - Post_Mean | -6,3125 | 3,5075 | ,6200 | -7,5771 | -5,0479 | -10,181 | 31 | ,000 |

As presented in Table 6, the paired-samples t-test revealed a statistically significant improvement in the experimental group's outlining performance following the implementation of Perplexity AI-assisted outlining instruction ($t(31) = -10.181$, $p < .001$). The substantially larger mean difference ($M = -6.312$) compared with that of the control group ($M = -2.218$) indicates a greater improvement in students' outlining performance after the intervention. These findings suggest that integrating Perplexity AI into outlining instruction enhanced students' ability to generate and organize ideas during the pre-writing stage. The extent of this improvement is further verified through the between-group comparison presented in the subsequent analysis.

Building upon the within-group analyses, a between-group comparison was subsequently conducted to determine whether the improvement in outlining performance differed significantly between students who received conventional outlining instruction and those who received Perplexity AI-assisted outlining instruction. An independent-samples t-test was performed using students' gain scores, with the results presented in Table 7.

Table 7. Independent Sample T-test

| **Independent Samples Test** | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Levene's Test for Equality of Variances | | t-test for Equality of Means | | | | | | |
| | | | | | | | | 95% Confidence Interval of the Difference | |
| | F | Sig. | t | df | Sig. (2-tailed) | Mean Difference | Std. Error Difference | Lower | Upper |

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| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| Gain_Score | Equal variances assumed | 1,366 | ,247 | -4,186 | 62 | ,000 | -4,09375 | ,97801 | -6,04876 | -2,13874 |
| | Equal variances not assumed | | | -4,186 | 59,703 | ,000 | -4,09375 | ,97801 | -6,05025 | -2,13725 |

As presented in Table 6, the independent-samples t-test revealed a statistically significant difference in gain scores between the two groups, $t(62) = -4.186$, $p < .001$. Accordingly, the null hypothesis ($H_0$) was rejected, and the alternative hypothesis ($H_1$) was accepted, indicating that students who received Perplexity AI-assisted outlining instruction achieved significantly greater improvement in outlining performance than those who received conventional outlining instruction. These findings demonstrate that integrating Perplexity AI into the outlining stage was more effective in enhancing students' outlining performance than conventional outlining instruction alone.

**Effect Size**

To determine the magnitude of the instructional effect, Cohen's d was calculated based on the gain scores of the experimental and control groups (Cohen et al., 2007). While the independent-samples t-test determines whether the difference between groups is statistically significant, Cohen's d indicates the magnitude of that difference in standardized units.

$$d = \frac{M_{gain,experimental} - M_{gain,control}}{SD_{pooled\ gain}}$$

The experimental group obtained a mean gain score of 6.3125, whereas the control group obtained 2.2188. The pooled standard deviation was 3.91. Therefore, the effect size was calculated as follows:

$$d = \frac{71.422 - 65.109}{2.23} = \frac{6.313}{2.23} = 2.83$$

The obtained Cohen's d value of 1.05 indicates a large effect size according to (Cohen et al., 2007). This finding demonstrates that Perplexity AI-assisted outlining instruction produced a substantial practical effect on students' outlining performance. The large effect size further supports the results of the independent-samples t-test, indicating that the superiority of the experimental group reflects a meaningful educational improvement beyond statistical significance.

**Discussion**

The findings of this study demonstrate that Perplexity AI-assisted outlining instruction effectively enhanced vocational high school students' outlining performance in analytical exposition writing. Although both groups showed improvement following the instructional period, students who received Perplexity AI-assisted outlining instruction achieved substantially greater progress than those who received conventional outlining instruction. Specifically, the experimental group obtained a mean gain score of 6.31, compared with 2.22 in the control group, and the difference was confirmed to be statistically significant through the independent-samples t-test ($p < .001$). Furthermore, the large effect size (Cohen's $d = 1.05$) indicates that the superiority of the experimental group was not only statistically

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significant but also educationally meaningful. These findings suggest that integrating Perplexity AI into the outlining stage provides effective instructional support for helping students generate, organize, and structure arguments before composing analytical exposition texts.

The greater improvement demonstrated by the experimental group may be explained through the perspective of Cognitive Load Theory, which posits that learning becomes more effective when instructional support reduces unnecessary cognitive demands and enables learners to allocate greater cognitive resources to essential learning processes (Sweller et al., 2011; Van Merriënboer & Sweller, 2005). Constructing an analytical exposition outline requires students to generate ideas, evaluate their relevance, establish logical relationships, and organize arguments before drafting (Zuana, 2020), all of which impose substantial cognitive demands. In this study, Perplexity AI functioned as an instructional scaffold by providing structured prompts and organizational guidance that supported students in exploring ideas and arranging arguments systematically rather than generating complete responses. Such support likely reduced extraneous cognitive load, allowing students to focus more effectively on planning, organizing, and refining their arguments during the outlining stage (Raza et al., 2025). This interpretation is consistent with Sweller (2011), who argued that reducing unnecessary cognitive load enables learners to perform complex cognitive tasks more efficiently.

The present findings are consistent with previous studies reporting the pedagogical benefits of artificial intelligence in supporting writing instruction. Gayed (2022) found that AI-assisted writing activities helped learners organize ideas more systematically during the planning stage, resulting in better text preparation. Likewise, Son (2023) emphasized that AI technologies are most effective when integrated as learning support throughout the writing process rather than being used solely to generate final written products. The findings of this study further reinforce Krajka (2024) argument that AI can function as an instructional scaffold by guiding learners through cognitively demanding writing tasks while maintaining students' active involvement in constructing their own ideas. Similarly, Demartini (2024) highlighted that AI-supported learning environments promote greater learner engagement, independence, and confidence during writing activities, which may have contributed to the greater improvement demonstrated by the experimental group. However, unlike these previous studies, which primarily examined overall writing quality or AI-assisted text production, the present study specifically investigated outlining as a distinct and measurable stage of the writing process within a vocational high school EFL context. Therefore, this study extends the existing literature by providing empirical evidence that Perplexity AI-assisted instruction can effectively enhance students' outlining performance before the drafting stage begins.

Further analysis of the four outlining dimensions revealed that Perplexity AI-assisted outlining instruction promoted a more balanced development of students' outlining performance than conventional instruction. Although both groups demonstrated the greatest improvement in idea adaptation and student voice, the experimental group consistently improved across all dimensions Brown (2015), including organization of ideas (+0.66), sequencing of arguments (+1.28), and clarity of structure (+1.19), whereas the control group showed only marginal improvement in organization of ideas (+0.10) and declines in sequencing of arguments (-0.67) and clarity of structure (-1.22). This finding is consistent with Wei (2023), who reported that generative AI enhances students' planning quality and argumentative organization, and Wang (2025), who found that AI-based writing support facilitates the development of coherent text structures through guided planning. Unlike previous studies that primarily evaluated the quality of the final written product, the present study demonstrates that the instructional value of Perplexity AI is evident during the

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outlining stage, where improvements occur simultaneously across multiple planning dimensions before drafting begins.

Despite these encouraging findings, several limitations should be acknowledged. This study was conducted in a single vocational high school with a relatively small sample of 64 students and employed a quasi-experimental design, limiting the generalizability of the findings to broader EFL contexts. Moreover, the study focused exclusively on students' outlining performance and did not examine whether the improvement in outlining quality was subsequently reflected in the quality of the final written product. Future studies are therefore encouraged to involve larger and more diverse samples, adopt more rigorous experimental designs, and investigate the extent to which AI-assisted outlining contributes to the overall quality of students' analytical exposition writing. Overall, the present findings suggest that Perplexity AI-assisted outlining instruction provides an effective instructional scaffold for strengthening students' planning processes, enabling them to generate, organize, and structure arguments more systematically before drafting. Rather than replacing the teacher's role, Perplexity AI appears to complement classroom instruction by supporting students' cognitive processes during the pre-writing stage, making it a promising pedagogical tool for EFL writing instruction.

## CONCLUSION

The findings of this study demonstrate that Perplexity AI-assisted outlining instruction significantly improved vocational high school students' outlining performance in analytical exposition writing. Compared with conventional outlining instruction, students in the experimental group achieved substantially greater improvement, as confirmed by the statistically significant difference in gain scores ($p < .001$) and a large effect size (Cohen's *d* = 1.05). These findings indicate that integrating Perplexity AI into the pre-writing stage provides meaningful instructional support for helping students generate, organize, sequence, and refine arguments before drafting analytical exposition texts.

The improvement was reflected across all four dimensions of outlining performance, namely organization of ideas, sequencing of arguments, clarity of structure, and idea adaptation with student voice. Rather than merely facilitating idea generation, Perplexity AI supported students in constructing more coherent and systematically organized outlines, suggesting that AI-assisted outlining can strengthen learners' planning processes while maintaining their active cognitive engagement throughout the writing task.

From a pedagogical perspective, the findings suggest that Perplexity AI can be integrated as an instructional scaffold to complement teacher-guided writing instruction, particularly during the planning stage of analytical exposition writing. By providing structured prompts and organizational guidance, the tool may help students manage the cognitive demands of planning and develop more effective outlining strategies before composing complete texts.

Nevertheless, the findings should be interpreted in light of several limitations. The study involved only 64 students from a single vocational high school and employed a quasi-experimental design using intact classes, which may limit the generalizability of the findings. In addition, the investigation focused exclusively on outlining performance without examining whether improvements in outlining were subsequently reflected in the quality of students' final written products.

Future research is therefore encouraged to replicate the study with larger and more diverse samples across different educational contexts and to employ more rigorous experimental designs where feasible. Further investigations should also examine the relationship between AI-assisted outlining and the quality of students' completed analytical

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exposition texts to provide a more comprehensive understanding of how improvements during the planning stage contribute to overall writing performance.

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