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AI-Powered Flipped Instruction in Higher Education: Effects on Conceptual Understanding in Psychology of Language Learning

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ABSTRACT

Background and Objectives: Flipped instruction (FI) inverts the traditional lecture-homework model, engaging learners with content before class through a variety of technologies. AI in this regard can bring adaptability and interactivity to both the pre-class and in-class phases, especially in understanding scientific concepts in higher education courses. While there is growing research on the value of AI-assisted FI in subjects such as science and engineering, the impact of this revolutionary instructional practice in teacher education courses remains open to further research. This study employs a quasi-experimental design to investigate the effects of AI-assisted FI on the understanding of technical and scientific concepts in the course Psychology of Language Learning.

Materials and Methods: The participants included three groups of BA students who enrolled in the course Psychology of Language Learning (n=73). Group 1 (n=26) received AI-assisted FI, where pre-class instructional content was prepared by NotebookLM, an AI-powered research and writing tool. Group 2 (n=25) received conventional FI, where pre-class instructional content included the instructor's PowerPoints with voiceovers. Group 3 (n=22) received conventional instruction utilizing a lecture-based instructional approach. In-class phase activities included quizzes, group/pair work, completion of task sheets, question-and-answer activities, and oral discussions. Post-class reinforcement included summary writing, transcribing, and generating concept maps. The participants' achievement in the course and understanding of the technical concepts were assessed by the researcher-made midterm and final exams.

Findings: A two-way Multivariate analysis of Variance (MANOVA) was used to compare the participants' achievement in the course and understanding of the technical terms. The results illustrated a significant difference between the three groups in general achievement and in both the midterm and final exams of the course with a strong effect size. Tukey's HSD test showed that Group 1, who experienced AI-assisted FI, outperformed both Groups 2 and 3 in midterm and final exams. It was also found that Group 2, who learned the technical concepts using conventional FI, outperformed Group 3, who participated in a traditional and lecture-based course, in both exams. No difference was observed between male and female students.

Conclusions: The significant improvement in conceptual understanding among students who experience AI-assisted FI suggests that integrating AI tools, such as NotebookLM, can meaningfully enhance learning experiences by providing personalized, adaptive, and interactive pre-class content. This implies a shift in pedagogical design, from traditional, instructor-centered delivery models to learner-centered environments where students actively engage with content before class. Moreover, the use of AI in pre-class instruction supports differentiated learning by accommodating individual pacing and comprehension levels, thus promoting educational equality. For instructors, AI tools reduce the need for repetitive content delivery, enabling them to focus on facilitating higher-order learning, critical thinking, and collaborative in-class activities. From an institutional perspective, the successful application of AI-assisted FI in this study can reform curriculum development, faculty training, and the integration of AI tools into learning. Notably, while this study focused on educational psychology in ELT, the model has broad potential for transferability to other fields, particularly those requiring mastery of complex or technical concepts, such as engineering education, STEM curricula, or health education.

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مقاله پژوهشی

آموزش معکوس مبتنی بر هوش مصنوعی در آموزش عالی: اثر بخشی بر درک مفاهیم علمی در روانشناسی یادگیری زبان

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چکیده

پیشینه و اهداف: کلاس معکوس مدل آموزشی سنتی سخنرانی-محور را دگرگون کرده و فراگیران را با استفاده از فناوری‌های متنوع قبل از کلاس درس با محتوای آموزشی درگیر می‌کند. در این ارتباط، هوش مصنوعی می‌تواند قابلیت سازگاری و تعامل را به ویژه در آموزش مفاهیم علمی به مراحل پیش کلاسی و درون کلاسی بیافزاید. با وجود پژوهش‌های رو به رشد مرتبط با بکارگیری هوش مصنوعی در کلاس معکوس، تأثیر این فناوری در دوره های تربیت معلم نیازمند پژوهش‌های تکمیلی است. از این رو، این مطالعه با بکارگیری طرح شبه تجربی به بررسی تأثیر کلاس معکوس با کمک هوش مصنوعی بر عملکرد دانشجویان در درس روانشناسی یادگیری زبان می پردازد.

روش‌ها: شرکت کنندگان شامل سه گروه دانشجوی مقطع کارشناسی آموزش زبان انگلیسی بودند که در درس روانشناسی یادگیری زبان ثبت نام کرده بودند (۷۳ نفر). محتوای آموزشی گروه اول (۲۶ نفر) با استفاده از NotebookLM که یک ابزار هوش مصنوعی برای پژوهش، نگارش و تولید محتوی است آماده شد و آموزش معکوس از طریق آن صورت گرفت. گروه دوم (۲۵ نفر) کلاس معکوس را با استفاده از پاور پوینت های صداگذاری شده استاد تجربه کردند. گروه سوم (۲۲ نفر) درس را از طریق آموزش سنتی سخنرانی فرا گرفتند. فعالیت های درون کلاسی، شامل آزمون ها، کار گروهی/دو نفره، تکمیل برگه های تمرین، فعالیت های پرسش و پاسخ، و بحث های شفاهی بود. تمرین های پس از کلاس شامل خلاصه نویسی، پیاده کردن متن فایل های صوتی، و درست کردن نقشه های مفهومی بود. عملکرد و یادگیری مفاهیم علمی هر سه گروه از طریق آزمون های محقق ساخت میان ترم و پایان ترم مورد ارزیابی قرار گرفت.

یافته‌ها: برای مقایسه فراگیری مفاهیم علمی، از تحلیل واریانس چند متغیره دو سویه استفاده شد. نتایج نشان داد که بطور کلی بین عملکرد سه گروه شرکت کنندگان در درس روانشناسی یادگیری زبان تفاوت معناداری با ضریب تأثیر قوی وجود داشت. این تفاوت در بین آزمون های میان ترم و پایان ترم نیز معنادار بود. آزمون تعقیبی توکی نشان داد که گروه اول که آموزش معکوس با کمک هوش مصنوعی را دریافت کرده بودند، در هر دو آزمون عملکرد بهتری نسبت به گروه دوم و سوم داشتند. همچنین، گروه دوم که آموزش معکوس متداول را دریافت کردند، نسبت به گروه سوم که آموزش سنتی سخنرانی-محور را تجربه کردند، عملکرد بهتری داشتند. تفاوت معناداری بین عملکرد دانشجویان دختر و پسر مشاهده نشد.

نتیجه‌گیری: بهبود قابل توجه در عملکرد گروه کلاس معکوس با کمک هوش مصنوعی نشان می دهد که بکارگیری ابزارهای هوش مصنوعی مانند NotebookLM می تواند تجارب یادگیری را ازطریق شخصی سازی، سازگاری و تعامل با محتوای آموزشی تقویت کند. این موضوع نشان دهنده نیاز به تحول در طراحی مدل های آموزشی از روش های سنتی استاد-محور به محیط های یادگیرنده-محور است که در آن فراگیر بتواند بطور فعال با محتوای آموزشی قبل از دریافت آموزش درگیر شود. استفاده از هوش مصنوعی در کلاس معکوس می تواند آموزش را فردی سازی کرده و با در نظر

گرفتن سرعت و توانایی درک مناسب هر دانشجو برابری آموزشی را ارتقا بخشد. ابزارهای هوش مصنوعی به اساتید کمک می کند تا بدون نیاز به ارائه های تکراری بر ارتقا یادگیری های سطح بالاتر، تفکر نقادانه، و فعالیت های گروهی درون کلاسی تمرکز بیشتری داشته باشند. از منظر سازمانی، بکارگیری موفق آموزش معکوس با کمک هوش مصنوعی می تواند انقلابی در طراحی برنامه درسی، تربیت مدرس و کاربست فناوری های نوین در آموزش ایجاد کند. با اینکه یافته های این مطالعه بر درس روانشناسی یادگیری در حوزه آموزش زبان متمرکز بود، مدل ارائه شده قابل تعمیم به سایر حوزه های آموزش مانند آموزش مهندسی، آموزش تلفیقی (STEM) و حوزه سلامت که بطور ویژه بر یادگیری مطلق مفاهیم پیچیده علمی تأکید دارند، است.

Introduction

With revolutionary advancements in computer science, creating intelligent machines and systems, Artificial Intelligence (AI) is becoming an integral part of modern society, exerting a considerable influence on all aspects of human life, from industry and healthcare to transportation and education. Being capable of performing tasks that typically require human intelligence, the potential of AI in education to transform learning environments and personalize instruction is particularly profound. The role of AI in curriculum design across various disciplines and subject matters, supporting AI-related future careers, is among the critical issues educators face today [1].

One area of education that has been extraordinarily affected by intelligent systems is language teaching and learning, as the bridge between computer science, linguistics, and machine learning has enabled the processing and analyzing of large amounts of natural language data and the fabrication and application of sophisticated AI language systems and services [2]. The practical outcomes of AI incorporation in TEFL can be identified in different aspects of language teaching, reshaping the way students learn English and the way teachers consider pedagogical positions. AI-based programs such as chatbots, interactive writing feedback tools, and pronunciation software are designed to respond to the input of individual learners in real time, providing individualized pacing, corrective feedback, and practice matching an individual learner's level of proficiency. Unlike a one-size-fits-all model teaching where students must conform to the group's pace, AI delivers differentiated learning paths, allowing slow learners to have attention and support while advanced learners are kept on their toes all the time, so they do not become uninterested. Over the long term, this responsiveness can mitigate frustration, support the development of learners' confidence, and lead to greater sustained engagement with the learning of a foreign language [3].

Away from the classroom, AI is also making an impact on accessibility and inclusivity in language learning. Students in disadvantaged and poorly equipped areas can still engage with AI-powered platforms to practice language when the classroom is not in session [4]. Similarly, AI tools may be personalized for diverse learner needs, such as students with learning problems and remedial work. Multimodal AI environments that incorporate text, audio, visual cues, and potentially gesture recognition can support various learning styles, making language training more inclusive. Moreover, AI systems might incorporate some gaming features like scoring, ranking, and progress tracking to foster fun and persistent motivation among young learners who can experience fatigue in conventional practice methods. It is also worth mentioning what the contribution of AI can be for the cultivation of learner autonomy. By providing continual, personalized support outside classroom doors, AI enables students to take more ownership over their learning [5].

The use of AI in language learning is transforming the learning process of the students as well as the roles of the teacher for pedagogical practice. Through personalization, inclusivity, and learner autonomy, AI enables more effective, self-directed, and equitable language learning. In this scheme, AI features and affordances offer considerable potential for flipped instruction (FI), where the inverted and innovative teaching procedure demands learners' responsibility to engage in instructional content and higher-order cognitive processing before class sessions. FI has gained prominence as a pedagogical approach that redefines the traditional lecture-based and teacher-centered instruction by engaging students with course content before attending the class session, allowing for more active learning during in-class sessions [6-7]. Rooted in constructivist and learner-centered theories, FI has demonstrated potential for enhancing student engagement, autonomy, and deeper cognitive processing [8]. However, the effectiveness of FI largely depends on the quality, interactivity, and adaptability of pre-class instructional materials [9]. Hence, AI-powered platforms with their potential to transform passive content consumption into dynamic, learner-centered experiences are eminently suitable for content development and delivery. AI tools can facilitate personalized summaries, clarifications, and conceptual explanations based on user queries and enrich FI environments by intelligent tutoring and real-time feedback [10]. While there is growing research on the value of AI-assisted FI in subjects such as science and engineering, the impact of this revolutionary instructional practice in education-related domains remains open to further research. This study thus employs a quasi-experimental design to investigate the effects of AI-assisted FI on the understanding of technical and scientific concepts in the course Psychology of Language Learning. As AI tools can help make complex and intangible ideas more concrete, interactive, and personalized by promoting visualization and simulation, offering data-driven insights, and encouraging critical thinking and deeper understanding, their use in teaching technical concepts of psychology is expected to be fruitful. This gap is noteworthy given that educational psychology courses often involve abstract and complex constructs critical to pedagogical reasoning and professional development in teaching [11]. The study thus aims to answer these questions:

- Does AI-assisted FI have any significant impact on learning scientific concepts as compared to conventional FI and traditional lecture-based instruction?
- Does gender influence learning scientific concepts across different instructional models, that is, AI-assisted FI, conventional FI, and traditional lecture-based instruction

Review of the Related Literature

Theoretical Framework of FI

The flipped classroom, also referred to as flipped instruction (FI), is underpinned by several educational theories that collectively emphasize active learning, learning autonomy, and constructivist engagement. At its core, FI reverses the traditional pedagogical model, where in-class lectures or presentations are followed by out-of-class homework and extensive practice. This is achieved by delivering instructional content outside the class that is typically prepared through videos of the teacher's lectures, followed by classroom tasks that focus on collaborative, interactive, and student-centered activities [12].

The constructivist theory, associated with Piaget and Vygotsky, posits that learners build knowledge actively rather than passively absorbing information, thus changing the role of learners to active agents of learning. FI aligns closely with this view as it facilitates student-led inquiry and problem-solving before the actual teaching, and collaboration and cooperation during face-to-face sessions. This structure supports deeper cognitive engagement as students process, question, and apply content in socially interactive environments [9]. In this framework, Vygotsky's Zone of Proximal Development (ZPD) is operationalized in pre-class materials that provide the initial cognitive scaffolding, allowing classroom time to be used for guided application and peer discussion. In support of how individuals engage with tasks within a community by mediated tools, Activity Theory can also underline FI, emphasizing how technological tools and environments, and structure and patterns of collaboration, shape educational outcomes in a flipped class [13].

FI often increases student self-efficacy and motivation by supporting self-directedness through giving students control and pace of learning when the students interact with the content before the class instruction. Self-Determination Theory underscores this type of learning when the interplay among autonomy, competence, and relatedness needs fosters intrinsic motivation for learning. Autonomy is developed and enhanced when students access the instructional content outside of the class at their own pace, time, and even knowledge. The students' sense of competence and mastery is often supported by interactive activities in class sessions when students focus on problem-solving skills, discussion, and application of their knowledge. Relatedness is also backed during collaboration in the class when the interaction between the peers and/or teacher-peer interaction is meaningful, as everybody tries to be a part of the learning experience [14].

FI also aligns well with cognitivism as Bloom's taxonomy of cognitive processing underpins the design and implementation of flipped classes. In FI, the traditional cognitive engagement structure is reversed, where the lower-order thinking skills are addressed before the class and the higher-order thinking skills are developed during class. Usually, the two lower-order thinking skills, that is, remembering and understanding, are done out of class so that the students can develop foundational knowledge on the matter. Then, classroom time is consumed by active and collaborative learning tasks to promote students' critical and creative thinking. Thus, tasks that demand applying, analyzing, evaluating, and creating based on the learned topics are done in the class phase [15]. Notably, FI aligns with Cognitive Load Theory (CLT) by allowing students to manage intrinsic and extraneous loads more effectively by engaging with complex topics at their own pace and preference outside the class. As most videos are interactive, the students can watch and rewatch the teacher's lecture and thus feel less mentally bothered than they do in single-shot classroom teachings [16].

AI-assisted FI

Although the flipped approach is "a pedagogical change and not a technological one" [17, p. 1], technology plays a key role in designing teaching materials and delivering instructional practice in FI. As extensive research on educational technology illustrates, technology is a delivery channel that fosters developing and sharing instructional content and facilitates student-centered learning, leading to better learning gains in many subjects. The technologies that are used to prepare FI instructional content can be classified into low-tech, mid-tech, and high-tech based on three basic criteria that is teacher IT literacy and access, the need for programming knowledge, and the presence of Intelligent Tutoring Systems (ITS) [18].

Teachers can use simple technological devices/environments to prepare and deliver the content to students. The conventional FI class that dominates the literature [19] consists of teacher's PowerPoint files with voiceovers that are shared with students via social media or cloud services. Mid-tech systems such as LMSs or streaming platforms are often online modules that can be used as they are or are tailored to the needs of the class by adjusting the system's features. High-tech systems have not been very prevalent in FI before users' widespread access to AI services and tools. The intelligent systems are capable of making smart decisions about strategies of tutoring/learning and thus are ideal tools for personalization of instruction, without disregarding mastery of critical skills and knowledge [18].

AI, defined as "the development of systems that can simulate, augment, or replace human cognitive functions …. through algorithmic and data-driven models capable of improving autonomously over time" [20], can revolutionize FI, enhancing both the pre-class and in-class learning experiences. Ray and Sikdar remarked that AI tools can be integrated into FI for personalized learning paths, adaptive assessments, content curation and recommendation, virtual tutoring and support, and data analytics for educators [21]. They also noted the potential of AI-assisted FI to enhance engagement, improve learning outcomes, use class time effectively, enhance educational equity, and contribute to teachers' professional empowerment.

Recently, a body of research has been done to elucidate the potential of implementing AI tools to flip the instruction. In their review on the impacts of AI-chatbots in FI, Low and Hew reported certain merits for AI-assisted FI, including improvement of class preparation, increased student interaction with learning content, and implementation of data-driven teaching and learning [22]. Katona and Gyonyoru showed that implementing AI-based adaptive feedback in FI leads to significant improvements in learning outcomes and motivation, as well as an increase in student autonomy that caused more collaboration and participation in class sessions [23]. Similarly, Chu et al. illustrated a significant impact of AI-assisted FI to improve learning outcomes as well as increased interaction and engagement in class participation [24]. Li and Peng's study demonstrated that AI-assisted FI can generate more positive attitudes to learning experiences in regard to interest, study skills, and class participation. Integrating AI into FI lowered mental processing loads and boosted students' confidence by lowering their anxiety about class interaction [25]. Hu's study showed that integrating a generative AI into FI not only prevents autonomous mental task load but also maintains students' pre-class preparation and enhances confidence in ethical learning [26]. Chen et al. illustrated that AI-generated virtual instructors of FI can significantly enhance affective engagement and academic performance and lower cognitive load compared to the human instructor [27]. Silitonga et al. reported that AI-assisted FI was influential in boosting motivation and higher-order thinking, including creativity, critical thinking, and problem-solving [28]. Jayaraman and Kolarkar found that AI-assisted FI not only increases student engagement and achievement but also decreases course withdrawals by 18.5% [29].

Despite the positive findings of these studies, certain limitations and potential challenges for flipping instruction with AI tools and services are pinpointed. Aligning teaching objectives with AI techniques, ethical considerations, and human-computer interaction should be carefully observed to ensure the successful use of AI in FI [30]. Equity and access to AI, privacy and data security, students' low motivation [21], and teachers' empowerment to use new technologies [31] as well as AI's limited technical functionality and lack of authenticity are among other challenges of AI-assisted FI that demand more examination of the impact of AI generative on learning gains in various educational contexts [22].

AI-assisted FI and Language Learning

The integration of AI into the FI model can impact course design and instructional practices to create more adaptive, personalized, and data-informed learning environments for language learners. The confluence of AI and FI in language curriculum affects both cognitive and affective domains of language acquisition by promoting engagement, self-regulation, and communicative competence [18].

AI-driven systems are increasingly used to personalize pre-class language learning modules, particularly in listening, speaking, and grammar-oriented content. Rahmawati and Fitriati, for instance, introduced a four-strand approach integrating AI-assisted pre-class modules in adaptive listening tasks and pronunciation feedback systems. Results suggested that AI-facilitated software improved access to input, language accuracy, and learner engagement, but drawbacks related to contextual appropriacy, reliability of feedback, and continuity of pedagogy also arose [16]. In another study, Choudhary et al. documented improvement of oral proficiency among EFL learners within an AI-enhanced FI environment. Tools such as speech recognition engines, accent analyzers, and grammar checkers allowed for autonomous improvement before class sessions [32]. Ouahmiche and Bouguebs explored the intersection of AI, flipped learning, and intercultural competence and argued that AI can simulate cross-cultural communication scenarios and enable learners to practice real-world interaction in safe, controlled environments [34]. Namaziandost reported that AI-enhanced FI significantly improved EFL learners' metacognitive awareness, promoted their writing development, and reduced boredom [28]. Phanwiriyarat et al. explored the impact of an AI-powered gamified flipped classroom in an English-speaking course and reported significant improvements in speaking skills, particularly in topic communication and discussions, with students reporting increased confidence in casual conversations and presentations [35].

A limited number of studies have also focused on exploring the influence of AI-assisted FI in understanding scientific topics in the language curriculum. Chan and Liu implemented a GenAI-supported pronunciation model that provided real-time feedback on scientific and academic terms, improving learners' oral academic discourse skills, which is a crucial asset for language educators in training [35]. In another study, Reinders et al. documented how Korean language teacher candidates trained with AI-assisted FI tools developed an improved understanding of content-language integrated learning frameworks and were more confident in explaining scientific terms [37]. The synopsis of literature shows that, while the innovative model of AI-assisted FI is more extensively used in STEM education [38], its potential for teaching and learning scientific concepts, particularly in social sciences and language education, is unexplored.

Method

Participants

The participants included three groups of BA students who enrolled in the course Psychology of Language Learning I (n=73). The students' major was Teaching English as a Foreign Language (TEFL). The sample included 32 male (44%) and 41 female (56%) students. They ranged in age between 20-23 (Mean=20.24). None of the students had passed any course in Psychology of Language Learning, and they were not familiar with the scientific concepts of the course. The participants were randomly assigned to be of three groups: Group 1 (n=26) received AI-assisted FI, Group 2 (n=25) received conventional FI, and Group 3 (n=22) received a lecture-based instructional.

All participants were fully informed about the purpose of the study, including the use of NotebookLM in instruction. Participation was voluntary, and AI was only used as an assistive tool under human supervision. The study adhered to ethical guidelines for educational research and AI ethics, ensuring fairness, transparency, accountability, and respect for human dignity.

Instruments

Two researcher-made knowledge tests were developed to assess the participants' understanding of the topics presented in the course by midterm and final exams. The questions were designed considering Bloom's hierarchy of cognitive processing, including remembering, understanding, applying, analysing, evaluating, and creating.

Each test had 25 explanatory items organized into two sections. Questions that assessed students' remembering and understanding were organized in section 1, Theory, and questions that assessed students' ability to apply what they learned, analyze problems, evaluate the scenarios, and create materials were put in section 2, Practice.

Both tests had been piloted in previous courses with samples similar to the current study's participants (N=44). The content validity of the test was assessed by three TEFL instructors who reviewed the items based on the accuracy of the information presented, clarity of the language, and correspondence between the number of items and the syllabus of the course and the discussed topics. Based on the received feedback, the format and wording of a few items were revised.

All papers were corrected twice, with a time interval of 2 weeks, by the instructor using an analytical rubric. The intra-rater reliability was found to be 0.92.

Teaching Materials

The course Psychology of Language Learning I is a 2-unit theoretical course in the curriculum of the BA of English Language Teaching approved by Iran's Ministry of Science, Technology, and Research [39]. The objectives of the course include the history and frameworks of language learning psychology and their components (e.g., affect, motivation, memory, intelligence, etc.). The main textbook of the course was Exploring Psychology in Language Learning and Teaching [40]; however, a variety of sources were used to prepare and deliver instructional content and lectures.

AI Platform

NotebookLM (notebooklm.google.com) was used to prepare the instructional content for the AI-assisted FI group. NotebookLM is an AI-powered research and study tool developed by Google, designed to support learners and professionals in synthesizing information across multiple sources. Functioning as a personalized knowledge assistant, NotebookLM allows users to upload documents-such as PDFs, lecture notes, or web content, based on which it generates summaries, concept maps, definitions, and contextual explanations through natural language interaction [41].

One of the tool's distinguishing features is its 'Discovery Window', which automatically identifies key ideas, organizes core concepts, and surfaces thematic relationships among documents. This function facilitates deep learning by enabling users to engage with source material in a structured, inquiry-based manner. Users can also prompt the system with specific questions, generate outlines, or explore thematic 'deep dives', which are customized narratives derived from uploaded content (Fig. 1).

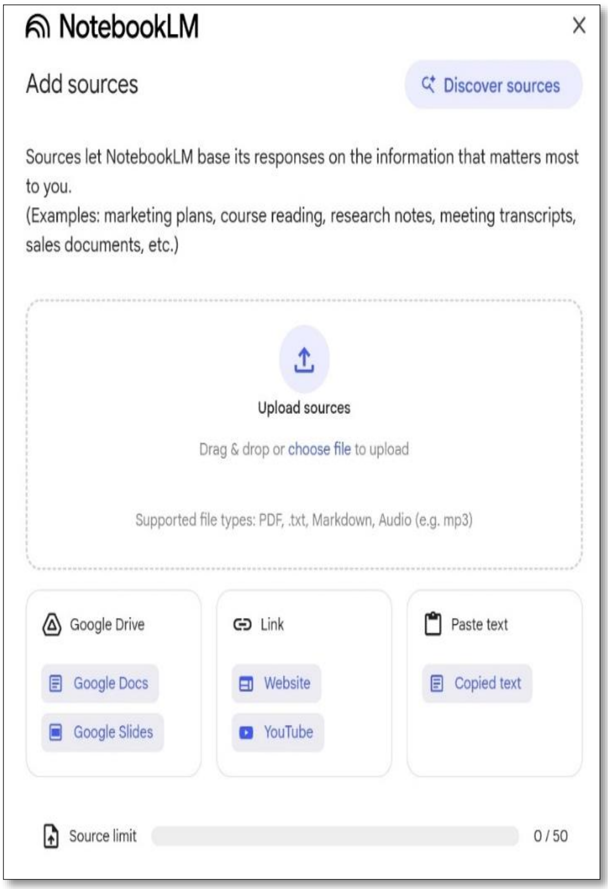

Fig. 1: NotebookLM (notebooklm.google.com)

From a pedagogical perspective, NotebookLM aligns with contemporary constructivist and cognitive learning theories, particularly in its support for metacognition, conceptual mapping, and personalized feedback. NotebookLM has begun to gain attraction in educational research, especially in exploring AI tools for teaching and learning, and engaging learners with the content. Therefore, it was considered a suitable tool for AI-enhanced FI as a core element to prepare content for Group 1. Deep dives generated through NotebookLM served as pre-class instructional materials, replacing traditional reading or lecture content. These materials included synthesized topic overviews, mind maps, and audio recordings based on AI-curated knowledge paths, all of which were reviewed and refined by the instructor of the course to ensure conceptual accuracy and pedagogical soundness.

Procedure

Three groups of BA students enrolled in the Psychology of Language Learning course were channeled into three types of instruction. They received instruction based on three teaching models for one semester that lasted for 17 weeks. The class met once a week and each session lasted 90 minutes. The midterm exam was held in session 8. The final exam was held two weeks after session 17. The instructional models for each group are detailed below and summarized in Table 1.

AI-assisted FI Group

The AI-assisted FI group received a flipped class following the standard procedure of pre-class, in-class, and post-class phases that were designed based on AI tool affordances.

Table 1: Instructional Models for the Context of the Current Study

Components	AI-assisted FI	Conventional FI	Lecture-based instruction
Pre-class content	AI-generated deep dives (audio, notes, mind maps)	Instructor voiceover slides (PowerPoint presentations)	None
In-class activities	Review, group/pair activities, summary writing, or oral talk	Review, group/pair activities, summary writing, or oral talk	Lecture followed by Q&A
Post-class tasks	Summarizing, worksheet completion, and optional continued AI use	Summarizing or worksheet completion	Not formally assigned (students advised to review the textbook
Interaction pattern	Collaborative, AI-enhanced	Collaborative, non-AI	Primarily instructor-led

Pre-class Phase

A total of 22 deep dives were developed on the official syllabus of the Psychology of Language Learning course. Each deep dive was designed to introduce, elaborate, and reinforce key theoretical and conceptual components of the course content in alignment with FI principles.

The deep dives were created using NotebookLM based on prompts developed by the instructor to target core concepts outlined in each weekly topic. The platform's Discovery Window was employed to gather and organize relevant excerpts, definitions, and frameworks. All AI-generated outputs were refined and curated by the instructor to ensure conceptual accuracy, academic reliability, and alignment with instructional goals and objectives. Each deep dive module included a podcast-style audio file, ranging in length from approximately 3.5 to 5 minutes. The audio content featured a scripted conversation between a male and female speaker, both using a standard American English accent. The podcast structure was consistent across episodes: it began with an introduction of the topic, followed by conceptual expansion, and concluded with a summary of reflective questions to encourage critical thinking. Some episodes included open-ended questions designed to stimulate further inquiry and class discussion. In addition to the audio files, each deep dive package included key summary notes, mind mapping to visualize the relationships between subtopics and concepts, and links or prompts for further exploration.

Group 1 was encouraged to interact with the AI tools independently (e.g., generating follow-up questions, using mind maps for revision) to deepen their understanding of the content. These structured pre-class materials replaced traditional readings and were made available through the university's learning management system (LMS) before in-class sessions. The procedure thus embedded AI as both content generator and cognitive scaffold, aligning with principles of technology-enhanced learning and FI models [13-15].

In-class Phase

Each class session began with a brief knowledge check to assess student engagement with the pre-class materials, mainly the deep dives. This was achieved through mini quizzes, oral discussions, or question-and-answer exchanges. When necessary, key podcast segments were replayed in class to reinforce understanding or clarify misconceptions.

Following the knowledge check, students participated in pair or small-group activities that required them to apply, extend, or reflect on the concepts introduced during the AI-generated deep dives. Activities included completing structured task sheets or worksheets, analyzing sample classroom interactions, or generating examples relevant to the applications of psychological concepts/theories in language teaching/learning. These collaborative tasks encouraged peer dialogue and co-construction of knowledge, aligning with constructivist principles and interactive goals of FI [17].

Subsequently, each group or pair was invited to share their interpretations or responses with the whole class, either through brief oral presentations or guided discussions. This sharing phase allowed for diverse perspectives to emerge and provided opportunities for clarification, debate, and instructor feedback.

The final part of the session focused on individually synthesized outputs, such as summary writing tasks, reflective notes, or brief spoken reports that helped students consolidate their learning. The activities also supported the development of key academic and communication skills relevant to their future roles as EFL teachers.

Post-class Phase

After class, students were assigned follow-up tasks intended to reinforce learning and extend the in-class experience. These included writing summaries, completing additional sections of the worksheet, or interacting further with AI tools to explore unanswered questions or related topics. The structured post-class tasks ensured continuous engagement and helped prepare students for subsequent sessions.

Conventional FI Group

The students of Group 2 received conventional FI designed and implemented in three phases of pre-class, in-class, and post-class sessions.

Pre-class Phase

The pre-class materials for this group were in the form of PowerPoint presentations with embedded voiceovers, created and narrated by the course instructor. These materials were designed to present the core content of each weekly topic as outlined in the course syllabus. The voiceovers aimed to simulate lecture delivery and provided explanations, examples, and guiding questions to support student comprehension.

Unlike the AI-assisted group, students of the conventional FI did not interact with AI tools. Their pre-class preparation was instructor-led, limited to viewing the narrated slides independently before the class session.

In-class Phase

The in-class sessions followed a structure similar to that of the AI-assisted FI group to maintain instructional consistency across groups. Each session included a brief review activity, optional replay of selected voiceover segments, group/pair work, whole-class sharing and instructor feedback, and a final summary writing task or oral report. No instructional AI tools were embedded in the teaching/learning process of this group. Instead, all guidance and content scaffolding were provided by the instructor or through the voiceover slides.

Post-class Phase

Post-class tasks included summarizing key points, completing worksheets, and preparing for upcoming sessions.

Lecture-based Instruction

Group 3 received content through lecture-based delivery, following a teacher-centered model. Unlike the FI groups, students in this condition did not engage with any pre-class materials. Instructional content was presented in class through live lectures conducted by the instructor, supported by textbook chapters and PowerPoint slides.

The majority of the time of the session was dedicated to the direct transmission of course content. The instructor explained key concepts, provided examples, and occasionally asked questions to promote brief student participation. However, there was no structured group or pair work, worksheets, or AI-based exploration tasks. The final 15-20 minutes of each session were allocated to a question-and-answer segment, where students could seek clarification or revisit complex ideas discussed during the lecture.

This group was not assigned any structured post-class tasks. They were instead encouraged to review the textbook chapters covered during the lecture.

Results and Findings

A two-way Multivariate Analysis of Anova (MANOVA) was used to compare the groups' learning gains in the course. In this analysis, types of instruction (AI-assisted FI, conventional FI, and lecture-based instruction) and gender (male and female) served as the independent variables, and knowledge test scores (midterm and final exams) were the dependent variables. Before running the MANOVA, preliminary assumption testing was conducted to check for normality, linearity, and univariate and multivariate outliers [42]. Homogeneity of variance-covariance matrices was assessed by Box's M Test of Equality of Covariance Matrices (Table 2), implying that the observed covariance matrices of the dependent variables were equal across groups.

Table 2: Box's Test of Equality of Covariance Matrices

Box's M	23.199
F	1.419
df1	15
df2	13216.594
Sig.	0.128

The result of Multivariate Tests for the first main effect, that is the impact of intervention on learning outcomes, revealed a significant difference between three groups on the combined dependent variables [Wilks' Lambda=0.473; F (4, 132) = 14.966; *p*=0.000<0.001] with a large effect size (ηp^2=0.312> 0.14) based on Cohen's guideline [43]. The large effect size suggests that the intervention had a meaningful impact on students' learning gains and can explain over 30% of the improvement in participants' performance. Before examining Tests of Between-Subjects effects, Levene's test of Equality of Error Variances was checked (Table 3), showing that the assumption of equality of variance for dependent variables was not violated.

Table 3: Levene's Test of Equality of Error Variances

	Levene Statistic	df1	df2	Sig.
Midterm Exam	0.116	5	67	0.988
Final Exam	1.358	5	67	0.251

Tests of Between-Subjects Effects were then examined, and as the results for the dependent variables separately (midterm and final exam) showed, both differences reached statistical significance (Table 4). Both effects were strong (ηp^2=0.478 and ηp^2=0426, respectively), implying that the intervention had a strong effect in enhancing students' understanding of technical and scientific concepts, as measured by both midterm and final exams.

Post hoc comparisons using Tukey's HSD test and descriptive statistics (Table 5) revealed that students in Group 1 scored significantly higher than those in Groups 2 and 3 in midterm and final exams. Additionally, Group 2 performed significantly better than Group 3 in midterm and final exams, confirming a hierarchy of instructional effectiveness, with AI-assisted FI yielding the highest gains in conceptual understanding.

The result of Multivariate Tests for the second main effect, that is, gender, [Wilks' Lambda=0.975; F (2, 66) = 0.836; *p*=0.438>0.001] and the interaction effect between gender and instructional method [Wilks' Lambda=0.963; F (4, 132) = 0.628; *p*=0.644>0.001] were not statistically significant. This implies that the observed differences in achievement across groups were not moderated by gender.

Table 4: Tests of Between-Subjects Effects

Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared
Corrected Model	Midterm	1489.871[a]	5	297.974	12.991	0.000	0.492
	Final	1871.593[b]	5	374.319	11.335	0.000	0.458
Intercept	Midterm	18001.869	1	18001.869	784.868	0.000	0.921
	Final	24420.706	1	24420.706	739.478	0.000	0.917
Group	Midterm	1404.989	2	702.494	30.628	0.000**	0.478
	Final	1641.705	2	820.853	24.856	0.000**	0.426
gender	Midterm	12.789	1	12.789	0.558	0.458	0.008
	Final	9.699	1	9.699	0.294	0.590	0.004
Group * gender	Midterm	44.120	2	22.060	0.962	0.387	0.028
	Final	62.506	2	31.253	0.946	0.393	0.027
Error	Midterm	1536.724	67	22.936			
	Final	2212.626	67	33.024			
Total	Midterm	22351.938	73				
	Final	30494.250	73				
Corrected Total	Midterm	3026.594	72				
	Final	4084.219	72				

a. R Squared = .492 (Adjusted R Squared = 0.454)

b. R Squared = .458 (Adjusted R Squared =0 .418)

Table 5: Descriptive Statistics of Midterm and Final Exams across Three Groups

	Group	Mean	SD
Midterm Exam	AI-assisted FI	21.653	5.001
	Conventional FI	15.500	4.658
	Lecture-based	10.784	4.628
Final Exam	AI-assisted FI	25.221	5.016
	Conventional FI	17.750	6.440
	Lecture-based	13.136	5.596

The outcome showed a significant difference between the groups' achievement in the course, but not across genders, illustrating how AI can support more inclusive, accessible, and fair learning opportunities when the students benefit from equitable participation and access to the instructional content.

Discussion

The findings of this study confirm that integrating AI-assisted FI significantly enhances students' conceptual understanding, particularly in domains requiring a deep understanding of theoretical constructs, such as language learning psychology. Students in the AI-powered group significantly outperformed those in both conventional FI and traditional lecture-based formats, as measured by midterm and final exams.

What differentiates the instruction AI-assisted group received in this study is the use of NotebookLM deep dive synthesis feature, which allowed for tailored, multisource learning materials that emphasized coherence, explanation, and conceptual linkage. Unlike slides used in conventional FI models, the deep dives presented content as dynamically structured knowledge, offering students the opportunity to engage in personalized, self-paced learning with materials curated around course objectives. This method likely supported higher-order thinking skills, such as application, analysis, evaluation, and creation, which is backed by the fundamentals of FI [13-14]. Intelligence systems, particularly those driven by AI, transform the educational landscape as they enable adaptive learning by tailoring content delivery to individual learners' needs, thereby supporting differentiated instruction and promoting personalized learning pathways [45]. Recent research has demonstrated that AI-driven platforms can enhance learner engagement and motivation by offering context-sensitive feedback, interactive interfaces, and real-time scaffolding [46]. Moreover, intelligent educational systems facilitate data-informed instruction, allowing educators to track progress, predict learning gaps, and adjust strategies accordingly [47].

Particularly, the intelligent systems powered by AI tools are proving highly effective in supporting abstract and theory-driven learning, particularly in higher education. Abstract and theoretical content often challenge learners' working memory and conceptual understanding. Intelligent systems can mediate this by adapting instructional materials to learners' cognitive profiles, using interactive simulations, visualizations, and generative explanations that concretize abstract principles [48]. Moreover, the dialogic affordances of AI, such as question-answering, conceptual summarization, and semantic expansion, mirror Socratic pedagogies known to deepen theoretical understanding in FI [49]. These systems can also serve as cognitive scaffolds, aiding learners in constructing and refining mental models of abstract domains through repeated interaction, feedback, and reflection [50].

The study's outcomes are consistent with research emphasizing that AI tools can enhance learning by supporting adaptive content delivery and reducing cognitive load [44]. The pre-class AI materials likely acted as cognitive scaffolds, which, according to discovery learning theory, provided structured support that enabled students to reach higher levels of understanding than they could independently [28][51]. The AI-generated content not only summarized course materials, but also synthesized connections between key terms and concepts aligned with constructivist learning principles, wherein students construct meaning from active engagement with contextually rich material [26][52].

Importantly, the lack of gender differences in performance across instructional groups suggests that AI-powered instruction may foster a more equitable learning environment. Traditional instruction can sometimes perpetuate performance gaps rooted in different access to engagement or instructor bias. However, by delivering uniform on-demand and bias-free instructional materials, AI tools may help neutralize demographic disparities, offering all learners-regardless of their gender-access to high-quality, scaffolded support [53]. This finding supports prior evidence that personalized learning environments, when designed equitably, can minimize demographic performance gaps and promote inclusivity in education [54]. The equal benefit across gender implies that AI-assisted FI is not only pedagogically effective but also socially responsive, aligning with the goals of inclusive teaching [55-56].

Conclusions

This study demonstrates the instructional value of integrating AI-assisted FI in higher education, particularly when enhanced by structured, personalized content such as NotebookLM's deep dives. The AI group not only achieved higher performance on assessments but did so consistently across gender, indicating the equitable potential of AI-powered instructional design. By enabling deeper cognitive engagement and mitigating disparities through personalized, bias-free pre-class materials, AI-assisted FI instruction emerges as both a pedagogically sound and socially appropriate educational strategy.

Nonetheless, this study is not without limitations. The sample size was modest, and the study was limited to one institution and one subject area. Furthermore, the study lasted for one semester, and delayed evaluation of learning gains was not possible. Future research should examine the use of AI-generated deep dives across disciplines and academic contexts, incorporate qualitative feedback from students, and explore the longitudinal effects of AI-assisted instruction on academic development and skills mastery.

The findings hold critical implications for MOE, particularly in the context of EFL teacher preparation programs. As future educators, pre-service teachers need exposure to innovative instructional models that reflect 21st-century teaching realities. MOE is responsible for national teacher training standards and thus should consider formally integrating AI-supported instruction into the EFL curriculum, preparing teachers not only to teach language, but to teach with technology.

For higher education institutions, these results suggest that reimagining education through AI-enhanced instructional models can improve instructional efficacy and learner autonomy. Educators are encouraged to transition from content delivery to facilitation of professional skill development, guaranteeing lifelong learning through curriculum change.

Finally, for EdTech developers and policy advisors, this study signals the need to design AI tools that are context-sensitive, multilingual, and aligned with educational policy objectives in language learning and EFL teacher education. AI platforms should offer scalable support for diverse linguistic, cultural, and pedagogical contexts, while also promoting ethical AI use and data privacy within national systems.

Authors' Contribution

Author 1 conceptualized, designed, and supervised the research, and drafted, wrote, reviewed, and edited the manuscript. Author 2 gathered the data and helped in writing the manuscript. Both authors have read the article and approved the submitted version. The authors'

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Conflicts of Interest

The authors have no conflicts of interest.

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