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Sun, A. X., & Mizumoto, A. (2025). Exploring individual differences in AI-assisted and corpus-based data-driven learning: Insights into learners' perceptions and language learning outcomes. *International Journal of Applied Linguistics*, ijal.70063. <https://doi.org/10.1111/ijal.70063>

## Exploring Individual Differences in AI-Assisted and Corpus-Based Data-Driven Learning: Insights into Learners' Perceptions and Language Learning Outcomes

**Keywords:** DDL (data-driven learning); corpus; ChatGPT; AI-assisted DDL; individual differences; English proficiency; learner perceptions; learner preference

### Abstract:

This study examined the comparative effectiveness of corpus-based data-driven learning (DDL; Linguee) and AI-assisted DDL (ChatGPT) among 69 Japanese university EFL learners. Both approaches produced comparable learning gains, with no significant difference between groups after controlling for pretest performance. However, proficiency emerged as a key moderating factor: intermediate-level learners achieved greater improvements than low-proficiency learners. Learner perceptions, assessed through the Technology Acceptance Model (TAM), indicated higher ratings of perceived ease of use, behavioral intention, and overall preference for AI-assisted DDL. These findings underscore the importance of aligning DDL implementation with learner proficiency and technology acceptance. AI-assisted tools such as ChatGPT offer accessible, engaging alternatives to traditional corpus-based methods, broadening opportunities for inductive, data-driven language learning.

### Introduction

The rapid advancement of technology has significantly impacted language education. Among these innovations, DDL stands out as an approach that enables learners to interact with authentic linguistic data for inductive learning (Johns, 1991). Corpus-based DDL effectively promotes linguistic awareness (Boulton & Cobb, 2017; Boulton & Vyatkina, 2021) but poses challenges such as technical complexity, cognitive overload, and limited accessibility for lower-proficiency learners (Vyatkina, 2020). Using traditional concordancers requires mastering search syntax, interpreting raw concordance lines, and handling large data sets, which can overwhelm both teachers and students (Sun & Mizumoto, 2025). Consequently, teachers often find DDL tasks time-consuming and difficult to integrate into regular instruction, limiting classroom implementation (Boulton & Vyatkina, 2021). These issues call for alternative approaches that retain the benefits of DDL while reducing its barriers.

Generative artificial intelligence (GenAI), particularly ChatGPT, has emerged as a promising solution. Unlike conventional corpus tools, AI-assisted DDL platforms such as ChatGPT offer immediate feedback and context-rich examples through intuitive, interactive interfaces (Flowerdew, 2024). Such tools can make DDL more accessible and engaging across proficiency levels (Wang & Fan, 2025), allowing natural language interaction that simplifies corpus exploration and enhances learner motivation.

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However, AI-assisted tools also involve risks, including inaccurate or fabricated information (“hallucinations”), overreliance on AI-generated outputs, and ethical concerns such as data privacy and learner autonomy (Crosthwaite & Baisa, 2023). Given these opportunities and limitations, it is vital to examine how AI-assisted DDL compares with traditional corpus-based methods in learning outcomes and engagement. While previous studies have explored proficiency and cognitive style in DDL (Mizumoto & Chujo, 2016), little evidence exists on how these factors operate in AI-assisted contexts. Moreover, concerns remain regarding the pedagogical soundness, accessibility, and long-term cognitive impact of AI integration in education (Crosthwaite & Baisa, 2023).

Therefore, this study addresses these gaps by empirically comparing AI-assisted DDL (ChatGPT) and corpus-based DDL (Linguee) in EFL learning. Specifically, it investigates (a) the effects of both approaches on learning outcomes, (b) learner perceptions within the Technology Acceptance Model (TAM) framework (Huang & Mizumoto, 2024), and (c) how individual differences—language proficiency and learning preferences (inductive vs. deductive)—influence DDL effectiveness. By clarifying these relationships, this study contributes to ongoing debates on AI integration in language education and informs the design of more inclusive and personalized digital learning strategies.

## Literature Review

### Corpus-Based DDL

Corpus-based data-driven learning (DDL), first introduced by Johns (1991), promotes active learner engagement with authentic language data through inductive exploration. Rather than relying on explicit instruction, learners analyze corpora to discover linguistic patterns independently. Numerous studies have confirmed DDL's effectiveness in improving vocabulary, collocation, grammar, and writing quality. Meta-analyses further support its positive effects across learning contexts (Boulton & Cobb, 2017; Boulton & Vyatkina, 2021; Mizumoto & Chujo, 2015). Learners also report favorable attitudes toward corpus-based tasks, indicating that DDL fosters engagement and noticing of authentic language patterns consistent with discovery learning and the Noticing Hypothesis (Schmidt, 1990). A key factor influencing corpus-based DDL effectiveness is learner proficiency. Traditional DDL tasks using large corpora (e.g., BNC, COCA) demand specialized interface skills and interpretation of complex concordance output, which can overwhelm less experienced learners. Studies report that lower-proficiency students often face cognitive overload without adequate scaffolding, leading some researchers to caution against unmediated corpus use for beginners (Chen & Tian, 2020). Consequently, DDL adoption remains limited, particularly in contexts favoring explicit instruction (Sun & Mizumoto, 2025). Effective implementation thus requires scaffolding strategies such as guided or “hands-

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on/hands-off' tasks to balance support and autonomy. Hence, proficiency alone is not a barrier to learning gains, but additional instructional and affective support is needed to maximize DDL's benefits.

Beyond proficiency, individual learner characteristics also shape engagement and success with corpus-based DDL. Boulton (2009) noted that DDL's exploratory nature can appeal to learners with varied preferences. Empirical research supports this, showing that different cognitive styles influence interaction with corpus tasks. For instance, Al-Mahbashi, Noor, and Amir (2017) found that learners' dominant intelligences (e.g., linguistic or logical-mathematical) affected their performance in DDL vocabulary activities, suggesting the importance of aligning tasks with learner strengths. Similarly, Mizumoto and Chujo (2016) reported that both inductive and deductive learners significantly improved grammar through guided corpus instruction, with no clear advantage for either group. These findings indicate that well-designed DDL tasks can accommodate diverse learning styles, emphasizing that thoughtful task design and scaffolding, rather than targeting specific learner types, determine successful implementation.

## AI-Assisted DDL

In this study, AI-assisted data-driven learning (DDL) was operationalized as the use of ChatGPT as an AI-based corpus tool enabling learners to access authentic linguistic input and engage in autonomous discovery learning. This operationalization aimed to examine how ChatGPT, as an interactive and generative platform, mediates learner engagement with language data and whether it can mitigate the practical challenges commonly associated with traditional corpus tools.

Recent advances in generative AI have made DDL more accessible and adaptive. Tools such as ChatGPT have been proposed as "AI-assisted DDL" platforms that complement traditional corpus work (Cheung & Crosthwaite, 2025). Unlike conventional concordancers requiring technical expertise, ChatGPT provides a conversational interface that enables intuitive, human-like interaction. Empirical studies suggest that this interactivity reduces cognitive load and facilitates corpus exploration for learners with limited experience (Lo et al., 2024; Satake, 2024; Flowerdew, 2024). Practically, ChatGPT can simulate corpus functions—generating examples, highlighting collocations, and providing contextualized explanations—while supporting varied skills from vocabulary to writing (Wang & Fan, 2025). These affordances suggest that AI-assisted DDL can flexibly support learning across proficiency levels, though empirical validation remains limited.

While AI-assisted DDL can support inductive learning by providing multiple contextualized examples, it remains uncertain whether learners consistently engage in the hypothesis-testing and generalization processes central to inductive reasoning. Crosthwaite and Baisa (2023) caution that, without explicit scaffolding or structured tasks, learners may depend excessively on AI-generated generalizations,

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thereby limiting the depth of cognitive processing that DDL seeks to promote. Moreover, AI-assisted DDL raises additional pedagogical and ethical concerns. Generative AI systems such as ChatGPT are susceptible to “hallucinations,” producing plausible but inaccurate linguistic output that can mislead uncritical users (Lin, 2023; Uchida, 2024). Issues related to data privacy, transparency, and learner autonomy further underscore the need for careful integration and oversight (Yang & Li, 2024). These limitations highlight the importance of establishing clear pedagogical guidelines and providing learners with critical literacy training to ensure informed and ethical engagement with AI-generated language data.

Despite these concerns, a key affordance of AI-assisted DDL lies in its adaptability to individual learner needs. Murgia et al. (2023) found that ChatGPT adjusted the complexity of its responses to match learners' literacy levels, providing “tailored responses at the appropriate literacy level” for young learners. Such flexibility enables ChatGPT to serve a wide range of proficiency levels: advanced learners can explore syntactic nuances, while lower-proficiency learners can focus on basic lexical or collocational patterns. The AI's capacity for adaptive scaffolding effectively mirrors Vygotsky's (1978) notion of the Zone of Proximal Development, positioning ChatGPT as an individualized learning facilitator capable of adjusting support in real time.

Individual learner characteristics significantly influence the acceptance and utilization of AI-assisted DDL technologies. Drawing on the TAM, Huang and Mizumoto (2024) reported that higher technology acceptance correlated with stronger preference for AI-assisted learning. These findings indicate that learners' technological confidence and prior experience influence their willingness to engage with AI-mediated DDL.

Although AI-assisted DDL is relatively new, emerging research has begun to evaluate its effectiveness on language learning outcomes. A systematic review of 70 studies found consistent positive effects of ChatGPT on EFL writing and engagement (Lo et al., 2024), while Wang and Fan's (2025) meta-analysis reported a large positive overall impact (Hedges'  $g = 0.87$ ). Such findings suggest that AI tools enhance both learning performance and user experience.

Despite these advantages, scholars caution against overreliance on AI output. Instant feedback may discourage learners from analyzing linguistic patterns independently, undermining DDL's discovery-based nature (Mizumoto & Eguchi, 2023; Crosthwaite & Baisa, 2023). To preserve the inductive spirit of DDL, AI should support—not replace—active hypothesis testing and noticing.

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### Comparative Insights: Corpus vs. AI-Assisted Approaches

Compared with traditional corpus-based DDL, AI-assisted DDL offers distinctive pedagogical affordances, particularly in accessibility, immediacy, and learner engagement. While corpus-based tools promote linguistic accuracy and data literacy, they often demand technical expertise and extensive teacher mediation. In contrast, AI-assisted platforms such as ChatGPT provide natural language interaction and personalized feedback, enhancing motivation and reducing the cognitive load associated with concordancer-based searches (Flowerdew, 2024). These affordances, however, come with trade-offs: AI-generated examples may lack authenticity or verifiable frequency data, and learners may rely on AI outputs without engaging in deeper linguistic analysis (Crosthwaite & Baisa, 2023). Thus, both approaches exhibit complementary strengths and limitations that warrant further empirical examination.

Both corpus-based and AI-assisted DDL foster inductive, discovery-oriented learning by helping learners notice and generalize authentic linguistic patterns. When implemented effectively, both have demonstrated positive impacts on learning outcomes. The rationale for comparison lies not in establishing superiority but in understanding how each accommodates individual learner differences and shapes learner experience.

Corpus-based DDL has traditionally benefited learners with higher proficiency, strong analytical ability, and corpus literacy. In contrast, lower-proficiency learners often face challenges without adequate scaffolding. AI-assisted DDL lowers the entry threshold through intuitive interaction, instant feedback, and built-in support, thereby broadening participation to learners with more diverse linguistic backgrounds and proficiencies. By mitigating technical and cognitive barriers, AI-assisted tools make pattern-based learning more inclusive and flexible.

Learner perceptions and affective responses also distinguish the two approaches. While corpus-based DDL can be cognitively demanding and at times discouraging, AI-assisted DDL tends to yield higher ratings for perceived ease of use and learner enjoyment, leading to greater engagement and reduced anxiety (Huang & Chiu, 2025).

Importantly, these methods should be viewed as complementary rather than competing. ChatGPT represents an accessible entry point for inductive engagement with linguistic data, expanding the reach of DDL to contexts where traditional concordancers may be impractical. As Crosthwaite and Baisa (2023) note, it may be time to “open up the ‘D’ in DDL to new, GenAI-assisted possibilities” (p. 4). ChatGPT thus functions not as a replacement for corpora but as a valuable addition to the pedagogical toolkit, enhancing flexibility and inclusivity (Mizumoto, 2023).

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Beyond pedagogy, the integration of AI-assisted DDL raises broader ethical considerations. Recent research has highlighted concerns regarding the transparency of AI-generated content, biases embedded in training data, and the protection of learner information (Zheng & Yang, 2024). Addressing these issues is crucial for ensuring that technological innovation aligns with principles of ethical, equitable, and responsible language education.

## Rationale and Research Questions of the Present Study

1. Given these insights, a direct empirical comparison between corpus-based and AI-assisted DDL is warranted. Although previous studies have examined learner proficiency, cognitive preferences, and technology acceptance in each context separately, little research has investigated how these factors interact within a single instructional framework. To address this gap, the present study directly compared corpus-based and AI-assisted DDL, guided by the following research questions: How effective is AI-assisted DDL compared to traditional DDL in the classroom?
2. How does the impact of AI-assisted DDL and traditional DDL on language learning outcomes vary between intermediate and low-proficiency learners?
3. How do learners' perceptions of AI-assisted DDL compare to traditional DDL within the Technology Acceptance Model framework?
4. How do inductive and deductive learning preferences interact with different DDL types in shaping outcomes?

By addressing these points, the present research aims to clarify the strengths and limitations of each approach for diverse learner profiles. Ultimately, findings will inform more personalized, effective integration of corpus-based and AI-assisted DDL, ensuring inclusive, evidence-based pedagogical practices in language education.

## Methods

### Participants

Participants were 69 second-year EFL learners majoring in law (39 males, 30 females; aged 19–21) enrolled at a private university in Japan. The study employed convenience sampling and was conducted in four intact classes as part of a compulsory English course during the fall semester of 2024. Learners' English proficiency was assessed using their official Test of English for International Communication

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(TOEIC) scores (Educational Testing Service, 2016). As shown in Table 1, 29 students in Classes A and B were classified as intermediate (CEFR B1; TOEIC = 550–785), while 40 students in Classes C and D were classified as low proficiency (CEFR A2; TOEIC = 225–550). The four classes were divided by instructional condition: Classes A and C received corpus-based DDL instruction using Linguee, whereas Classes B and D received AI-assisted DDL instruction using ChatGPT. Ethical approval for the study was obtained from the Institutional Review Board of the authors' university. All participants provided written informed consent prior to participation.

**Table 1**

*Average TOEIC Scores and DDL Types Across Four Classes*

Class No.	Number of Students	Listening Score	Reading Score	TOEIC Total	Proficiency	Types of DDL
A	16	349	325	674	Intermediate	Corpus-based, Linguee
B	13	327	316	634		AI-assisted, ChatGPT
C	21	253	250	504	Low	Corpus-based, Linguee
D	19	258	214	471		AI-assisted, ChatGPT

## Instruments

**Pretest and Posttest:** The pretest comprised 60 multiple-choice items selected from the three most recent official TOEIC practice test books (Volumes 8–10; Educational Testing Service, 2021, 2022, 2023), following procedures consistent with the actual TOEIC. All items were drawn from Part 5, which assesses grammar and vocabulary knowledge. Based on the pretest results, 20 items with a correct response rate below 70% were selected for the posttest to measure learning gains from each DDL condition. This approach ensured that posttest items targeted areas that had been challenging in the pretest. To minimize memory effects, these items were collected immediately after the pretest and not reused during instruction.

Both tests focused on grammatical and lexical knowledge commonly assessed in TOEIC Part 5, including verb–noun collocations, prepositional phrases, and adjective–noun combinations. Each item featured four options with a single correct answer, assessing rule recognition and lexical choice accuracy across categories such as tense, word formation, and syntactic structure.

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All items were sourced from standardized ETS materials to ensure reliability and construct validity. The internal consistency of the posttest was acceptable (Cronbach's  $\alpha = .67$ ). Content validity was further verified through expert review by two EFL instructors with experience in TOEIC test development, who confirmed that the items represented the grammatical constructs taught during instruction. Although no separate pilot testing was conducted, the use of validated TOEIC materials and expert review ensured the appropriateness of the instruments.

Both the pretest and posttest were administered online via Google Forms. All questions required responses, and scores were automatically calculated based on the number of correct answers (one point each). To prevent test contamination, none of the items appeared in the instructional materials. The complete set of pretest and posttest items is available in the online supplementary material ([https://osf.io/ah4yw/?view\\_only=b3e0e8bcf0d846818adb0e4ed013f2c6](https://osf.io/ah4yw/?view_only=b3e0e8bcf0d846818adb0e4ed013f2c6)).

**Learning Preferences Questionnaire:** Participants' learning preferences were measured using a 13-item questionnaire developed by Mizumoto and Chujo (2016). Seven items assessed inductive and deductive learning preferences, which, while useful for analyzing responses to DDL activities, represent simplified models of more complex and flexible learner characteristics. The remaining six items measured task value, defined as learners' perceived usefulness of the tasks (Pintrich et al.). This scale also served as an outcome measure to examine correlations with learning preferences, indicating whether certain learner types value DDL more highly. The survey, administered in Japanese, used a six-point Likert scale ranging from 1 (not at all true of me) to 6 (very true of me). **Learner Perceptions Questionnaire:** In addition, a questionnaire measuring the technology acceptance of the learners (Huang & Mizumoto, 2024) was administered to investigate learners' perceptions of two types of DDL activities. This questionnaire consisted of 21 items designed to assess the five constructs of the TAM: Perceived Ease of Use (4 items), Perceived Usefulness (5 items), Attitude (4 items), Behavioral Intention (3 items), and Actual Usage (5 items). The survey was conducted in Japanese, and participants provided responses to all items using a six-point Likert Scale, with a rating of 1 indicating "strongly disagree" and 6 indicating "strongly agree." Items of the two questionnaires are available in the online supplementary material for reference ([https://osf.io/ah4yw/?view\\_only=b3e0e8bcf0d846818adb0e4ed013f2c6](https://osf.io/ah4yw/?view_only=b3e0e8bcf0d846818adb0e4ed013f2c6)).

## DDL Tools

**Linguee:** Linguee (<http://www.linguee.es>) is an online parallel corpus that combines a dictionary-like interface with examples drawn from translated official documents. Freely accessible via its website

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and mobile applications, it supports multiple languages and offers an intuitive, dictionary-style interface for bilingual concordance searches (see Figure 1). Owing to its simplicity and accessibility, Linguee is particularly suitable for intermediate and lower-level English learners, such as those in this study.

**Figure 1**

*Interface of Linguee*

The screenshot shows the Linguee dictionary interface. At the top, there is a language selector set to 'English ↔ Japanese'. Below that is a search bar containing the word 'renovation'. Underneath the search bar are three options: 'Translate text', 'Translate files', and 'Improve your writing'. The main content area is titled 'Dictionary English-Japanese' and shows the search results for 'renovation'. It lists the Japanese equivalents: 'リノベーション' and 'リニューアル', followed by 'less common:' and a list of related terms: '刷新', '修築', 'しゅうちく', 'ころもがえ', '衣更え', '更衣', 'さっしん', '衣替え'. Below this, there are 'Examples:' and three example sentences with their Japanese translations. At the bottom, there is a section for 'External sources (not reviewed)' which lists several examples of the word 'renovation' used in context, each with a source link.

renovation ◀

リノベーション①

リニューアル①

less common:

刷新① · 修築① · しゅうちく · ころもがえ · 衣更え · 更衣 · さっしん · 衣替え

Examples:

plant renovation – プラントリノベーション  
renovation specialist – リフォームインストラクター  
renovation plan (usu. of a house) – リフォームプラン

See more examples · See alternative translations ↗

© Linguee Dictionary, 2025

External sources (not reviewed)

Each of these properties is maintained well, having benefited from a certain degree of <b>renovation</b> and repair work during the period when they were managed by the private fund. <a href="#">nre-rt.co.jp</a>	これら物件については、私募ファンドで運営されていた期間に、一定程度の改修・修繕が施されており、現状の各物件の管理状況は良好である。 <a href="#">nre-rt.co.jp</a>
▲ [...] maintenance service business and for administrative functions by the vertical launch of ongoing production <b>renovation</b> initiatives. <a href="#">fielding.co.jp</a>	▲ また、継続して取り組んでいる生産革新活動の水平展開により、保守サービス領域および間接業務処理の効率化を加速してまいります。 <a href="#">fielding.co.jp</a>
However, other measures may be required in accordance with regulations in the event of <b>renovation</b> or demolition of the building. <a href="#">tokyu-reit.co.jp</a>	ただし、建物の改修、解体などを実施する際には法令に従い措置する必要があります。 <a href="#">tokyu-reit.co.jp</a>
[...] the budget, provide loans without interest to a prefectural or municipal government for part of the funds appropriated to the expenses spent for such new construction, repair, <b>renovation</b> , expansion or improvement of child and family support centers as falling under Article 2 paragraph (1) item (ii) of the Act on Special Measures concerning Infrastructure Development. <a href="#">japaneselawtranslation.go.jp</a>	国は、当分の間、都道府県又は市町村に対し、児童家庭支援センターの新設、修理、改造、拡張又は整備で社会資本整備特別措置法第二条第一項第二号に該当するものに要する費用に充てる資金の一部を、予算の範囲内において、無利子で貸し付けることができる。 <a href="#">japaneselawtranslation.go.jp</a>
The Company implemented a number of structural reforms aimed at improving profitability, including selectively focusing on certain businesses and <b>renovation</b> of business processes, a significant reduction of personnel and other expenses, which involved the reduction of headcount, and a reduction of capital expenditures. <a href="#">advantest.co.jp</a>	事業の選択と集中を進めるとともに事業プロセスの革新を進め、さらに人員の削減を含めた人件費・経費の大幅削減、設備投資抑制などの施策の実施による収益性の改善を目指し、事業構造の改革を推進してまいりました。 <a href="#">advantest.co.jp</a>

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Research has highlighted Linguee's benefits for autonomous learning. Ortner and Weber (2019) describe it as "freely available and searchable online parallel corpora," offering users insights into word usage. Molés-Cases and Oster (2015) further note its practical application in enabling students to search for examples and contextual meanings independently. As Boulton and Vyatkina (2021) emphasize, tools like Linguee provide user-friendly, aesthetic, and fast interfaces, increasing their appeal for both teaching and research.

**ChatGPT:** ChatGPT, developed by OpenAI and launched in 2022, is a large language model (LLM) designed to simulate human-like conversation through natural language processing. Unlike traditional rule-based chatbots, it generates contextually relevant responses using probabilistic models trained on extensive linguistic data. While its versatility has been widely acknowledged, scholars have cautioned that learners may passively accept AI-generated outputs without sufficient critical engagement, potentially diminishing the analytical depth of inductive learning (Mizumoto & Eguchi, 2023).

ChatGPT supports language learning across multiple domains—reading, writing, speaking, listening, and grammar development—while offering automated feedback and contextualized examples. Studies have demonstrated its pedagogical effectiveness: Mizumoto et al. (2024) found strong agreement between ChatGPT's automated writing assessments and human ratings; Yang and Li (2024) reported improvements in writing proficiency and learner autonomy; and Satake (2024) highlighted its potential to complement corpus-based tools by providing contextual lexical support. Despite these affordances, ChatGPT differs from corpora in that it does not provide verifiable frequency data or concordance lines (Uchida, 2024).

To mitigate these limitations, learners in the AI-assisted DDL condition received brief training in prompt design and critical evaluation of AI output. During the orientation phase, they were introduced to reference corpora such as Linguee and COCA to develop basic corpus awareness and to promote analytical engagement rather than passive reliance on AI-generated text. These corpora were not used in the experimental treatment but served as conceptual scaffolds to familiarize learners—especially those without prior corpus experience—with data-driven analysis principles.

In this study, ChatGPT functioned as the sole AI-assisted DDL platform rather than a corpus substitute. Learners performed structured query tasks mirroring traditional corpus searches. Instruction emphasized effective prompting strategies to elicit linguistic patterns, such as "What verbs are commonly used before improve?" or "What adjectives frequently modify performance?" (see Figure 2). These activities aimed to guide learners toward discovering authentic usage patterns while compensating for ChatGPT's lack of frequency-based retrieval.

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## Figure 2

### An Example of learner–ChatGPT interaction

performanceを修飾する形容詞にはどのようなものがありますか？例を挙げてください。

「performance（パフォーマンス、性能、演技、成果など）」を修飾する形容詞には、その文脈によってさまざまなものがあります。以下にいくつかの代表的な形容詞と、それぞれの使用例を挙げます。

---

**1. high / low – 性能や成果の良し悪し**

- **high performance** : 高性能
  - *This is a high-performance engine.* (これは高性能のエンジンです。)
- **low performance** : 低性能
  - *The machine showed low performance under stress.* (その機械は負荷がかかると低性能を示した。)

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**2. poor / excellent / strong / weak – クオリティや評価**

- **excellent performance** : 素晴らしいパフォーマンス
  - *Her excellent performance impressed the audience.* (彼女の素晴らしい演技に観客は感動した。)
- **poor performance** : 低調な成果
  - *The company was criticized for its poor performance last quarter.* (会社は前四半期の低調な業績を批判された。)

Learners also underwent guided training sessions on prompt optimization, where they practiced refining queries to obtain more reliable responses. The instructor guided learners on optimizing prompts by encouraging specific queries and iterative refinement to extract accurate and relevant patterns. During the explanation phase, the instructor highlighted incorrect usage found in students' answers and reinforced generalization of the underlying language structures.

Table 2 contrasts Linguae and ChatGPT based on data source, information provided, instructional emphasis, interactivity, and inherent constraints.

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**Table 2**

*Comparison of Design Features: Linguee vs. ChatGPT*

Feature	Linguee	ChatGPT
Data Source	Human-edited bilingual dictionary + automatically harvested parallel corpora (e.g. EU Parliament proceedings, patents); approx. 100 million translations	Large-scale transformer model pre-trained on diverse public datasets (Common Crawl, WebText, books, Wikipedia) and fine-tuned with RLHF (reinforcement learning from human feedback)
Provided Information	L1 translations; POS/grammar tags; dozens to ~100 example sentences with quality ratings; source metadata user-accessible	User-contextualized example sentences, paraphrases, explanations; no frequency data or explicit corpus provenance
Instructional Emphasis	Primarily deductive (translation-first), though contexts embed inductive discovery via parallel examples	Flexible: supports inductive or deductive prompts; accuracy depends on prompt design; hallucination risk present
Real-Time Interaction	Fixed examples retrieved per query; no dynamic generation or conversational capability	Real-time generation and interaction; content adapts to user prompts
Constraints	Limited number of examples (~100); does not allow large-scale concordance browsing	Possible inaccuracies (hallucinations); lacks explicit frequency or citation metadata

## DDL Instruction

Before instruction, an introductory session was conducted to familiarize participants with corpora and data-driven learning (DDL). The teacher, who was also the first author, introduced the tools used in the study through lectures and role-play demonstrations. As participants had no prior experience with corpus tools, the session focused on explaining commonly used corpora, including COCA, WebParaNews, CorpusMate, and Linguee. Based on learners' feedback and classroom engagement, Linguee was selected as the corpus-based DDL tool. Introducing ChatGPT required less orientation, given participants' prior exposure to it; however, a brief operational guide was provided to ensure effective use during instruction.

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To align with learners' motivation, training was scheduled before the university's free TOEIC examination, which contributed 20% to their semester grade. Four 90-minute DDL sessions were conducted once a week for all four classes (N = 69), totaling 360 minutes of instruction. Two classes used Linguee and two used ChatGPT, as shown in Table 1.

Each session followed a consistent structure: 1. **15 minutes:** Participants completed 20 TOEIC Reading Part 5 (Incomplete Sentences) questions via Google Forms. Feedback on incorrect responses was provided, but correct answers were withheld.

2. **40 minutes:** Learners used their assigned DDL tool to independently identify correct answers and explanations, recording their findings.

3. **35 minutes:** In-class discussion followed, during which randomly selected students explained the correct answers and underlying language patterns.

The instructional design adopted the guided-induction framework known as the “four I’s” (illustration, interaction, intervention, induction) proposed by Flowerdew (2009) and elaborated by Smart (2014). This model encourages learners to infer linguistic rules from authentic data rather than rely on explicit explanation. In practice, learners first examine corpus or AI-generated examples (illustration), then collaborate to identify patterns (interaction). When difficulties arise, the instructor provides support or additional input (intervention) and finally guides learners to generalize rules (induction). Research suggests that this sequence helps learners notice discrepancies between their interlanguage and target input, facilitating form–meaning mapping.

During the initial session, learners analyzed examples from Linguee or ChatGPT to identify collocations and recurring patterns. The instructor intervened as necessary and guided students to formulate grammatical or lexico-grammatical generalizations. This explicit illustration phase occurred only once; in subsequent sessions, learners proceeded directly to tool-based exploration after the quiz phase.

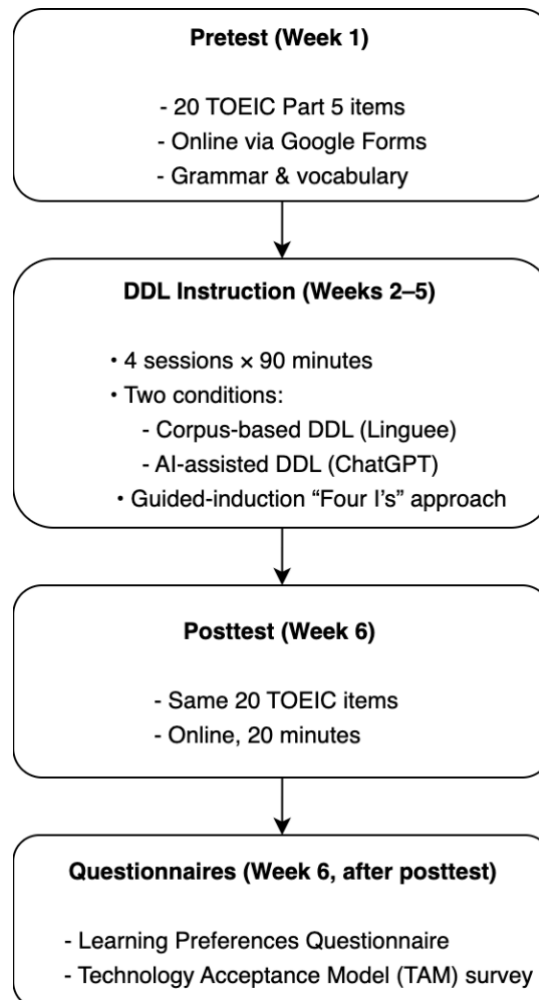
After completing the four instructional sessions, participants took the posttest and responded to two questionnaires assessing learning outcomes and perceptions. The entire research procedure—including the pretest, instructional treatment, posttest, and questionnaire phases—is summarized in Figure 3 below.

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### Figure 3

Flowchart of the Methodological Procedure



### Data Analysis

The data analysis focused on evaluating the effectiveness of AI-assisted DDL (ChatGPT) and traditional corpus-based DDL (Linguee) in improving English language learning outcomes among low- and intermediate-proficiency learners. All analyses in this study were conducted using R version 4.4.2 (R Core Team., 2024). All data and R codes used in this study are shared online ([https://osf.io/ah4yw/?view\\_only=b3e0e8bcf0d846818adb0e4ed013f2c6](https://osf.io/ah4yw/?view_only=b3e0e8bcf0d846818adb0e4ed013f2c6)). Pre- and posttest scores, as

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well as learner perceptions, were analyzed using statistical methods, including ANCOVA and cluster analysis, to address the research questions.

## Results

To address RQ1—How effective is AI-assisted DDL compared to traditional DDL in the classroom?, descriptive statistics were calculated for pre- and posttest scores to evaluate overall improvement. an ANCOVA (Analysis of Covariance) was conducted with the pretest as a covariate. This approach was chosen to statistically control for the pretest scores of the two groups, ensuring equivalence before comparing their posttest scores. Prior to running the ANCOVA, the assumptions of homogeneity of variance and homogeneity of regression slopes were tested, and no violations were detected.

The pretest consisted of 20 TOEIC questions with a correct response rate below 70%, which were repeated in the posttest. Reliability analysis yielded a Cronbach's alpha of .67 for the posttest. The pretest mean score was 11.07 ( $SD = 2.91$ ) for all participants, while the posttest mean score increased to 15.26 ( $SD = 3.06$ ), indicating a significant overall improvement.

**Table 3**

*Pre-and Posttest Descriptive Statistics*

Breakdown	<i>n</i>	Pre		Post	
		Mean	<i>SD</i>	Mean	<i>SD</i>
All	69	11.07	2.91	15.26	3.06
ChatGPT	37	10.86	2.78	14.81	2.71
Linguee	32	11.31	3.08	15.78	3.40
Low	40	10.28	2.86	14.23	3.14
Intermediate	29	12.17	2.65	16.69	2.32
ChatGPT					
Low	21	9.86	2.69	14.19	2.75
Intermediate	16	12.19	2.37	15.63	2.50
Linguee					
Low	19	10.74	3.05	14.26	3.60
Intermediate	13	12.15	3.05	18.00	1.15

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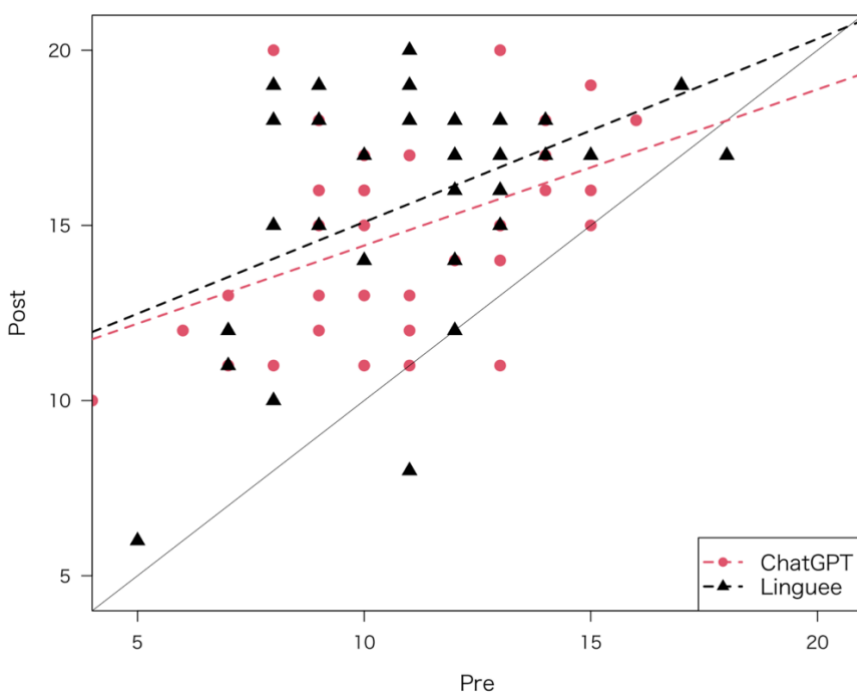
As shown in Table 3, the analysis revealed no significant difference between the posttest scores of the two groups ( $t = 1.15, p = .26$ ), with the adjusted mean scores for the ChatGPT group ( $M = 14.91$ ) and the Linguee group ( $M = 15.66$ ) after adjusting for the pretest as a covariate. The mean difference in posttest scores was 0.75, with a 95% confidence interval of -0.56 to 2.07. The effect size was also small,  $d [95\% \text{ CI}] = -0.28 [-0.75, 0.20]$ . These findings indicate that there was no meaningful difference between the posttest scores of the two groups. Thus, the results for RQ1 suggest that “the two approaches had equivalent effects.”

Figure 4 presents a scatter plot showing the pretest and posttest scores for all participants. If points are located in the upper-left half of the figure, it indicates that the posttest scores are higher than the pretest scores. As is evident from Figure 4, the overall scores have improved, demonstrating that the instruction using the two-types of DDL tools was effective.

The following Figure 5 further illustrates how scores changed between the pretest and posttest for each group (ChatGPT/Linguee) and proficiency level (Low/Intermediate). It is clear that scores improved across all groups and proficiency levels.

### Figure 4

Scatter Plot of Pretest and Posttest Scores

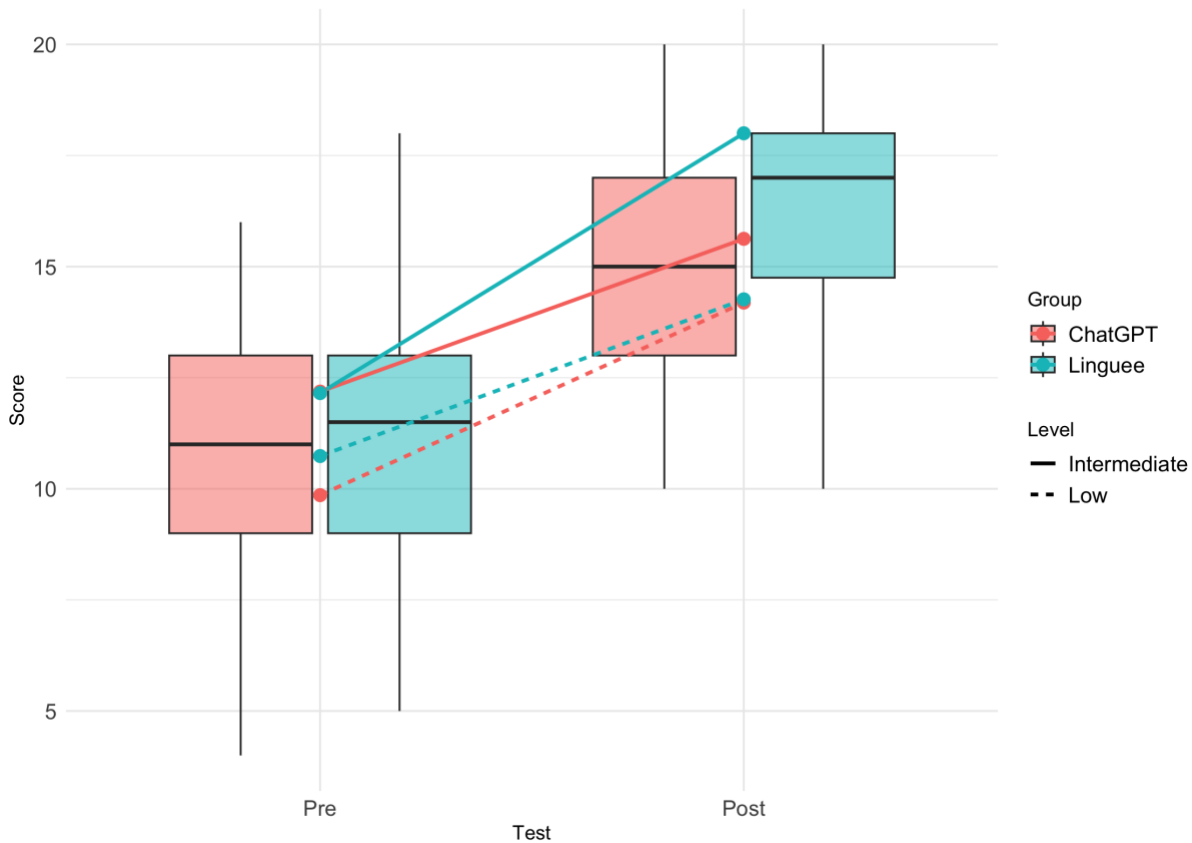


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### Figure 5

*Average Pre and Post Scores by Group and Level*



To examine whether the effects of AI-assisted and traditional DDL on learning outcomes differed by proficiency level (RQ2), comparisons were made between the low- and intermediate-proficiency groups. This analysis addressed the role of proficiency, a factor frequently emphasized in prior DDL research. As established in the RQ1 results, no significant difference was observed in posttest performance between the ChatGPT and Linguee groups. Building on this finding, changes from pretest to posttest were analyzed using ANCOVA, following the same procedures as in RQ1. Because participants at different proficiency levels naturally differed in pretest performance, pretest scores were entered as a covariate to control for initial disparities and allow a fair comparison of posttest outcomes. Tests for homogeneity of variance and regression slopes confirmed that the assumptions for ANCOVA were met.

The results showed a statistically significant difference in the adjusted posttest scores ( $t = 2.53$ ,  $p = .014$ ), with the adjusted mean scores for the Low group ( $M = 14.54$ ) and the Intermediate group ( $M = 16.25$ ), as illustrated in the Figure 6 below. The effect size, based on Plonsky and Oswald's (2014) benchmarks for between-group contrasts in second language research, was medium,  $d$  [95% CI] = 0.63

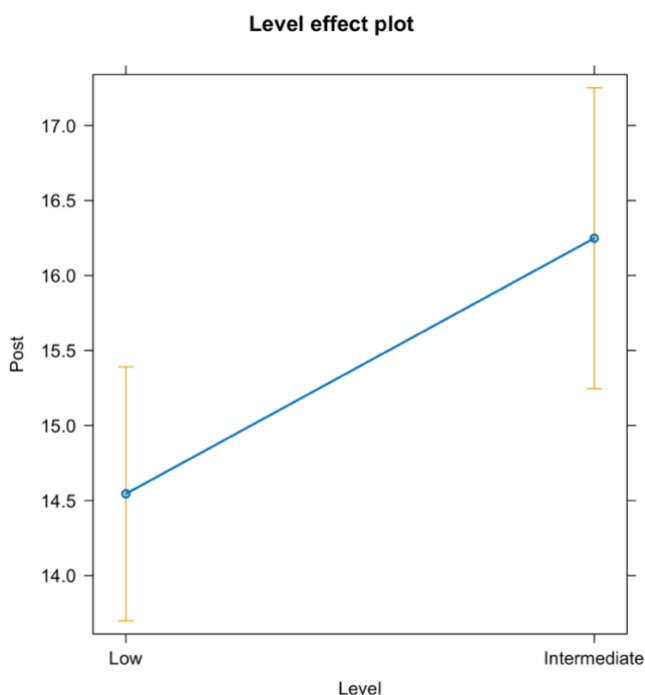
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[0.14, 1.12]. These findings indicate that participants in the Intermediate proficiency group achieved higher learning outcomes when exposed to the guided DDL induction approach.

### Figure 6

Level Effect Plot



This result is consistent with previous DDL studies, reinforcing the conclusion that proficiency, as an individual difference, plays a critical role in influencing the effectiveness of DDL.

To address RQ3, which examined learners' perceptions of AI-assisted versus traditional DDL within the TAM framework, participants completed a questionnaire comprising TAM subscales. These subscales, previously validated by Huang and Mizumoto (2024), demonstrated satisfactory internal consistency reliability in the present study. Table 4 summarizes the number of items, descriptive statistics (means and standard deviations), and Cronbach's  $\alpha$  values for each scale, all of which fell within acceptable reliability ranges.

The final sample for this analysis included 67 participants, slightly fewer than the pre-/posttest sample ( $N = 69$ ) due to two instances of incomplete responses. Inter-scale correlations among the five TAM

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constructs, presented in Figure 7, revealed moderately to strongly positive associations, suggesting that learners’ perceptions across the TAM dimensions were closely related.

**Table 4**

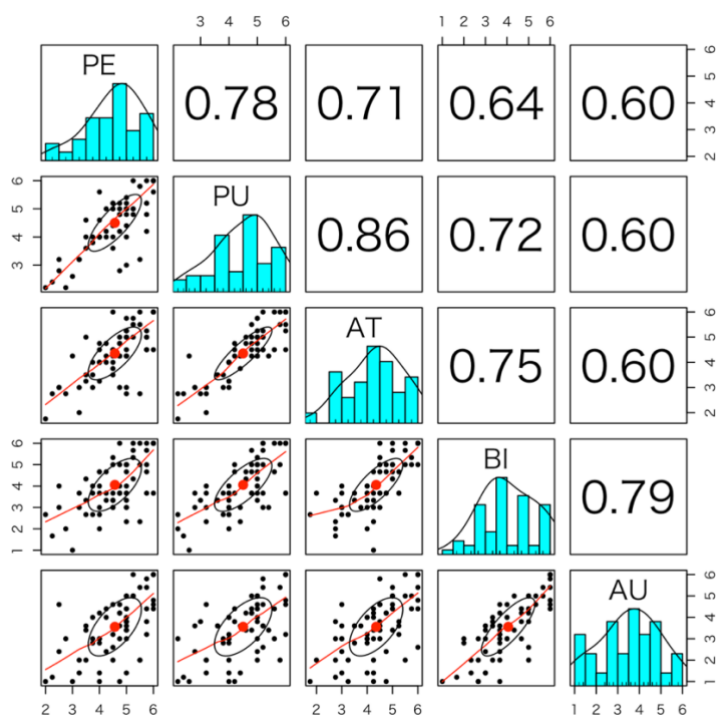
*Descriptive Statistics for TAM Subscales*

Scales	Number of Items	Mean	SD	$\alpha$
Perceived Ease of Use (PE)	4	4.57	0.98	.86
Perceived Usefulness (PU)	5	4.50	1.01	.95
Attitude (AT)	4	4.35	1.05	.91
Behavioral Intention (BI)	3	4.05	1.24	.91
Actual Usage (AU)	5	3.56	1.36	.94

$N = 67$

**Figure 7**

*Pairwise Correlations Among TAM Subscales*



*Note.*  $N = 67$ . PE: Perceived Ease of Use, PU: Perceived Usefulness, AT: Attitude, BI: Behavioral Intention, AU: Actual Usage

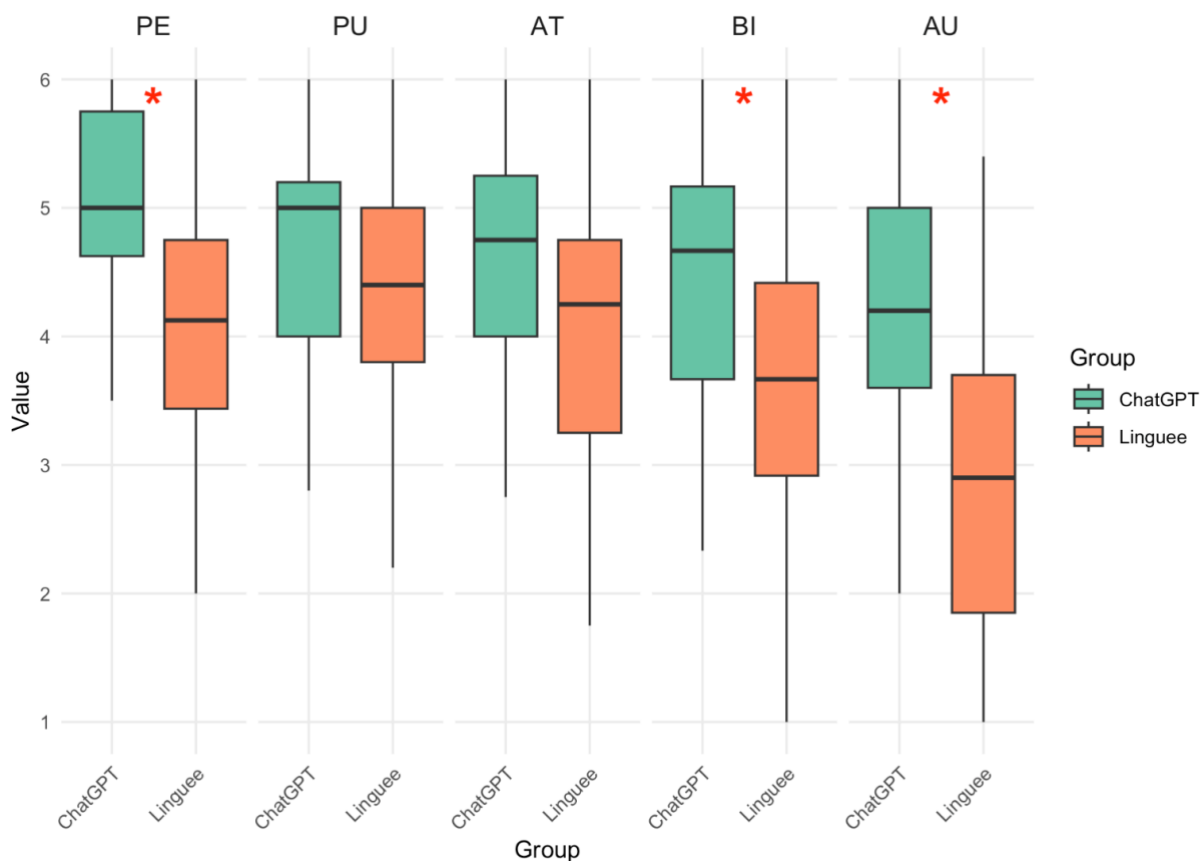
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To examine whether learner perceptions differed between the ChatGPT and Linguee groups across the five TAM subscales, a Mann–Whitney U test was performed. This nonparametric test was chosen because several variables deviated from normality (see Figure 7). The results revealed that the ChatGPT group scored significantly higher on three constructs—Perceived Ease of Use (PE), Behavioral Intention (BI), and Actual Usage (AU). As illustrated in Figure 8, the ChatGPT group also showed higher mean ranks on the remaining subscales, though these differences were not statistically significant. Overall, these findings indicate that learners perceived the AI-assisted DDL condition (ChatGPT) more positively than the traditional corpus-based condition (Linguee), supporting the results reported for RQ3.

**Figure 8**

*Comparative TAM Subscale Boxplots by Group*



*Note.* \*  $p < .05$  PE: Perceived Ease of Use, PU: Perceived Usefulness, AT: Attitude, BI: Behavioral Intention, AU: Actual Usage

To determine which type of learner—deductive or inductive—benefits more from the two types of DDL activities, a cluster analysis was conducted. This analysis examined learning outcomes using

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several indicators: two learning preference measures (deductive and inductive), task value, the mean scores of all 21 items of the TAM, and the difference score as the outcome measure, calculated by subtracting the pretest score from the posttest score.

The measures for learning preferences and the measure on perceived task value are based on Mizumoto and Chujo (2016). Mizumoto and Chujo reported weak correlations between inductive–deductive learning preferences and DDL task value. Their Deductive scale originally consisted of three items; however, item analysis showed that  $\alpha$  fell below .50. Removing one problematic item (i.e., DE1 in Table 2) improved it to two items. Our final 2-item Deductive scale achieved Cronbach's  $\alpha = .64$ , and the Inductive scale also fell below .70 ( $\alpha = .68$ ). These marginal  $\alpha$  values likely result from the limited number of items, a common issue for brief scales. As shorter scales often produce lower  $\alpha$  yet remain acceptable for preliminary research (Nunnally, 1967), these constructs should be interpreted with caution. Other constructs—Task Value and TAM—achieved acceptable reliability (Table 5).

**Table 5**

Descriptive Statistics for Learning Preference Scales

Scales	Number of Items	Mean	<i>SD</i>	$\alpha$
Deductive	2	4.20	0.93	.64
Inductive	4	3.66	0.91	.68
Task Value	5	4.74	0.73	.86
TAM	21	4.20	0.98	.97

The use of the overall mean score of the 21 TAM items as a representative measure for the five subscales was validated in RQ1. The TAM subscales exhibited strong intercorrelations, and the correlation between the component scores derived from a principal component analysis (PCA) and the simple mean score was  $r = .998$ , confirming that the mean score reliably represented the overall TAM construct.

To explore which learner profiles benefited most from the guided DDL induction approach, cluster analysis was conducted, following procedures commonly employed in learning strategy research (Mizumoto & Takeuchi, 2018). As an exploratory technique, cluster analysis identifies meaningful patterns rather than discrete constructs. The optimal number of clusters was determined through several criteria—the dendrogram, silhouette method, elbow method, and gap statistics—all supporting a two-cluster solution. Results are shown in Figure 9.

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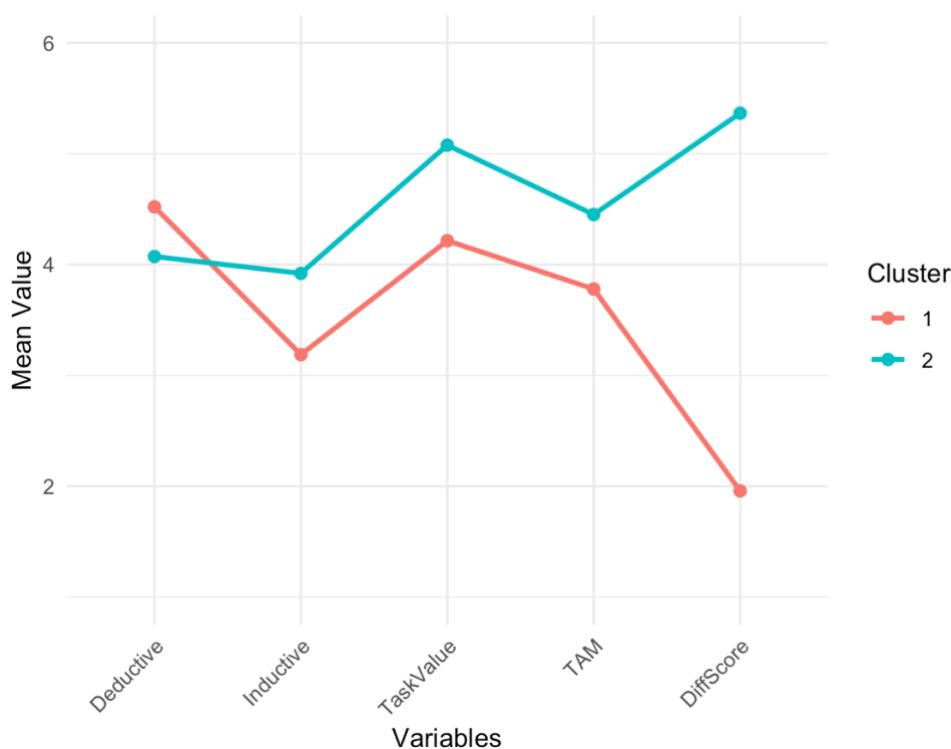
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Cluster 1 demonstrated generally lower values across all variables except Deductive Learning, whereas Cluster 2 showed higher values overall. Mann–Whitney U tests confirmed statistically significant differences between the two clusters for Inductive Learning, Task Value, TAM, and the learning gain (Difference Score), but not for Deductive Learning.

These findings indicate that learners characterized by stronger inductive preferences, higher task value, and greater acceptance of technology achieved superior outcomes under the guided DDL induction condition. This pattern underscores that DDL effectiveness is shaped by a constellation of learner characteristics rather than a simple inductive–deductive dichotomy. Considering perceptions of DDL alongside cognitive and motivational variables provides a more nuanced understanding of individual differences in data-driven learning.

**Figure 9**

Cluster Analysis of Learning Preferences and Learner Perceptions



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## Discussion

This study examined the effectiveness of AI-assisted and traditional corpus-based DDL, represented by ChatGPT and Linguee, respectively. The findings illuminate how these approaches interact with learner proficiency, individual differences, and perceptions. Although both yielded comparable learning outcomes, they diverged in learner engagement, proficiency effects, and cognitive preferences, offering nuanced pedagogical insights.

The absence of significant posttest differences indicates that both ChatGPT and Linguee can effectively facilitate inductive learning, though they operate through distinct mechanisms. Learners reported greater ease and adaptability with ChatGPT, reflected in higher scores for Perceived Ease of Use (PE), Behavioral Intention (BI), and Actual Usage (AU). These perceptions suggest that ChatGPT alleviates the technical and cognitive barriers commonly associated with corpus tools, thereby increasing accessibility for lower-proficiency learners. This finding corroborates previous research emphasizing the motivational and affective benefits of AI-mediated learning (Yang & Li, 2024; Mizumoto, 2023). However, caution is warranted in generalizing these results beyond the present EFL university context, as the pedagogical affordances of AI-assisted DDL may vary across languages and educational settings.

Learner proficiency and individual differences emerged as critical factors. Intermediate learners benefited most, likely because their linguistic foundation enabled deeper engagement with inductive tasks, whereas low-proficiency learners required greater scaffolding. Learners with inductive learning preferences and stronger task-value beliefs achieved higher gains across both tools, highlighting the influence of cognitive and motivational variables. Although deductive orientation did not significantly affect outcomes, the findings underscore the importance of tailoring instruction to individual learner profiles, as also observed by Mizumoto and Chujo (2016).

From a pedagogical standpoint, the advantage observed among intermediate learners (mean difference = 1.71,  $d = 0.63$ ) indicates that DDL is particularly effective when learners possess sufficient linguistic knowledge to participate in discovery-based learning. Teachers might therefore optimize instruction by explicitly fostering inductive reasoning through structured DDL tasks.

The inductive–deductive dichotomy adopted here was intentionally simplified to facilitate analysis, yet learner preferences are more complex and fluid than this binary suggests. Future work should employ multidimensional or qualitative approaches to capture these dynamics more precisely.

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Theoretically, this study supports the view that AI tools such as ChatGPT can complement traditional corpus-based approaches. Within the MRU framework (Mizumoto, 2023), ChatGPT fosters hypothesis testing and real-time feedback that promote learner autonomy and engagement. Its adaptive scaffolding also resonates with sociocultural theory, particularly Vygotsky's (1978) notion of the Zone of Proximal Development. Nevertheless, reliance on AI-generated explanations raises concerns about superficial engagement, emphasizing the need for task designs that sustain analytical depth. ChatGPT's generation of contextualized examples parallels traditional concordancing while offering greater accessibility (Lin, 2023). Combined, these affordances enable instructors to integrate immediacy and authenticity without compromising analytical rigor (Leńko-Szymańska & Boulton, 2015).

At the same time, critical issues remain. AI-generated inaccuracies ("hallucinations"), the absence of verifiable frequency data, and ethical challenges related to data privacy and learner autonomy continue to pose risks (Crosthwaite & Baisa, 2023; Lin, 2023; Uchida, 2024; Yang & Li, 2024). Pedagogical frameworks must therefore incorporate explicit training to help learners critically evaluate AI outputs and use such tools responsibly.

Future research should examine AI-assisted DDL across broader educational contexts. In primary and secondary education, AI tools may scaffold inductive learning through age-appropriate feedback, while in higher education, they may enhance learner autonomy and metacognitive awareness. For adult or professional learners, AI-assisted DDL offers flexible, context-sensitive access to linguistic input. These possibilities highlight its adaptability but also the need for careful calibration of task complexity and teacher involvement.

A key challenge is balancing AI's convenience with meaningful cognitive engagement. While AI-assisted DDL enhances immediacy and efficiency, excessive reliance may reduce hypothesis testing and independent analysis. Teachers should thus design tasks that exploit AI's strengths while preserving learner agency. Moreover, institutions must establish transparent policies regarding data privacy, academic integrity, and ethical AI use.

Finally, integrating AI-assisted DDL with other pedagogical paradigms—such as grammar-focused instruction and task-based language teaching (TBLT)—may yield a more balanced instructional model. By embedding AI tools into pre- or post-task stages, learners can notice linguistic patterns and consolidate grammatical awareness derived from communicative practice. Such hybrid designs could offer a sustainable model for combining data-driven discovery, explicit learning, and communicative engagement in applied linguistics.

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## **Practical Implications**

The findings highlight the pedagogical value of integrating AI tools with traditional corpus-based methods to create more comprehensive and inclusive learning environments. Teachers should capitalize on the complementary strengths of both: AI tools provide real-time feedback and adaptive scaffolding, while corpora offer authentic linguistic data for deeper analytical engagement (Satake, 2024).

The study also underscores the importance of professional development that equips teachers with the skills and critical awareness necessary for integrating AI into classroom practice. As Shevchenko et al. (2021) note, successful pedagogical innovation depends on the alignment of teacher beliefs, professional training, and institutional support. Accordingly, institutions play a crucial role in ensuring the sustainable and meaningful adoption of such technologies.

Professional development initiatives could include (a) workshops on designing effective prompts for eliciting accurate linguistic data from ChatGPT, (b) sessions on integrating corpus-based and AI-based activities into existing curricula, and (c) seminars on cultivating learners' critical evaluation skills to address potential inaccuracies or "hallucinations" in AI outputs. Institutional adoption also faces challenges related to technical infrastructure, funding, and pedagogical resistance. These may be mitigated by piloting small-scale AI-DDL projects, developing evidence-based implementation guidelines, and establishing collaborative communities of practice among educators.

## **Future Directions**

This study highlights the importance of aligning technological affordances with pedagogical principles while accounting for individual differences. Future research should examine the long-term effects of AI-assisted DDL on learner autonomy, critical thinking, and sustained language development. Longitudinal and mixed-methods approaches would provide deeper insight into how learners' engagement and outcomes evolve over time.

Particular attention should be directed toward enhancing accessibility for low-proficiency learners through adaptive systems that tailor task difficulty to individual needs. In addition, prior studies have shown that learners' attitudes toward DDL evolve with familiarity and training (Mizumoto & Chujo, 2016; Boulton, 2009b). Future investigations should therefore include extended instructional interventions to capture these attitudinal shifts more comprehensively.

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Methodologically, several limitations should be acknowledged. First, the repeated use of identical test items in pre- and post-tests, although effective for measuring progress on specific items, may have inflated scores through familiarity effects. Although precautions were taken—such as withholding answers and avoiding overlap between instruction and testing—future studies should employ parallel test forms of equivalent difficulty to ensure greater measurement validity.

Second, this study lacked detailed background data on learner motivation, prior experience, and strategy use, which may have influenced engagement with DDL tools. Incorporating such variables in future designs would allow for a more comprehensive understanding of individual learning trajectories.

A further limitation concerns the restricted number of items in the learning preference measure, particularly the Deductive scale, which included only two items after the removal of one with low reliability. While this improved internal consistency, it likely constrained construct validity. Future research should adopt more comprehensive instruments to better capture the multidimensionality of learners' cognitive preferences.

Finally, the classification of Linguee as a DDL tool warrants caution. Unlike traditional concordancers, Linguee provides L1 translations alongside corpus examples, potentially shifting learner processing from inductive discovery toward deductive verification. Although Linguee has been recognized as a DDL-like resource (Boulton & Vyatkina, 2021; Buyse & Verlinde, 2013), future studies should compare tools differing in the degree of inductive and deductive support to clarify their respective pedagogical affordances and learning impacts.

## Conclusion

This study demonstrates the potential of AI-assisted tools like ChatGPT to transform DDL practices by addressing traditional barriers and aligning with contemporary theories of learner engagement and autonomy. By combining the strengths of generative AI and traditional corpus-based methods, teachers can create integrative, adaptive, and learner-centered approaches that meet the evolving demands of 21st-century language education. The findings highlight the need for continued research and innovation to optimize these technologies for diverse educational contexts, ensuring that their benefits are accessible to all learners.

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