Enhancing Sustainable AI-Driven Language Learning: Location-Based Vocabulary Training for Learners of Japanese

Yang, Liuyi

Chen, Sinan

Li, Jialong

(Citation)
Sustainability,17(6):2592

(Issue Date)
2025-03

(Resource Type)
journal article

(Version)
Version of Record

sustainability

MDPI

Article

Enhancing Sustainable AI-Driven Language Learning: Location-Based Vocabulary Training for Learners of Japanese

Liuyi Yang [1,*], Sinan Chen [1,*] and Jialong Li [2]

[1] Graduate School of System Informatics, Kobe University, 1-1 Rokkodai-cho, Nada-ku, Kobe 657-8501, Japan
[2] Department of Computer Science and Engineering, Waseda University, 1-104 Totsukamachi, Shinjuku-ku, Tokyo 169-8050, Japan; lijialong@fuji.waseda.jp
* Correspondence: 211x508x@gsuite.kobe-u.ac.jp (L.Y.); chensinan@gold.kobe-u.ac.jp (S.C.)

Abstract: With the rapid advancement of mobile technology, e-learning has expanded significantly, making language learning more accessible than ever. At the same time, the rise of artificial intelligence (AI) technologies has opened new avenues for adaptive and personalized e-learning experiences. However, traditional e-learning methods remain limited by their reliance on static, predefined materials, which restricts equitable access to learning resources and fails to fully support lifelong learning. To address this limitation, this study proposes a location-based AI-driven e-learning system that dynamically generates language learning materials tailored to real-world contexts by integrating location-awareness technology with AI. This approach enables learners to acquire language skills that are directly applicable to their physical surroundings, thereby enhancing engagement, comprehension, and retention. Both objective evaluation and user surveys confirm the reliability and effectiveness of AI-generated language learning materials. Specifically, user surveys indicate that the generated content achieves a content relevance score of 8.4/10, an accuracy score of 8.8/10, a motivation score of 7.9/10, and a learning efficiency score of 7.8/10. Our method can reduce reliance on predefined content, allowing learners to access location-relevant learning resources anytime and anywhere, thereby improving accessibility and fostering lifelong learning in the context of sustainable education.

Keywords: AI; e-learning; location-based learning; sustainable language learning

check for updates

Academic Editor: David González-Gómez

Received: 16 February 2025
Revised: 10 March 2025
Accepted: 10 March 2025
Published: 15 March 2025

Citation: Yang, L.; Chen, S.; Li, J. Enhancing Sustainable AI-Driven Language Learning: Location-Based Vocabulary Training for Learners of Japanese. *Sustainability* **2025**, *17*, 2592. https://doi.org/10.3390/su17062592

1. Introduction

With the advancement of technology, computer-assisted language learning (CALL) has played a crucial role in improving language education by integrating digital tools into learning environments [1,2]. One of its key branches is mobile-assisted language learning (MALL), which leverages mobile technologies to enable flexible, on-the-go learning experiences [3–5]. The MALL approach allows students to learn at their own pace, thereby improving learning efficiency [6]. Particularly in language learning, it fully leverages the flexibility of mobile technology to facilitate training in listening, speaking, reading, and writing skills [7]. Studies have shown that using MALL for vocabulary learning is significantly more effective than conventional textbook-based learning methods [8]. However, unlike subjects such as mathematics and physics, language learning often requires contextualization to aid comprehension [9,10]. For instance, courses are typically designed in a dialogue format to enhance the sense of immersion and learning outcomes. While traditional classroom exercises provide structured learning opportunities, they primarily focus on predefined vocabulary lists and controlled practice activities [11]. However, topical vocabulary learning requires exposure to dynamically evolving, contextually embedded language, which is often limited in classroom-based instruction [12]. Learners may struggle to retain vocabulary that is not directly linked to their personal experiences or real-world usage [13].

Moreover, language learning on mobile devices often lacks immersion and is highly fragmented [14,15]. Learners frequently use scattered moments, such as waiting for a bus or standing in line, to memorize vocabulary [16]. Although courses are usually structured around thematic units, memorizing words from a different scenario in an unrelated environment leads to low learning efficiency.

This challenge is particularly evident in learning Japanese, where the correct use of honorific expressions depends heavily on social context. The Japanese honorific system consists of three forms: respectful language (sonkeigo), humble language (kenjogo), and polite language (teineigo), which vary depending on different social contexts. For example, in a restaurant setting, staff members typically use polite speech (e.g., "Kochira no seki e dozo."—"Please take this seat."), while customers use either plain expressions or more humble forms (e.g., "Mizu o kudasai."—"Can I have some water?" or "Omizu o itadakemasu ka?"—"May I receive some water?"). MALL methods often lack intuitive guidance on the appropriate use of honorific expressions in specific real-world situations.

The rise of AI technology has introduced new possibilities for learning [17,18]. AI can assist in developing personalized learning plans and summarizing key knowledge points from textbooks [19,20]. However, current AI-based language learning systems remain heavily dependent on predefined textbooks and struggle to dynamically adapt content based on real-life learning contexts [21].

In summary, despite advancements in e-learning and AI, language learning still faces three key challenges: lack of immersion, low efficiency in fragmented learning, and heavy reliance on predefined textbooks. Existing classroom-based methods provide structured content but lack real-world contextualization, while mobile-assisted learning enhances flexibility but often results in fragmented, low-immersion experiences. Even AI-driven approaches remain dependent on static materials, limiting their adaptability to real-world learning contexts. Furthermore, a broader concern arises regarding the sustainability of digital education—particularly in ensuring equitable access to learning opportunities and fostering lifelong learning. To address these issues, we propose a location-based AI-generated content language learning method. This method leverages mobile devices' location data to provide a more context-aware learning experience. Specifically, the system first retrieves the latitude and longitude information from the mobile device and maps it to a specific address. The address name is then sent to an intermediary server, which forwards a request to an AI model to generate language learning materials relevant to the specific location. This approach enables learners to engage with contextualized content that aligns with their real-world location, thereby enhancing immersion and learning efficiency.

The main contributions of this study include the following:

- The AI-generated learning materials are tailored to the learner's current location, eliminating reliance on predefined textbooks. This approach enhances educational accessibility and promotes sustainable education by providing adaptive learning resources that can be accessed anytime and anywhere.
- The location-based language learning materials offer strong immersion, improving learning efficiency. By utilizing the surrounding environment for learning, this approach encourages lifelong learning habits, contributing to sustainable education.

To validate the effectiveness of the location-aware AI-generated content language learning approach, this study tested learning materials generated by DeepSeek-V3, ChatGPT-4o, and Claude-3.5 in four real-world learning scenarios: a library, train station, restaurant, and observation deck.

The evaluation combined the jWriter [22] system with user surveys. The AI-generated language learning content demonstrated strong performance in language proficiency, diversity, and readability, reaching or approaching an advanced level. Results indicate that this approach provides high contextual adaptability, enhances fragmented learning efficiency, and fosters strong learner immersion and motivation. First, the AI-generated content received an average relevance score of 8.4/10 and a learning efficiency score of 7.8/10, confirming its high effectiveness for fragmented learning. User feedback consistently reported that the learning materials aligned well with their real-world environments and that learning within the given context was efficient. Contextualized language learning can enhance content applicability and strengthens language acquisition skills [23–25]. For instance, in the restaurant scenario, the system provided expressions related to ordering and dining, while in the train station scenario, the learning content focused on ticket purchasing, navigation, and common travel dialogues. The high learning motivation score is also a key highlight. Contextualized learning proved to be more engaging and interactive than traditional classroom-based methods [26,27]. Various innovative vocabulary learning approaches exist, including bilingual resources such as manga tailored for language learners, contextualized videos, and music-based learning.

For instance, bilingual manga [28] and dual-language books can help learners understand conversational patterns, but they lack situational immediacy. Contextualized videos, such as language learning content on YouTube [29], offer authentic dialogues, yet they do not adapt dynamically to the learner's real-world surroundings. Similarly, songs [30] and movies immerse learners in natural speech patterns but do not facilitate direct, interactive learning tied to their immediate environment.

While these approaches enhance exposure and engagement, they may not provide the same level of real-time contextual reinforcement as location-based learning. For example, in the observation deck scenario, AI-generated content included not only relevant vocabulary but also commonly used expressions for describing landscapes, making the learning experience more immersive.

In conclusion, this study confirms that integrating location-awareness technology with AI-generated content can effectively enhance language learning experiences, optimize fragmented learning processes, and improve learner engagement and interest. Furthermore, by reducing reliance on predefined materials and enabling adaptive, real-world learning experiences, this approach supports sustainable education by improving accessibility and fostering lifelong learning.

The remainder of this paper is structured as follows. Section 2 reviews related work on MALL, location-based language learning, and AI applications in education. Section 3 presents the methodology of our location-aware AI-driven language learning system, including system architecture, key features, and discussion of its advantages. Section 4 details the implementation, covering frontend and middleware server development, AI model selection, and prompt engineering strategies. Section 5 evaluates the proposed system through comparative analysis of AI models, assessments of generated learning content in different locations, and a user survey. Then, we discuss the findings, highlighting the strengths and potential limitations of the proposed approach in Section 6. Finally, Section 7 concludes the paper and outlines future research directions.

2. Related Work

In recent years, advancements in mobile technology have significantly driven the digitalization of language learning, particularly in MALL and e-learning. Learners can utilize fragmented time to engage in self-directed learning through mobile devices, while the emergence of AI has further enhanced the possibilities for personalized and dynamically adaptive learning.

To improve the contextualization of language learning, location-based language learning has gradually become a research focus. It leverages the geographic information of mobile devices to integrate learning content with real-world scenarios, enabling learners to acquire language input that is more relevant to their actual surroundings. However, existing methods primarily rely on predefined scenarios, making them less adaptable to diverse environments and individual learning needs, which limits their applicability.

As illustrated in Table 1, current language learning systems still face three major challenges: lack of immersion, low efficiency in fragmented learning, and heavy reliance on predefined materials. These issues hinder learners from fully engaging in the language environment, thereby affecting long-term learning outcomes. Furthermore, some studies have adopted high-cost technological solutions, which may limit access to education for learners in low-resource settings. These limitations highlight the fact that existing approaches fail to align with the principles of sustainable education, which emphasize accessibility, adaptability, and lifelong learning.

Table 1. Comparison of language learning methods.

Author (Year)	Technology Cost	Immersive (Y/N)	Reliance on Predefined Materials	Learning Mode (Fragmented /Systematic/Both)
Pikhart (2020) [31]	Low	No	High	Fragmented
Getman et al. (2023) [32]	Medium	Yes	Low	Both
Polakova & Klimova (2022) [33]	Low	No	High	Both
Lee & Park (2019) [34]	Medium	Yes	Low	Both
Kacetl & Klímová (2019) [35]	Low	No	High	Fragmented
Ours (2025)	Low	Yes	No	Fragmented

2.1. E-Learning in Language Learning

In recent years, MALL and e-learning have both made notable strides in theory and practice [36]. Cakmak [37] systematically examined design principles for mobile learning, emphasizing how the integration of technology and learning theory can drive innovation in foreign language education. Gholami and Azarmi [38] further explored ways to incorporate listening, reading, and speaking skills into mobile contexts, offering learners a variety of pathways. This body of research indicates that the convenience and efficiency of mobile devices not only transform traditional learning methods but also enhance learners' motivation, autonomy, and overall effectiveness [39].

Building on this progress, Read and Bárcena [40] proposed a theoretical framework that integrates language-oriented massive open online courses (MOOCs) with MALL, using the common European framework of reference for languages (CEFR) to tailor content for different proficiency levels. By combining online courses with mobile learning, this approach provides greater flexibility and, to some extent, improves the accessibility and relevance of educational resources. However, because mobile learning tends to be fragmented, personalized, and susceptible to distractions, sustaining a high-quality and lasting learning experience remains a critical challenge [41].

Meanwhile, some researchers have shifted their focus to the learner's environment and how deeply learning content can be woven into it. For example, Foomani and Hedayati [42] proposed a seamless learning design that integrates activities into daily life, encouraging interaction by having students generate their own content. Although these strategies promise more engaging and immersive learning, the limited availability of resources continues to be an unresolved issue, restricting accessibility in sustainable education [43].

2.2. Location-Based Language Learning

The widespread adoption of mobile devices in e-learning has laid the technological foundation for location-based language learning, with a stronger emphasis on contextualized learning content.

Location-based language learning has gained significant attention in recent years due to its ability to provide contextualized, personalized, and interactive learning experiences. Chen and Tsai [44] proposed an interactive location-based English learning game that uses wireless positioning technology to deliver location-specific English learning scenarios on mobile devices. By combining virtual objects with real-world environments in a mixed-reality mode, the system effectively stimulates learners' interest and enhances their motivation to learn. Similarly, Fallahkhair [45] developed a system called TAMALLE+, which integrates internet TV and mobile phone functionalities to offer learners a location-based, informal, collaborative language learning platform.

For specific target groups, Gaved and Peasgood [46] utilized Bluetooth beacons in smart cities to provide personalized language learning activities for immigrants. The study not only tackles challenges related to privacy and user data collection but also underscores the system's potential to facilitate flexible learning methods. Perry [47] designed a location-based augmented reality language learning game to help French learners develop their language skills through location-based tasks, emphasizing the importance of collaboration and high-level co-regulated learning behaviors.

Furthermore, Holden and Sykes [48] demonstrated the critical role of physical locations in language learning by engaging learners in real-world interactions through an augmented reality game. Wu et al. [49] developed a location-based vocabulary learning application that offers relevant vocabulary learning games based on users' current locations, such as cinemas or restaurants. Preliminary findings indicate that learners have responded positively to the app, demonstrating its significant potential for further development. Collectively, these studies suggest that incorporating location-based technologies into language learning fosters immersive, learner-centered environments that enhance language acquisition and encourage lifelong learning habits.

2.3. AI for Education

The integration of AI in education has revolutionized learning experiences, enhancing personalization, automation, and interactivity [50,51]. Key research areas include intelligent tutoring systems (ITSs), personalized learning, automated assessment, and the application of generative AI in education [52,53].

AI-powered ITSs provide adaptive feedback and personalized instruction, allowing students to receive real-time guidance. Paladines and Ramírez [54] examined ITSs that incorporate natural language dialogue, demonstrating their effectiveness in enhancing conceptual understanding in STEM education. Ghali et al. [55] introduced an ITS designed for English grammar learning, showing improvements in learner engagement and grammatical accuracy. These studies collectively highlight the role of ITSs in improving learning efficiency and accessibility across different disciplines.

Personalized learning systems utilize AI to dynamically adjust learning materials and instructional strategies based on individual students' abilities, preferences, and progress. Kanchon et al. [56] developed an AI system that detects learning styles (visual, auditory, kinesthetic) and modifies content using machine learning and NLP, enhancing engagement and retention. Ellikkal and Rajamohan [57] explored AI-enabled personalized learning in management education, showing that self-determination theory (SDT)-based AI interventions improve motivation and autonomy. While AI personalization enhances learning, challenges remain in data privacy, model transparency, and inclusivity.

Automated assessment tools aim to reduce grading workloads, standardize evaluations, and provide instant feedback. Bevilacqua et al. [58] found that ML-based scoring models tend to overrate AI-generated content, highlighting potential bias in AI grading. Gao et al. [59] compared AI-driven text-based assessments, emphasizing the need for transparency in large language model (LLM)-based grading. Chiu [60] explored AI's impact on educational policy, advocating for new frameworks to integrate AI grading with traditional assessments. While automated grading enhances scalability, challenges such as ensuring equitable assessment across diverse student populations, mitigating biases in AI scoring, and addressing ethical concerns regarding AI-based evaluation remain pressing research priorities.

Generative AI, particularly ChatGPT and other LLMs, has introduced new possibilities for education. Do et al. [61] demonstrated that AI-generated educational podcasts, particularly those tailored to students' interests and majors, improved engagement and learning outcomes compared to traditional textbooks. Marandi and Hosseini [62] explored AI-driven assessment and found that automated item generation (AIG) systems effectively created test questions, allowing educators to optimize assessments based on student proficiency. Similarly, Nasution [63] evaluated AI-generated multiple-choice questions in higher education and reported that most AI-generated questions were valid, reliable, and well received by students due to their clarity and relevance.

While generative AI has demonstrated considerable potential across multiple educational domains, its application in immersive language learning environments remains underexplored. This study aims to bridge this gap by integrating location-based sensing with generative AI, dynamically generating situationally relevant language learning materials, thereby enhancing equitable access to education and fostering lifelong learning within a sustainable learning framework.

2.4. Preliminary Study

Despite the progress in AI-driven language learning, existing systems often rely on predefined content, limiting their ability to provide dynamic, real-world contextual learning experiences. To address this gap, we conducted a preliminary study that leveraged AI to summarize education materials and deliver knowledge through digital instructors [64]. The workflow of our preliminary study is illustrated in Figure 1. Education materials are first processed by AI to generate two types of content: written content for creating instructional slides and spoken content for audio synthesis. The audio is generated using text-to-speech (TTS) and simultaneously drives the digital teacher's animated facial expressions and movements. Finally, the slides, audio, and digital teacher animations are integrated to produce a complete e-learning instructional video.

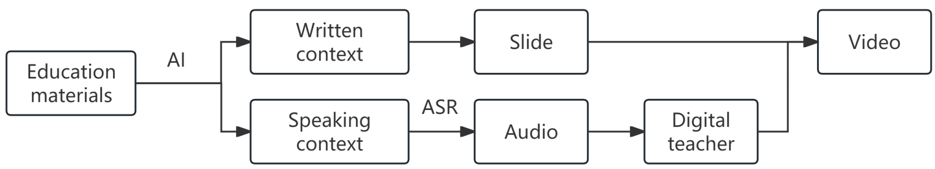


Figure 1. Workflow of preliminary study.

Although our previous research incorporated AI in content generation, it still relied on existing educational materials, which limited accessibility. Furthermore, while the use of digital teacher provided a more classroom-like experience, it lacked contextualized learning, limiting its effectiveness and preventing more efficient learning outcomes.

3. Methodology

Previous studies have shown that MALL offers a convenient learning approach. However, due to the lack of contextual awareness, its learning content is often disconnected from real-world environments. While location-based language learning enhances contextualized learning by incorporating location information, it predominantly relies on predefined scenarios, making it challenging to dynamically adapt to different environments. Building on these foundations, this study proposes a location-based AI-driven language learning application that integrates location-awareness technology with generative AI to dynamically generate language learning materials. This approach enables adaptation to real-world contexts and optimizes fragmented learning experiences. This section introduces the system architecture, key functionalities, and core research methodology.

3.1. App Architecture

The app architecture consists of three components as shown in Figure 2:

1. App Client: Obtains location, provides a user interaction interface, and displays language learning materials.
2. Middleware Server: Facilitates communication between the app and AI, stores API keys, AI prompts, and other related messages.
3. AI API: Generates context-relevant learning content based on requests from the middleware server and returns the output. By incorporating prompt engineering techniques, this study optimizes content generation across different learning levels, including word, sentence, and paragraph levels.

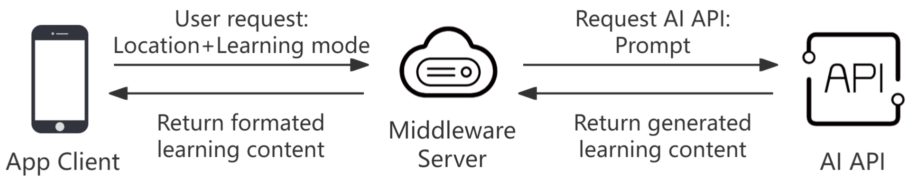


Figure 2. Overall system architecture.

3.2. App Features

The application integrates location-aware technology with generative AI to provide Japanese language learners with a contextual language learning experience. It incorporates several key functionalities as shown in Figure 3. The system begins by obtaining the user's real-world location (e.g., a train station, restaurant, or attraction). This location information is sent to an AI model, which dynamically generates learning materials tailored to the specific environment.

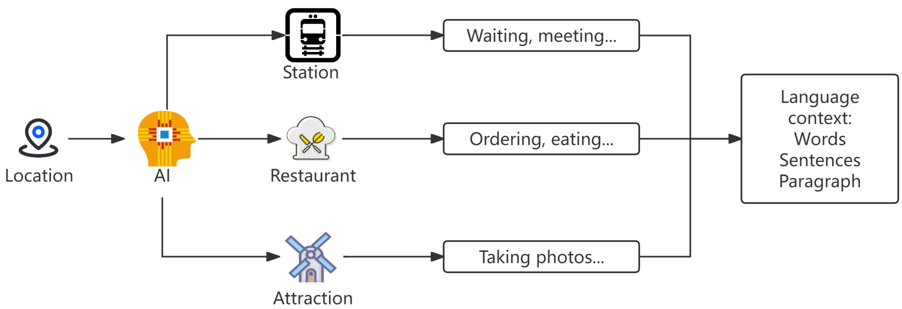


Figure 3. App features.

For example, users can practice asking for directions while waiting at a train station, learn ordering phrases while dining at a restaurant, or practice describing scenery while resting at an observation deck. This enhances contextual learning and improves the efficiency of fragmented learning. Our method supports different learning modes tailored to various proficiency levels, allowing users to choose between word-, sentence-, or paragraph-based learning. The word mode is suitable for beginners, the sentence mode facilitates daily communication, and the paragraph mode helps improve writing and spoken expression skills.

4. Implementation

4.1. Frontend Implementation

The application serves as the user interface for interacting with the system, allowing users to receive AI-generated Japanese language learning content based on their real-time location. To retrieve the user's location, the app utilizes FusedLocationProviderClient [65], which provides efficient access to the device's GPS data. The location information is then processed using the Nominatim API [66] to obtain a list of nearby places. For communication with the backend, the app employs OkHttpClient [67] to send HTTP requests containing the selected location and learning mode. The server processes the request and returns relevant language learning content, which is displayed within the app's interface. The following Listing 1 demonstrates how the application constructs and sends HTTP requests to the backend, incorporating both the user's current location and the selected learning action. The response is processed asynchronously and updates the UI accordingly.

Listing 1. Asynchronous HTTP request using OkHttpClient.

```
private fun queryWordsFromServer(location: String, action: String) {
    val client = OkHttpClient()
    // Construct a text/plain request body with action and location
    val requestBody = "$action:$location".toRequestBody("text/plain".
        toMediaType())
    // Build the request
    val request = Request.Builder()
        .url(serverUrl) // Server URL remains unchanged
        .post(requestBody)
        .build()
    // Execute the request asynchronously
    client.newCall(request).enqueue(object : Callback {
        override fun onFailure(call: Call, e: IOException) {
            runOnUiThread {
                Toast.makeText(this@MainActivity, "Failed: ${e.message}",
                    Toast.LENGTH_SHORT).show()
            }
        }
        override fun onResponse(call: Call, response: Response) {
            val responseBody = response.body?.string()
            runOnUiThread {
                if (response.isSuccessful && !responseBody.isNullOrEmpty()
                    ) {
                    displayResults(responseBody)
                } else {
                    Toast.makeText(this@MainActivity, "Error: Unable to
                        fetch data", Toast.LENGTH_SHORT).show()
                }
            }
        }
    })
}
```

4.2. Middleware Server Implementation

The middleware server, built with Flask [68], acts as a bridge between the Android App and the AI API. It receives user requests containing the learning mode (word, sentence, or paragraph) and location, validates the input, and constructs a relevant prompt. The request is then forwarded to the AI model, which generates context-aware Japanese learning content. The response is processed and returned to the app for display.

4.3. AI Model

Among the evaluated AI models, we selected DeepSeek-V3 [69] due to its superior performance across key evaluation metrics while maintaining a competitive cost. Table 2 illustrates the comparative results of DeepSeek-V3 against other leading AI models, including Qwen2.5 [70], Llama3.1 [71], Claude-3.5 [72], and GPT-4o [73].

Table 2. Comparison of performance metrics across models [74].

Metric	DeepSeek-V3	Qwen2.5	Llama3.1	Claude-3.5	GPT-4o
MMLU (EM)	88.5	85.3	**88.6**	88.3	87.2
MMLU-Redux (EM)	**89.1**	85.6	86.2	88.9	88
MMLU-Pro (EM)	75.9	71.6	73.3	**78**	72.6
DROP (3-shot F1)	**91.6**	76.7	88.7	88.3	83.7
IF-Eval (Prompt Strict)	86.1	84.1	86	**86.5**	84.3
GPQA-Diamond (Pass@1)	59.1	49	51.1	**65**	49.9
SimpleQA (Correct)	24.9	9.1	17.1	28.4	**38.2**
FRAMES (Acc.)	73.3	69.8	70	72.5	**80.5**
LongBench v2 (Acc.)	**48.7**	39.4	36.1	41	48.1
Price (USD/1M Tokens)	1.4	0.4	1.4	1.6	4.4

Note: Bold values indicate the best performance in each metric.

DeepSeek-V3 achieved the highest scores in MMLU (88.5) [75] and MMLU-Redux (89.1) [76], demonstrating broad knowledge coverage. It also excelled in DROP (91.6, highest) [77], showcasing strong numerical and logical reasoning, and outperformed Qwen2.5 and Llama3.1 in MMLU-Pro (75.9) [78], performing close to Claude-3.5. For instruction following and question answering, IF-Eval (86.1) [79] showed performance comparable to Claude-3.5, while GPQA-Diamond (59.1) [80] ranked just below Claude-3.5, highlighting strong generalization ability. Additionally, FRAMES (73.3%) [81] confirmed its strong multi-turn dialogue capabilities, second only to GPT-4o. Moreover, DeepSeek-V3 achieved the best performance in LongBench v2 (48.7, highest) [82], demonstrating its superior long-context understanding. Despite its high performance, it remains cost-effective, priced at $1.4 per million tokens, significantly lower than GPT-4o ($4.4), making it a highly efficient choice. Considering accuracy, reasoning ability, long-context processing, and cost factors, DeepSeek-V3 stands out as the optimal choice.

4.4. Prompt Engineering

4.4.1. Rationale for Prompt Engineering

Effective prompt engineering is essential for ensuring that the AI-generated language learning content is both relevant and structured [83]. However, in our initial tests, we observed several key challenges:

1. Some prompts led to inconsistent outputs, where AI responses varied significantly across repeated trials.
2. Certain prompts produced irrelevant or overly verbose explanations, reducing learning efficiency.

3. Prompts failed to generate scenario-related content, making the outputs less practical for contextual learning.

To address these issues, we implemented a manually guided iterative optimization strategy, refining prompts through multiple rounds of testing and evaluation.

4.4.2. Prompt Design

We designed our prompts using the role–task–output–constraint (RTOC) framework [84], ensuring clear and structured content generation. Prompt engineering was employed to achieve the following:

1. Clearly define the role of the AI as a Japanese language educator.
2. Provide explicit task instructions to ensure relevant content generation.
3. Enforce a structured output format to improve readability and usability.
4. Minimize extraneous information to keep responses concise and effective for learners.

To improve stability and contextual relevance, we iteratively refined prompts using a five-step optimization process:

1. Initial Prompt Testing: We first implemented general prompts based on RTOC.
2. Scenario-Based Evaluation: AI-generated content was tested in different locations (train stations, restaurants, libraries).
3. Manual Evaluation and Refinement:
   - Adjusted constraints to prevent excessive explanations.
   - Fine-tuned output formatting rules for readability.
4. Stability Testing: Ensured that AI-generated content remained consistent across multiple trials.
5. Final Adaptation: Prompt modifications were finalized based on user feedback.

The optimized prompts, as shown in Tables 3–5, resulted in improved consistency and scenario adaptability.

Table 3. Prompts for word generation.

Type	Prompt
Role	You are a Japanese language educator who provides precise words for learning.
Task	Based on what people often say and do at this place, provide six high-frequency Japanese words and their English meanings.
Output format	List the words and meanings in the format: word (reading)—meaning.
Constraint	Without any additional explanations or phrases.

Table 4. Prompts for sentence generation.

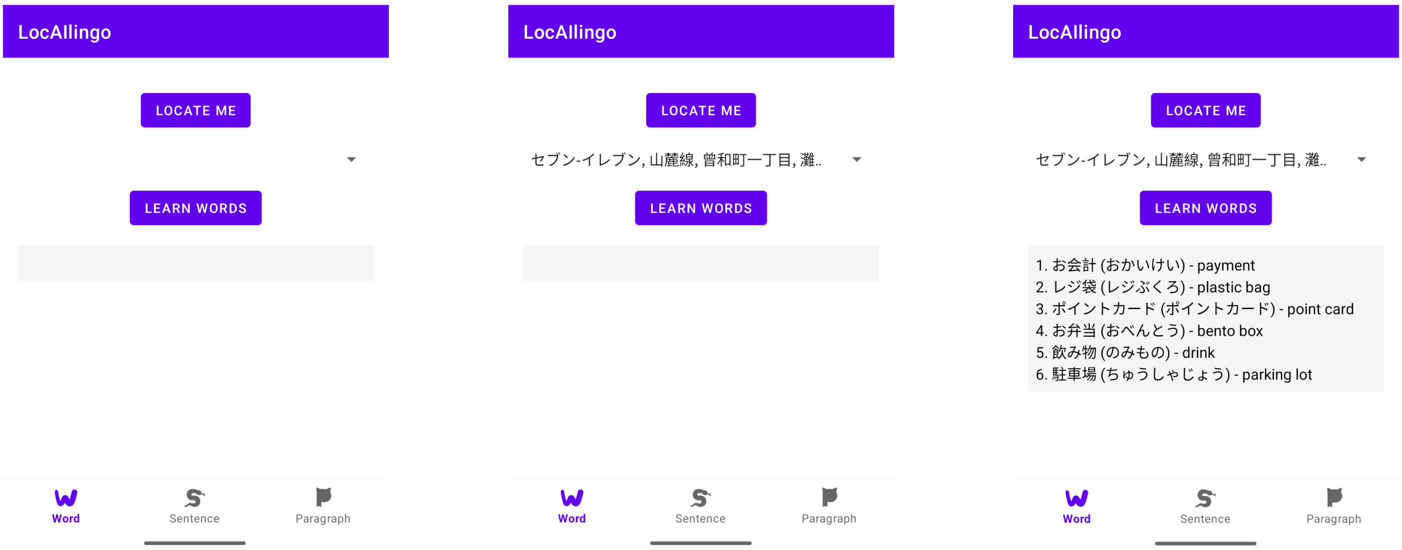
Type	Prompt
Role	You are a Japanese language educator who provides precise words for learning.
Task	Based on what people often say and do at this place, provide 4 high-frequency sentences with their English translations.
Output format	Use the format: sentence (Japanese)–translation (English).
Constraint	Without any additional explanations or phrases.

Table 5. Prompts for paragraph generation.

Type	Prompt
Role	You are a Japanese language educator who provides precise words for learning.
Task	Please give a paragraph in Japanese based on this place with their English translations.
Output format	Please keep the format: paragraph (Japanese)–translation (English).
Constraint	Paragraph should be related to this place and suitable for learning Japanese.

4.5. User Interface and Interaction Flow

Figure 4 illustrates screenshots of the user interface and the interaction flow of the application. Upon launching the app, users start on the initial interface as shown in Figure 4a. By tapping the "Locate Me" button, the system detects and displays the user's current location as shown in Figure 4b. The Japanese text below the "Locate Me" button indicates the name of the current location.Once the location is set, users can press the "Learn Word" button to generate words relevant to their surroundings as shown in Figure 4c. The Japanese and English text below the "Learn Word" button represent the learning materials, where the text in parentheses shows the Japanese pronunciation, and the English text provides the translation of the Japanese word.Additionally, they can switch between sentence and paragraph learning modes using the buttons at the bottom of the screen.



(**a**) (**b**) (**c**)

Figure 4. (**a**) Initial interface. (**b**) Location detection screen. (**c**) Generated words learning screen.

5. Evaluation

5.1. Comparative Analysis of AI Models and Environmental Factors in Language Learning Content Generation

To evaluate the language-learning content generation capabilities of different AI models, we conducted tests on three popular models: DeepSeek-V3, ChatGPT-4o, and Claude-3.5. The evaluation took place at Kobe university's Natural Science Library. To evaluate the impact of different location APIs and geocoding APIs on our method, we conducted separate tests using various location APIs. The Google Fused Location API integrates GPS, Wi-Fi, and cell tower signals for positioning. The Google GPS Provider relies solely on GPS signals, while the HERE Location API determines positioning using only Wi-Fi and cell tower signals.

For geocoding, we tested three different APIs: Nominatim, HERE Reverse Geocoder, and OpenCage Geocoder. The words, sentences, and paragraphs generated by the three AI models are shown in website [85].

To objectively assess the quality of the generated content, we employed jWriter [22], a Japanese language evaluation system. The assessment was conducted based on three key criteria:

1. Overall Language Level
2. Linguistic Diversity (higher is better)
3. Obscure Language Usage (lower is better)

The definition of overall language level set by jWriter is as follows:

- Beginner Level: Learners can use only very basic vocabulary and sentence structures.
- Elementary Level: Learners can express simple thoughts using fundamental words and grammar.
- Intermediate Level: Learners can use moderately complex words and grammar with a certain degree of fluency.
- Advanced Level: Learners can freely select words and grammatical structures without major restrictions and can express themselves objectively.
- Superior Level: Learners can utilize intricate sentence structures and advanced vocabulary to articulate their thoughts with precision.

For the accuracy evaluation, which is relatively subjective, our evaluator is a non-native Japanese speaker residing in Japan with an N1 [86] proficiency level. The evaluation is conducted on a scale from 1 to 10, where 1 signifies that the learning material is completely unrelated to the current location, while 10 indicates that it is entirely relevant.

The evaluation results are presented in Table 6. The three models generally achieve an advanced level in most cases, with only 1–2 instances out of 9 being at the intermediate level.

For linguistic diversity, the average score at the advanced level for JWriter is 0.41, and all our generated results surpass this average. For obscure language, the average score at the advanced level for JWriter is 0.18, and the evaluation scores of our generated content fluctuate around this average. These objective evaluations confirm that AI-generated language learning materials are of high quality.

According to research [87], the accuracy of the Google Fused Location API (which integrates GPS, Wi-Fi, and cell towers) is higher than that of the Google GPS Provider (which relies solely on GPS signals), which in turn outperforms the Here Location API (which only utilizes Wi-Fi and cell towers). Experimental results further support this conclusion, showing that the combination of the Google Fused Location API and Nominatim yields the highest relevance to the current location while maintaining comparable content quality to other approaches. Although our primary research focus is not on positioning systems or geocoding, leveraging the Google Fused Location API and Nominatim to obtain precise location information is necessary to enhance contextual relevance, immersion, and learning efficiency.

While the three AI models do not exhibit significant differences in the quality of generated content, considering the comparisons in Section 4.3 alongside cost-effectiveness, we selected DeepSeek-V3 as the primary model for subsequent evaluations. All further assessments will be conducted using DeepSeek-V3, the Google Fused Location API, and Nominatim.

Table 6. Evaluation of AI-generated learning content by jWriter.

Location API	Geocoding API	AI API	Level	Linguistic Diversity	Obscure Language	Rel.
Google Fused Location API	Nominatim	DeepSeek-V3	Advanced	0.56	0.25	10
		ChatGPT-4o	Advanced	0.54	0.30	10
		Claude-3.5	Advanced	0.58	0.23	10
	HERE Reverse Geocoder	DeepSeek-V3	Advanced	0.52	0.22	9
		ChatGPT-4o	Advanced	0.51	0.30	10
		Claude-3.5	Advanced	0.48	0.22	9
	OpenCage Geocoder	DeepSeek-V3	Intermediate	0.49	0.12	8
		ChatGPT-4o	Advanced	0.50	0.21	7
		Claude-3.5	Intermediate	0.52	0.23	8
Google GPS Provider	Nominatim	DeepSeek-V3	Advanced	0.45	0.20	6
		ChatGPT-4o	Advanced	0.56	0.20	7
		Claude-3.5	Advanced	0.55	0.25	10
	HERE Reverse Geocoder	DeepSeek-V3	Advanced	0.50	0.21	5
		ChatGPT-4o	Advanced	0.52	0.18	7
		Claude-3.5	Advanced	0.54	0.23	4
	OpenCage Geocoder	DeepSeek-V3	Advanced	0.54	0.14	6
		ChatGPT-4o	Intermediate	0.52	0.11	8
		Claude-3.5	Intermediate	0.52	0.14	7
HERE Location API	Nominatim	DeepSeek-V3	Intermediate	0.48	0.21	6
		ChatGPT-4o	Advanced	0.52	0.14	7
		Claude-3.5	Advanced	0.58	0.27	6
	HERE Reverse Geocoder	DeepSeek-V3	Advanced	0.52	0.17	6
		ChatGPT-4o	Advanced	0.59	0.27	5
		Claude-3.5	Advanced	0.54	0.22	5
	OpenCage Geocoder	DeepSeek-V3	Advanced	0.48	0.24	4
		ChatGPT-4o	Advanced	0.50	0.27	5
		Claude-3.5	Advanced	0.53	0.28	4

5.2. Performance of AI-Generated Learning Content in Different Locations

To evaluate the performance of our method across different locations, we conducted additional experiments at a train station, ramen shop, and observation deck. The outputs (words, sentences, and paragraphs) from these three locations are shown in Figure 5. The evaluation criteria for the generated content remain the same as in Section 5.1. Additionally, we added descriptions of the reasoning behind the relevance assessment.

Table 7 shows that the AI-generated content consistently achieves the advanced level across all locations. Linguistic diversity (0.57–0.59) surpasses the jWriter advanced level benchmark (0.41), while obscure language usage (0.16–0.20) remains close to the expected range (0.18), ensuring readability. Relevance scores are high, with the ramen shop and observation deck scoring 10, and the train station slightly lower at 9. These results confirm that the generated content is both high-quality and contextually relevant.

(**a**) Words for train station (**b**) Sentences for train station (**c**) Paragraph for train station

(**d**) Words for ramen shop (**e**) Sentences for ramen shop (**f**) Paragraph for ramen shop

(**g**) Words for observation deck (**h**) Sentences for observation deck (**i**) Paragraph for observation deck

Figure 5. Generated words, sentences, and paragraphs in different locations.

Table 7. Evaluation of AI-generated content across different locations.

Location	Level	Linguistic Diversity	Obscure Language	Rel.
Train station	Advanced	0.58	0.20	9
Ramen shop	Advanced	0.59	0.20	10
Observation deck	Advanced	0.57	0.16	10

The generated content for the train station is as shown in Figure 5a–c. The generated words, such as “station” and “bus”, were highly relevant to the train station context, covering essential vocabulary for travel. Sentences like ”How long does it take to go to Hankyu Rokko Station?” demonstrated practicality and relevance, though they lacked variations in formality. The paragraph provided a basic situational description of the train station, mentioning activities like waiting for trains and buying tickets.

The generated content in the ramen shop is shown in Figure 5d–f. Words such as extra noodles and topping accurately reflected the ramen dining context. Sentences like ”I’d like to order the chashu ramen” were practical and grammatically correct but could have included more cultural nuances, such as expressions for complimenting food. The paragraph effectively described the ramen shop environment, highlighting details like the specialty soup and friendly service.

The generated content for the observation deck is as shown in Figure 5g–i. Words such as ”night view” and ”tourist” were relevant to the sightseeing context. Sentences like ”Being able to see the entire cityscape of Kobe is amazing!” effectively captured the awe of the location. The paragraph provided a vivid description of the view and atmosphere, including details about the transition from dusk to evening.

5.3. User Survey

To comprehensively assess the effectiveness and user experience of AI-generated Japanese language learning content, we conducted a subjective evaluation. While objective metrics (such as linguistic accuracy and diversity) provide quantitative insights, subjective evaluation is crucial for understanding users’ actual learning experiences, preferences, and perceived effectiveness. This approach allows us to capture factors that are difficult to quantify, such as engagement, intuitiveness, and learning motivation.

The evaluation was conducted in four real-world scenarios: a library, a train station, a ramen shop, and an observation deck. Contents were generated by DeepSeek-V3. The survey focused on four key dimensions:

- Content Relevance—The extent to which the generated content aligns with real-world contexts and user expectations.
- Content Accuracy—The linguistic correctness of words, sentences, and paragraphs.
- Learning Motivation—The extent to which the AI-generated content fosters users’ intrinsic motivation and interest in language learning.
- Learning Efficiency—The effectiveness of the content in facilitating language acquisition within a short time frame.

The study involved 10 participants, all non-native Japanese speakers with varying proficiency levels, ranging from JLPT [86] N4 to N1. Specifically, eight participants were aged 21–30 years, while two participants were aged 31–40 years. In terms of gender distribution, seven participants were female, and three participants were male. Regarding Japanese proficiency levels, three participants were at the N4 level, four at the N3 level, two at the N2 level, and one at the N1 level. No personally identifiable information was collected. Each participant rated the generated content using a Likert-style rating scale (1–10), where 1 indicates “very poor” and 10 indicates “excellent.”

The survey results are summarized in Figure 6. The green triangle represents the average. The results indicate that users perceive both content relevance (average: 8.4, range: 8–9) and accuracy (average: 8.8, range: 8–10) at a high level, suggesting that the AI-generated content aligns well with real-world contexts and maintains strong linguistic precision. The narrow range indicates general agreement among participants regarding these aspects. Some users particularly appreciated how the system tailored content to their current environment, with one noting the following: "The sentences were highly relevant to my surroundings, making it easy to connect words with real-life situations."

In terms of learning motivation (average: 7.9, range: 5–9), the scores exhibit more variance, with some participants rating it lower. While many users found the location-based approach engaging, a few expressed a desire for more interactive elements or progressive difficulty levels. One participant commented: "The system is great for beginners, but I wish it had more challenging sentence structures for advanced learners." On the other hand, participants who rated motivation highly appreciated the real-world relevance of the content, which made learning feel more practical and immersive. Some users noted the following: "I found it very engaging because the words I learned were immediately useful in my surroundings."

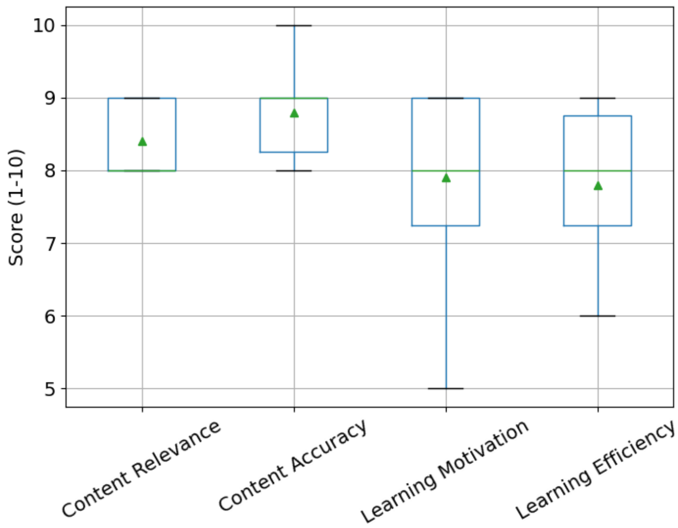


Figure 6. User survey results on content relevance, accuracy, learning motivation, and efficiency.

Similarly, learning efficiency (average: 7.8, range: 6–9) shows the widest spread. Advanced learners in particular noted that while the contextual learning approach was useful, the lack of complexity made it feel less efficient for higher proficiency levels. One participant shared the following: "I liked the contextual aspect, but I felt that the generated sentences were too simple for my level." Meanwhile, those who rated efficiency highly appreciated the quick reinforcement of learned vocabulary in real-world scenarios. As one participant put it, "Being able to immediately apply what I learned helped me remember words much faster than traditional study methods.'

We conducted paired *t*-tests and calculated the 95% confidence intervals as shown in Table 8. The results indicate that there is a statistically significant difference between "Content Accuracy" and "Learning Motivation" ($p = 0.02$, 95% CI: 0.19–1.61) and between "Content Accuracy" and "Learning Efficiency" ($p = 0.01$, 95% CI: 0.25–1.75). This suggests that higher content accuracy may enhance learners' motivation and learning efficiency. In contrast, the p-values for "Content Relevance" and "Learning Motivation" ($p = 0.24$, 95% CI: −0.41–1.41) and for "Content Relevance" and "Learning Efficiency" ($p = 0.14$, 95% CI: −0.24–1.44) were both greater than 0.05, and their 95% confidence intervals included zero, indicating no significant difference. These findings suggest that content accuracy may be more important than content relevance and has a stronger impact on learners' motivation and learning efficiency.

Table 8. Paired *t*-test and confidence intervals for learning metrics.

	***p*-Value**	**95% CI Lower**	**95% CI Upper**
Content Relevance vs. Learning Motivation	0.24	−0.41	1.41
Content Relevance vs. Learning Efficiency	0.14	−0.24	1.44
Content Accuracy vs. Learning Motivation	0.02	0.19	1.61
Content Accuracy vs. Learning Efficiency	0.01	0.25	1.75

Overall, users were highly satisfied with the relevance and accuracy of the content. The location-based learning model effectively motivates learners, especially beginners. Future efforts will focus on creating tailored and engaging content to meet the diverse needs of different language level learners, ensuring both relevance and efficiency in their learning journey.

5.4. Findings and Analysis

The evaluation of this study demonstrates that the location-based AI language learning system performs well in terms of content relevance, learning motivation, and fragmented learning efficiency.

The AI-generated learning materials effectively adapt to various scenarios, ensuring that the language content aligns with real-world environments and enhances contextualized learning experiences. By dynamically generating situationally relevant materials, this approach reduces reliance on predefined content, improving accessibility and supporting sustainable learning by making resources more flexible and inclusive.

Regarding content quality evaluation, jWriter scores indicate that the AI-generated content approaches an advanced level in terms of language proficiency, lexical diversity, and readability, confirming its ability to provide materials that meet learners' needs. Additionally, user feedback further validates this finding, with a content relevance score of 8.4/10 and a learning motivation score of 7.9/10, suggesting that learning in real-world contexts is more engaging and interactive. However, some advanced learners found the content to be insufficiently challenging, highlighting the need for more personalized learning strategies to accommodate different proficiency levels.

The fragmented learning efficiency score of 7.8/10 confirms the system's effectiveness in providing a productive learning experience within short time frames. Users generally agreed that learning environment-relevant expressions during fragmented moments, such as while waiting for transportation or standing in line, is more practical and facilitates faster language application compared to traditional mobile learning methods. By integrating language learning into everyday contexts, this system not only enhances engagement but also fosters lifelong learning habits, aligning with the principles of sustainable education.

6. Discussion

This study integrates contextual learning and fragmented learning while leveraging generative AI to overcome the limitations of traditional learning materials, enhancing the practicality and efficiency of language learning. By dynamically generating adaptive content, this approach reduces reliance on static resources, improving accessibility and supporting sustainable learning practices.

Existing research has shown that learning a language in real-life contexts significantly improves learners' fluency, grammar proficiency, and vocabulary retrieval ability [88,89]. In particular, learners in study-abroad environments use natural language apps [90,91]. This study employs location-aware technology to generate dynamic, context-based learning content, thereby enhancing language application skills and fostering lifelong learning by encouraging learners to engage with their surroundings as a continuous learning resource.

Our approach enables learners to acquire the most commonly used honorific expressions in specific environments. For instance, in a ramen shop, learners can naturally come across expressions such as "Okaikei onegaishimasu."—"May I have the bill, please?", which is commonly used by customers when requesting the check. By exposing learners to honorific expressions in real-life contexts, our approach facilitates more intuitive and practical acquisition of polite language, bridging the gap between textbook learning and real-world communication.

Additionally, fragmented learning has been proven to be an effective approach for improving learning outcomes in mobile learning environments [92,93]. For example, short, high-frequency learning applications such as Anki and Babbel have been shown to enhance vocabulary retention and grammar mastery [94,95]. By integrating generative AI, this study enables real-time generation of personalized learning content in different scenarios, maximizing the efficiency of fragmented learning time. For instance, while waiting for food at a restaurant, users can engage in practice exercises related to ordering food, whereas at a train station, they can utilize waiting time to learn dialogues for asking directions or purchasing tickets. Our approach not only enhances the contextual relevance of learning content but also optimizes the efficiency of fragmented learning time.

6.1. Limitations

Nonetheless, AI-generated content has certain limitations. Due to the inherent randomness of generative AI, learning materials may vary even for the same scenario, potentially affecting consistency, particularly in situations requiring repetitive practice. Future research could explore optimizing prompt engineering or integrating users' learning history to ensure more stable and coherent content generation. Additionally, the current study is limited by the small-scale user evaluation, which does not allow for generalizable conclusions regarding the system's effectiveness across diverse learner demographics. Factors such as age, gender, and language proficiency could influence learning outcomes, requiring a more extensive user study to verify applicability across different learner groups. While we have conducted subjective evaluations and employed jWriter for objective analysis of linguistic characteristics, our assessment of actual learning outcomes remains limited. Specifically, we have not yet systematically measured learners' vocabulary retention, comprehension improvements, or error patterns over time.

In terms of providing immersion, virtualized environment learning can also offer valuable experiences. For instance, scenario-based conversation simulations (e.g., Babbel Live [96], Pimsleur [97]) allow learners to practice structured dialogues in a controlled setting, helping them develop fluency before engaging in real-world interactions. Compared to our approach, virtualized learning does not rely on physical locations, making it more flexible in terms of accessibility. However, since it is based on predefined scenarios, it cannot fully simulate all possible real-world situations. Our method complements virtualized learning by increasing opportunities for learning anytime and anywhere, allowing learners to apply their knowledge in diverse, real-world contexts.

Integrating cultural elements into language learning accelerates the learning process and enhances learners' communicative competence [98]. In the AI-generated learning materials, some culturally appropriate expressions are incorporated. For example, in a restaurant scenario, the sentence "Can I get the bill, please?" is translated into a Japanese phrase that reflects politeness, aligning with Japanese communication norms. However, such integration is still limited. Japanese culture places significant emphasis on indirectness, honorifics, and context-sensitive phrasing, which are not yet systematically embedded in the generated content.

6.2. Contributions to Sustainable Education

Our approach contributes to sustainable education by minimizing reliance on printed materials, reducing paper consumption, and eliminating the need for traditional textbooks. By providing accessible learning opportunities in low-resource environments, it supports educational equity and ensures that learners, regardless of geographic or socioeconomic constraints, can benefit from high-quality educational content. Moreover, by enabling learners to engage with context-aware digital resources anytime and anywhere, this method fosters lifelong learning habits and encourages a more flexible and inclusive approach to education.

6.3. Future Work

Future research could further explore personalized learning paths by dynamically adjusting content difficulty and depth based on users' proficiency levels. Additionally, multi-modal learning methods, such as incorporating voice interaction and augmented reality [99,100], could enrich the learning experience and improve content authenticity. Further optimization of AI-generated content through improved prompt engineering may also enhance content accuracy and adaptability.

To enhance the generalizability of our findings, we plan to conduct a larger-scale user study with participants of varying age groups, proficiency levels, and cultural backgrounds. To further validate the effectiveness of our approach, we plan to supplement subjective assessments with objective learning indicators. This includes using standardized vocabulary and comprehension tests, tracking study duration, and analyzing user errors to better understand learning progress.

To improve cultural relevance, future iterations of our approach will incorporate customized prompt engineering to guide AI-generated content towards more authentic and culturally appropriate expressions.

We also plan to incorporate language feature visualization to enhance learners' understanding and engagement in the MALL environment. By leveraging visual representations of linguistic features, we aim to improve both grammar comprehension and vocabulary retention. For example, color-coded text highlighting can be used to emphasize subject–verb–object structures, tense variations, and verb conjugations within a sentence, allowing learners to quickly grasp essential grammatical patterns. Additionally, interactive grammar exercises will enable users to click on words to reveal their grammatical roles, inflections, and usage examples, making learning more intuitive and exploratory.

7. Conclusions

This study proposes a location-based AI-generated e-learning app that integrates location-awareness technology with AI to dynamically generate learning content tailored to the user's location, enhancing the immersiveness and practicality of language learning.

Evaluation results indicate that the AI-generated learning materials are of high quality. The proposed approach demonstrates strong performance in learning efficiency. In particular, when the learning content is closely aligned with real-world environments, users show high motivation and engagement with positive feedback. By reducing dependence on predefined materials, this approach improves accessibility, ensuring that learners can acquire relevant knowledge anytime and anywhere, while also fostering lifelong learning habits by integrating learning into daily contexts, thereby promoting sustainable learning.

Although this study confirms the potential of AI-generated content in contextual language learning, ensuring content consistency and adaptability remains a challenge. Future research will generate learning materials with varying difficulty levels based on learners' language proficiency. Optimizing AI-generated content through improved prompt engineering and learning history integration can enhance stability and personalization. Furthermore, by integrating speech recognition, computer vision, and immersive learning technologies, we aim to develop richer multi-modal interactions to further enhance learners' language input and output abilities. To further validate the effectiveness of this approach, a larger-scale user study incorporating standardized learning assessments will be conducted.

Author Contributions: Funding acquisition, S.C.; methodology, L.Y.; project administration, S.C.; software, L.Y.; supervision, S.C. and J.L.; writing—original draft, L.Y.; writing—review and editing, L.Y., S.C., and J.L. All authors have read and agreed to the published version of the manuscript.

Funding: This research was partially supported by the Kobe University CMDS Joint Project Promoting DX Inside & Outside the University under Grant Number PJ2024-03.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Although the user studies conducted in this research were exempt from ethical review by our institution, we proactively implemented measures to ensure participant privacy. Participants were provided with written consent detailing our privacy policy, including the purpose and disclosure of the experiment data, before the study commenced. No personally identifiable information was collected in the questionnaires, and no video recordings of participants were made. Furthermore, responses from questionnaires and interviews were manually anonymized to remove personal identifiers. The collected data will be securely stored and destroyed after five years, and participants retain the right to request the deletion and discontinuation of their data usage at any time.

Data Availability Statement: Dataset available on request from the authors.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Ima, N.; Jihad, A. Computer-Assisted Language Learning: The Impact in Language Education. *Vifada J. Educ.* **2024**, *2*, 36–42. . [CrossRef]
2. Mirani, J.I.; Lohar, S.A.; Jat, A.R.L.; Faheem, M. A Review of Computer-Assisted Language Learning (CALL): Development, Challenges, and Future Impact. *Educ. Linguist. Res.* **2019**, *5*, 37–45. . [CrossRef]
3. Osifo, A.; Radwan, A. Mobile-assisted language learning (MALL) applications for interactive and engaging classrooms: APPsolutely. In Proceedings of the ICT for Language Learning, Florence, Italy, 13–14 November 2014; p. 282.
4. Hassan Taj, I.; Sulan, N.; Sipra, M.; Ahmad, W. Impact of mobile assisted language learning (MALL) on EFL: A meta-analysis. *Adv. Lang. Lit. Stud.* **2016**, *7*, 2203–4714.
5. Rajendran, T.; Yunus, M.M. A systematic literature review on the use of mobile-assisted language Learning (MALL) for enhancing speaking skills among ESL and EFL learners. *Int. J. Acad. Res. Progress. Educ. Dev.* **2021**, *10*, 586–609. [CrossRef]
6. Miraz, S.; Ali, M. An Overview of Mobile Assisted Language Learning (MALL). In Proceedings of the International Conference on eBusiness, eCommerce, eManagement, eLearning and eGovernance 2014, London, UK, 30 July 2014.
7. Chanprasert, C.; Han, H.P. Learning on the Move: The Use of Mobile Technologies for Language Skill Development. *Exec. J.* **2013**, *34*, 98–107.
8. Ahmad, K.; Armarego, J.; Sudweeks, F. The Impact of Utilising Mobile Assisted Language Learning (MALL) on Vocabulary Acquisition among Migrant Women English Learners. *Interdiscip. J. E-Skills Lifelong Learn.* **2017**, *13*, 37–57. [CrossRef]
9. Svensson, L.; Anderberg, E.; Alvegård, C.; Johansson, T. The use of language in understanding subject matter. *Instr. Sci.* **2009**, *37*, 205–225. [CrossRef]
10. Korkmaz, S.; Korkmaz, Ş.Ç. Contextualization or de-contextualization: Student teachers' perceptions about teaching a language in context. *Procedia-Soc. Behav. Sci.* **2013**, *93*, 895–899. [CrossRef]

11. Golonka, E.M.; Bowles, A.R.; Frank, V.M.; Richardson, D.L.; Freynik, S. Technologies for foreign language learning: A review of technology types and their effectiveness. *Comput. Assist. Lang. Learn.* **2014**, *27*, 70–105. [CrossRef]
12. Mediha, N.; Enisa, M. A Comparative Study on the Effectiveness of Using Traditional and Contextualized Methods for Enhancing Learners' Vocabulary Knowledge in an EFL Classroom. *Procedia-Soc. Behav. Sci.* **2014**, *116*, 3443–3448. [CrossRef]
13. Kermani, S.; Seyedrezaei, S.H.; Branch, G. The Effect of Contextualized Vocabulary Teaching on Learners' Vocabulary Learning and Retention. *J. Lang. Sci. Linguist.* **2015**, *3*, 90–95.
14. Guo, J. Construction of MALL Vocabulary Acquisition Model from the Perspective of Deep Learning. *Int. J. High. Educ. Pedagog.* **2022**, *3*, 38–53. [CrossRef]
15. Ahmad, K.; Armarego, J.; Sudweeks, F. Utilising Mobile Assisted Language Learning (MALL) for Vocabulary Acquisition of Refugee Women English Learners. In Proceedings of the 2nd International Virtual Conference on Advanced Scientific Results (ScieConf) 2014, Zilina, Slovakia, 9–13 June 2014.
16. Zhang, S.J.; Yu, G.H. Mobile learning model and process optimization in the era of fragmentation. *Eurasia J. Math. Sci. Technol. Educ.* **2017**, *13*, 3641–3652. [CrossRef]
17. Ahn, H.Y. AI-Powered E-Learning for Lifelong Learners: Impact on Performance and Knowledge Application. *Sustainability* **2024**, *16*, 9066. [CrossRef]
18. Uğraş, H.; Uğraş, M.; Papadakis, S.; Kalogiannakis, M. ChatGPT-Supported Education in Primary Schools: The Potential of ChatGPT for Sustainable Practices. *Sustainability* **2024**, *16*, 9855. [CrossRef]
19. Lu, P.; Feng, X. Personalized Recommendation Algorithm in AI-Assisted Learning System. In Proceedings of the 2024 6th International Conference on Communications, Information System and Computer Engineering (CISCE), Guangzhou, China, 10–12 May 2024; pp. 1289–1294. [CrossRef]
20. Yu, D.; Ding, M.; Li, W.; Wang, L.; Liang, B. Designing an Artificial Intelligence Platform to Assist Undergraduate in Art and Design to Develop a Personal Learning Plans. In Proceedings of the 8th International Conference, DUXU 2019, Orlando, FL, USA, 26–31 July 2019; pp. 528–538. . [CrossRef]
21. Khamis, M.A. Adaptive e-learning environment systems and technologies. In Proceedings of the The First International Conference of the Faculty of Education, Hangzhou, China, 19–20 December 2015; pp. 13–15.
22. jReadability Portal. jWriter: Japanese Readability Assessment. Available online: https://jreadability.net/jwriter/ja (accessed on 2 February 2025).
23. Baddane, K.; Abdelghanie, E. Contextualization Strategies and Reading Comprehension: An Investigation among IELTS Test-Takers. *Int. J. Linguist. Lit. Transl.* **2023**, *6*, 148–156. [CrossRef]
24. Banegas, D. Content and Language Integrated Learning. *Ref. Modul. Soc. Sci.* **2024**. . [CrossRef]
25. Edge, D.; Searle, E.; Chiu, K.; Zhao, J.; Landay, J. MicroMandarin: Mobile language learning in context. In Proceedings of the CHI '11: CHI Conference on Human Factors in Computing Systems, Vancouver, BC, Canada, 7–12 May 2011; pp. 3169–3178. [CrossRef]
26. Minalla Alameen, A. Enhancing Young EFL Learners' Vocabulary Learning Through Contextualizing Animated Videos. *Theory Pract. Lang. Stud.* **2024**, *14*, 578–586. [CrossRef]
27. Ribahan, R. EFL Classroom Interaction through Contextual Teaching and Learning: A Qualitative Study. *EDULANGUE* **2023**, *6*, 1–21. [CrossRef]
28. Yasuta, T.; Pyshkin, E. Manga design and role language in the context of cross-cultural communication of language learners. In Proceedings of the Conference name: 14th International Technology, Education and Development Conference, Valencia, Spain, 2–4 March 2020. [CrossRef]
29. Bhusaery, R.; Chaerul, A.; Kamil, A.B. Investigating students response of using video based learning method through youtube on english vocabulary learning. *INFOTECH J.* **2024**, *10*, 128–131. [CrossRef]
30. Mallisa, I.C.B.; Mbato, C. Analyzing the Impact of Spotify and Wordwall.net on Vocabulary Acquisition: A Study of non-English major Students' Preferences. *Voices Engl. Lang. Educ. Soc.* **2023**, *7*, 665–674. [CrossRef]
31. Pikhart, M. Intelligent information processing for language education: The use of artificial intelligence in language learning apps. *Procedia Comput. Sci.* **2020**, *176*, 1412–1419. [CrossRef] [PubMed]
32. Getman, Y.; Phan, N.; Al-Ghezi, R.; Voskoboinik, E.; Singh, M.; Grósz, T.; Kurimo, M.; Salvi, G.; Svendsen, T.; Strömbergsson, S.; et al. Developing an AI-Assisted Low-Resource Spoken Language Learning App for Children. *IEEE Access* **2023**, *11*, 86025–86037. [CrossRef]
33. Polakova, P.; Klimova, B. Vocabulary Mobile Learning Application in Blended English Language Learning. *Front. Psychol.* **2022**, *13*, 869055. [CrossRef]
34. Lee, S.M.; Park, M. Reconceptualization of the context in language learning with a location-based AR app. *Comput. Assist. Lang. Learn.* **2019**, *33*, 936–959. [CrossRef]
35. Kacetl, J.; Klímová, B. Use of Smartphone Applications in English Language Learning—A Challenge for Foreign Language Education. *Educ. Sci.* **2019**, *9*, 179. [CrossRef]

36. Tezer, M.; Gülyaz, M. The Use of Mobile Learning Technologies for an Online Mathematics Course: Student Opinions in The Pandemic Process. *Int. J. Interact. Mob. Technol. (IJIM)* **2022**, *16*, 36–46. [CrossRef]
37. Cakmak, F. Mobile learning and mobile assisted language learning in focus. *Lang. Technol.* **2019**, *1*, 30–48.
38. Gholami, J.; Azarmi, G. An introduction to mobile assisted language learning. *Int. J. Manag. IT Eng.* **2012**, *2*, 1–9.
39. Jeong, K.O. Facilitating sustainable self-directed learning experience with the use of mobile-assisted language learning. *Sustainability* **2022**, *14*, 2894. [CrossRef]
40. Read, T.; Madera, E.B. Toward a framework for language MOOCs and mobile assisted language learning. *Propósitos Represent* **2020**, *8*, 20.
41. Kukulska-Hulme, A. Will mobile learning change language learning? *ReCALL* **2009**, *21*, 157–165. [CrossRef]
42. Foomani, E.M.; Hedayati, M. A seamless learning design for mobile assisted language learning: An Iranian context. *Engl. Lang. Teach.* **2016**, *9*, 206–213. [CrossRef]
43. Miangah, T.M.; Nezarat, A. Mobile-assisted language learning. *Int. J. Distrib. Parallel Syst.* **2012**, *3*, 309. [CrossRef]
44. Chen, C.M.; Tsai, Y.N. Interactive location-based game for supporting effective English learning. In Proceedings of the 2009 International Conference on Environmental Science and Information Application Technology, Wuhan, China, 4–5 July 2009; Volume 3, pp. 523–526.
45. Fallahkhair, S. Supporting geolearners: Location-based informal language learning with mobile phones. In Proceedings of the Fourth International Conference on Ubiquitous Learning, Berkeley, CA, USA, 11–12 November 2011.
46. Gaved, M.; Peasgood, A. Location-based language learning for migrants in a smart city. In Proceedings of the 15th International Conference on Technology, Policy and Innovation, Vilnius, Lithuania, 4–8 July 2015.
47. Perry, B. Gamified mobile collaborative location-based language learning. *Front. Educ. Front. Media* **2021**, *6*, 689599. [CrossRef]
48. Holden, C.L.; Sykes, J.M. Leveraging mobile games for place-based language learning. *Int. J. Game-Based Learn. (IJGBL)* **2011**, *1*, 1–18. [CrossRef]
49. Wu, S.; Pammi, K.; Yu, A. Location-based vocabulary learning app. In *mLearn 2016*; Dyson, L.E., Ng, W., Fergusson, J., Eds.; The University of Technology: Sydney, Australia, 2016; pp. 287–290.
50. Ferk Savec, V.; Jedrinović, S. The Role of AI Implementation in Higher Education in Achieving the Sustainable Development Goals: A Case Study from Slovenia. *Sustainability* **2025**, *17*, 183. [CrossRef]
51. Chen, J.; Zhuo, Z.; Lin, J. Does ChatGPT Play a Double-Edged Sword Role in the Field of Higher Education? An In-Depth Exploration of the Factors Affecting Student Performance. *Sustainability* **2023**, *15*, 16928. [CrossRef]
52. Luckin, R.; Holmes, W. *Intelligence Unleashed: An Argument for AI in Education*; UCL Knowledge Lab: London, UK, 2016.
53. Zawacki-Richter, O.; Marín, V.I.; Bond, M.; Gouverneur, F. Systematic review of research on artificial intelligence applications in higher education–where are the educators? *Int. J. Educ. Technol. High. Educ.* **2019**, *16*, 39. [CrossRef]
54. Paladines, J.; Ramirez, J. A systematic literature review of intelligent tutoring systems with dialogue in natural language. *IEEE Access* **2020**, *8*, 164246–164267. [CrossRef]
55. Abu Ghali, M.J.; Abu Ayyad, A.; Abu-Naser, S.S.; Abu Laban, M. An intelligent tutoring system for teaching English grammar. *Int. J. Acad. Eng. Res. (IJAER)* **2018**, *2*, 1–6.
56. Kanchon, M.K.H.; Sadman, M.; Nabila, K.F.; Tarannum, R.; Khan, R. Enhancing personalized learning: AI-driven identification of learning styles and content modification strategies. *Int. J. Cogn. Comput. Eng.* **2024**, *5*, 269–278. [CrossRef]
57. Ellikkal, A.; Rajamohan, S. AI-enabled personalized learning: Empowering management students for improving engagement and academic performance. *Vilakshan-Ximb J. Manag.* **2024**. [CrossRef]
58. Bevilacqua, M.; Oketch, K.; Qin, R.; Stamey, W.; Zhang, X.; Gan, Y.; Yang, K.; Abbasi, A. When automated assessment meets automated content generation: Examining text quality in the era of gpts. *arXiv* **2023**, arXiv:2309.14488. [CrossRef]
59. Gao, R.; Merzdorf, H.E.; Anwar, S.; Hipwell, M.C.; Srinivasa, A.R. Automatic assessment of text-based responses in post-secondary education: A systematic review. *Comput. Educ. Artif. Intell.* **2024**, *6*, 100206. [CrossRef]
60. Chiu, T.K. The impact of Generative AI (GenAI) on practices, policies and research direction in education: A case of ChatGPT and Midjourney. *Interact. Learn. Environ.* **2024**, *32*, 6187–6203. [CrossRef]
61. Do, T.D.; Shafqat, U.B.; Ling, E.; Sarda, N. PAIGE: Examining Learning Outcomes and Experiences with Personalized AI-Generated Educational Podcasts. *arXiv* **2024**, arXiv.2409.04645. [CrossRef]
62. Marandi, S.S.; Hosseini, S. AI-Driven Assessment in Iranian High School English Classes. In Proceedings of the 2024 11th International and the 17th National Conference on E-Learning and E-Teaching (ICeLeT), Isfahan, Iran, 27–29 February 2024; pp. 1–3. [CrossRef]
63. Nasution, N.E.A. Using artificial intelligence to create biology multiple choice questions for higher education. *Agric. Environ. Educ.* **2023**, *2*, em002. [CrossRef]
64. Chen, S.; Yang, L.; Xie, Y.; Zhu, Z.; Li, J.; Zhang, Y.; Zhang, M. Developing a Web Service for Creating E-Learning Video Using Digital Human and Educational Content. In Proceedings of the 8th Eurasian Conference on Educational Innovation 2025 (ECEI 2025), Bali, Indonesia, 6–8 February 2025.

65. Google Developers. Fused Location Provider API. Available online: https://developer.android.com/training/location/retrieve-current (accessed on 30 January 2025).
66. OpenStreetMap. Nominatim API documentation. Available online: https://nominatim.org/release-docs/latest/ (accessed on 30 January 2025).
67. Square Inc. OkHttp: HTTP & HTTP/2 client for Android. Available online: https://square.github.io/okhttp/ (accessed on 30 January 2025).
68. Flask. Welcome to Flask—Flask documentation. Available online: https://flask.palletsprojects.com/en/latest/ (accessed on 30 January 2025).
69. DeepSeek. Deepseek AI. 2025. Available online: https://www.deepseek.com/ (accessed on 31 January 2025).
70. Alibaba Cloud. Qwen 2.5. 2024. Available online: https://chat.qwenlm.ai (accessed on 31 January 2025).
71. Meta AI. Llama. 2024. Available online: https://www.llama.com (accessed on 31 January 2025).
72. Anthropic. Claude. 2025. Available online: https://claude.ai (accessed on 31 January 2025).
73. OpenAI. ChatGPT. 2024. Available online: https://chatgpt.com (accessed on 31 January 2025).
74. DeepSeek-AI. DeepSeek-V3 Technical Report. 2024. Available online: https://github.com/deepseek-ai/DeepSeek-V3 (accessed on 31 January 2025).
75. Hendrycks, D.; Burns, C.; Basart, S.; Zou, A.; Mazeika, M.; Song, D.; Steinhardt, J. Measuring massive multitask language understanding. *arXiv* **2020**, arXiv:2009.03300.
76. Gema, A.P.; Leang, J.O.J.; Hong, G.; Devoto, A.; Mancino, A.C.M.; Saxena, R.; He, X.; Zhao, Y.; Du, X.; Madani, M.R.G.; et al. Are We Done with MMLU? *arXiv* **2024**, arXiv:2406.04127.
77. Dua, D.; Wang, Y.; Dasigi, P.; Stanovsky, G.; Singh, S.; Gardner, M. DROP: A reading comprehension benchmark requiring discrete reasoning over paragraphs. *arXiv* **2019**, arXiv:1903.00161.
78. Wang, Y.; Ma, X.; Zhang, G.; Ni, Y.; Chandra, A.; Guo, S.; Ren, W.; Arulraj, A.; He, X.; Jiang, Z.; et al. Mmlu-pro: A more robust and challenging multi-task language understanding benchmark. *arXiv* **2024**, arXiv:2406.01574.
79. Zhou, J.; Lu, T.; Mishra, S.; Brahma, S.; Basu, S.; Luan, Y.; Zhou, D.; Hou, L. Instruction-following evaluation for large language models. *arXiv* **2023**, arXiv:2311.07911.
80. Rein, D.; Hou, B.L.; Stickland, A.C.; Petty, J.; Pang, R.Y.; Dirani, J.; Michael, J.; Bowman, S.R. Gpqa: A graduate-level google-proof q&a benchmark. *arXiv* **2023**, arXiv:2311.12022.
81. Yu, S.; Jin, C.; Wang, H.; Chen, Z.; Jin, S.; Zuo, Z.; Xu, X.; Sun, Z.; Zhang, B.; Wu, J.; et al. Frame-Voyager: Learning to Query Frames for Video Large Language Models. *arXiv* **2024**, arXiv:2410.03226.
82. Bai, Y.; Tu, S.; Zhang, J.; Peng, H.; Wang, X.; Lv, X.; Cao, S.; Xu, J.; Hou, L.; Dong, Y.; et al. LongBench v2: Towards deeper understanding and reasoning on realistic long-context multitasks. *arXiv* **2024**, arXiv:2412.15204.
83. Chen, B.; Zhang, Z.; Langrené, N.; Zhu, S. Unleashing the potential of prompt engineering in Large Language Models: A comprehensive review. *arXiv* **2023**, arXiv:2310.14735.
84. White, J.; Fu, Q.; Hays, S.; Sandborn, M.; Olea, C.; Gilbert, H.; Elnashar, A.; Spencer-Smith, J.; Schmidt, D.C. A prompt pattern catalog to enhance prompt engineering with chatgpt. *arXiv* **2023**, arXiv:2302.11382.
85. Yang, L. AI-generated Content. 2025. Available online: https://github.com/youryugi/AI-genernatedContent (accessed on 9 February 2025).
86. Japan Foundation and Japan Educational Exchanges and Services. Japanese-Language Proficiency Test (JLPT). 2025. Available online: https://www.jlpt.jp/ (accessed on 2 February 2025).
87. Saito, Y.; Okuzumi, J.; Suzuki, N. Comparison of GPS Data Acquisition for Open Air Museums by Two APIs. In Proceedings of the 2022 IEEE International Conference on Artificial Intelligence and Virtual Reality (AIVR), Virtual, 12–14 December 2022; pp. 248–251. [CrossRef]
88. Collentine, J.; Freed, B.F. Learning context and its effects on second language acquisition: Introduction. *Stud. Second Lang. Acquis.* **2004**, *26*, 153–171. [CrossRef]
89. Segalowitz, N.; Freed, B.F. Context, contact, and cognition in oral fluency acquisition: Learning Spanish in at home and study abroad contexts. *Stud. Second Lang. Acquis.* **2004**, *26*, 173–199. [CrossRef]
90. Díaz-Campos, M. Context of learning in the acquisition of Spanish second language phonology. *Stud. Second Lang. Acquis.* **2004**, *26*, 249–273. [CrossRef]
91. Young, R.; Astarita, A. Practice Theory in Language Learning. *Lang. Learn.* **2013**, *63*. [CrossRef]
92. Lu, M. Effectiveness of vocabulary learning via mobile phone. *J. Comput. Assist. Learn.* **2008**, *24*, 515–525. [CrossRef]
93. Hirschel, R.; Fritz, E. Learning vocabulary: CALL program versus vocabulary notebook. *System* **2013**, *41*, 639–653. [CrossRef]
94. Hanson, A.E.S.; Brown, C.M. Enhancing L2 learning through a mobile assisted spaced-repetition tool: An effective but bitter pill? *Comput. Assist. Lang. Learn.* **2020**, *33*, 133–155. [CrossRef]
95. Loewen, S.; Isbell, D.R.; Sporn, Z. The effectiveness of app-based language instruction for developing receptive linguistic knowledge and oral communicative ability. *Foreign Lang. Ann.* **2020**, *53*, 209–233. [CrossRef]

96. Babbel. Babbel—Learn Languages Online. 2025. Available online: https://www.babbel.com (accessed on 7 March 2025).
97. Pimsleur. Pimsleur—Learn a New Language. 2025. Available online: https://www.pimsleur.com (accessed on 7 March 2025).
98. Saba, P.; Noreen, F. Integration of culture in Second Language Learning. *Int. J. Sci. Res. Manag.* **2015**, *3*, 2624–2627.
99. Tezer, M.; Yıldız, E.; Masalimova, A.; Fatkhutdinova, A.; Zheltukhina, M.; Khairullina, E. Trends of augmented reality applications and research throughout the world: Meta-analysis of theses, articles and papers between 2001–2019 years. *Int. J. Emerg. Technol. Learn. (IJET)* **2019**, *14*, 154–174. [CrossRef]
100. Yildiz, E.P. Augmented Reality Applications in Education: Arloopa Application Example. *High. Educ. Stud.* **2022**, *12*, 47–53. [CrossRef]