SHORT-PAPER

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AIlingo: Contextual Language Learning with Artificial Intelligence in Real-World Contexts

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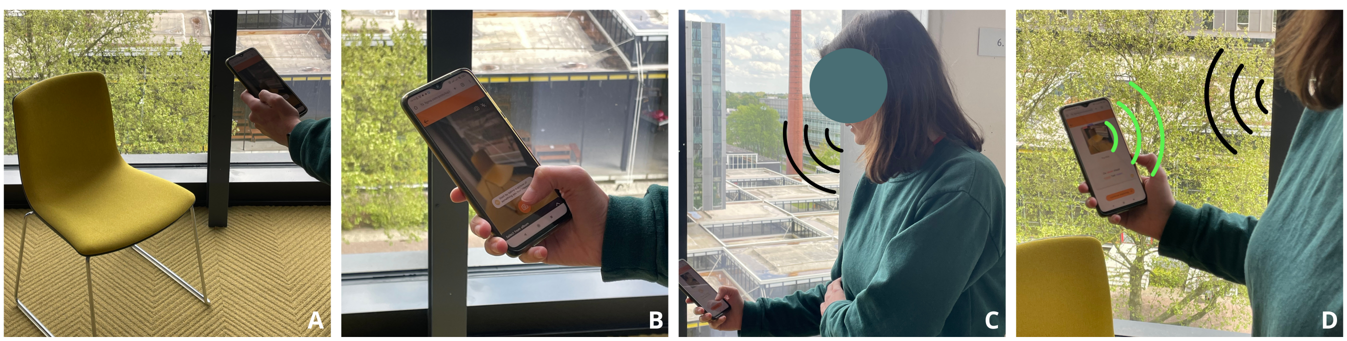

Figure 1: A user is using AIlingo to learn in their surroundings (A). The user captures a scene using their smartphone (B), describes the scene in their own words (C), receives object captions and scene descriptions in Dutch generated by AIlingo, and checks the verbal description, repeating it (D).

Abstract

Mastering foreign languages is essential in the globalized modern world in terms of career development and cross-cultural interactions. Mobile assisted language learning (MALL) provides a convenient and accessible platform, with recent advancements in artificial intelligence (AI) providing opportunities to improve contextualized learning experiences. This study presents AIlingo, an AI-enabled MALL tool designed to provide immersive language learning experiences within real-world contexts of learners. AIlingo uses pre-trained AI models for object detection, image captioning, text generation, and text-to-speech, enabling learners to improve vocabulary and sentence formulation by recognizing everyday objects. The user study evaluates AIlingo through the User Experience Questionnaire (UEQ) and semi-structured interviews, providing insights for further development efforts.

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CCS Concepts

• Human-centered computing → Ubiquitous and mobile computing; • Applied computing → Education.

Keywords

Mobile Assisted Language Learning, Contextual Learning, Artificial Intelligence

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1 Introduction

Learning foreign languages has become more crucial in today's globalized society. It offers benefits like enhanced cross-cultural understanding and expanded career opportunities [7]. Immersive language learning environments enable learners to acquire language more naturally and provide insights across diverse proficiency levels, whether in-person or computer-mediated [45, 46]. By nature, such learning exposes learners to the target language in various contextual settings [36], allowing them to immerse themselves and practice the target language using tangible objects, interactions with individuals, and contextual situations [46]. However, immersion, like interacting with native speakers or traveling abroad, is often inaccessible. Recent research demonstrated the potential of augmented reality (AR) and virtual reality (VR) technologies to provide immersive language learning experiences [35, 53]. However, barriers such as limited accessibility, physiological concerns, operational complexity, and high costs hinder widespread adoption of the technology and devices [2, 39, 41].

In contrast, mobile assisted language learning (MALL) offers a convenient and accessible platform for learners to access learning material and personalize digital learning content anytime and anywhere [10, 17]. Today's mobile devices are equipped with a variety of powerful features, such as internet connectivity, cameras, and global positioning system, which enable them to gather diverse information about the surrounding physical environment [54]. These capabilities open up new opportunities for situated and contextual learning experiences. By connecting learners with their real environments, MALL facilitates the acquisition and practice of the target language using tangible objects, social interactions, and contextual situations, resulting in an immersive learning experience [46]. Moreover, recent advancements in artificial intelligence (AI), such as natural language processing (NLP) [37], have been used to enhance learning experiences across various environments and contexts. Combining MALL tools with AI technology has produced a variety of effective and motivating educational tools, such as intelligent feedback systems [47], AI-powered chatbots [8], writing performance assessment [16] and image-to-text recognition [48]. However, limited research has been conducted to explore the extent of AI-enabled mobile learning in enhancing immersion through contextually relevant learning materials in real-world environments.

Hence, in this study, we introduce AIlingo, an AI-enabled MALL tool designed to facilitate immersive language learning experiences within learners' real-world contexts (Figure 1). AIlingo focuses on teaching Dutch as a target language but is poised to accommodate other languages in the future. AI is used for four tasks: object detection, image captioning, text generation, and text-to-speech conversion. The process begins with the user taking an image by their mobile devices, which is then fed into a Convolutional Neural Network (CNN) model, YOLOv8 [38], for object detection. Simultaneously, the same image undergoes processing by Bootstrapping Language Image Pre-training (BLIP), a transformer model, which generates text-based captions describing the visual content [26]. The captions are dynamically rewritten using Large Language Model (LLM), GPT-3.5 Turbo [32], guided by a predefined prompt. The rewritten captions are then synthesized into speech using the TTS-1 model [33], facilitating speaking practice. With these capabilities, AIlingo allows learners to expand their vocabulary and form sentences by recognizing real-world objects in their surroundings. This approach furnishes learners with a platform for independent exploration of real-life scenarios in real-world and ubiquitous learning settings, thereby fostering immersive learning experiences. The user study involved seven participants, in which we evaluated the user experience of AIlingo through the User Experience Questionnaire (UEQ) and semi-structured interviews. The results reveal positive evaluations across all dimensions of AIlingo's usability, particularly highlighting its clarity, efficiency, and dependability. Participants appreciated AIlingo's contextual learning experience but desired more adaptation and personalization features, suggesting opportunities for further development.

The contributions of this paper are (1) the design and implementation of a MALL tool, AIlingo, that leverages AI for contextual language learning. (2) An interactive prototype demonstrating AIlingo's functionalities. (3) A user study that explores user experience and gathers insights for future development.

2 Related Work

2.1 Mobile Assisted Language Learning

With the continued development and widespread use of mobile devices and the Internet, MALL has emerged as a vital and timely area of research since the early 2000s [49]. MALL is defined as "the use of mobile technologies in language learning, especially in situations where device portability offers specific advantages" [20]. These advantages include but are not limited to flexibility, affordability, portability, and user-friendliness [14]. Consequently, MALL provides learners with plenty of learning opportunities in both formal and informal settings [22]. MALL is widely employed in facilitating language skills and components such as vocabulary [1], grammar [9], speaking [27], and reading [5]. Yet, recent studies indicate that MALL can serve as a medium that provides a flexible, context-aware language learning environment [17, 51]. Such an environment allows learners to expand their exposure to the target language and engage in practice activities across various physical settings and contexts. Moreover, MALL features situated, real-world, and continuous assessment by taking advantage of mobile technologies [19]. Despite these advancements, previous literature has yet to fully explore the potential of MALL. Another notable deficiency in previous MALL research is the lack of emphasis on learners' learning experiences [17]. While language proficiency has been a primary focus of MALL research [13], non-linguistic factors such as self-directedness, autonomy, and immersion have been neglected. Therefore, there remains a need for further exploration to better understand and tap the potential of MALL.

2.2 Language Learning in Real-World Contexts

The situational learning approach highlights the importance of "context" in language acquisition, as it enhances learners' engagement and effectiveness [12]. Real-world contexts offer an ideal opportunity for learners to interact with physical objects and gain real-world, immersive language learning experiences [15, 34]. This enables learners to acquire knowledge and skills within specific contexts, thereby enabling them to infer word meanings from contextual clues. It is a strategy recognized for its potential to enhance long-term retention [50]. In an early study on vocabulary learning in contexts, Ogata and Yano proposed the use of Tagged Annotations for Learning Objects (TANGO), which allows students to learn vocabulary related to surrounding objects using mobile phones and radio frequency identification technology [31]. Furthermore, a quasi-experimental study, which was conducted to enhance English learners' speaking abilities, implemented a sensor-based, AI-enhanced augmented reality mobile learning environment [29]. The results demonstrated improved speaking skills within the immersive context-aware system.

The current state of connecting learning with its context in foreign language learning calls for enhanced practicality to enable broader use and application in diverse, real-world contexts with different target languages [24]. Developing a more universal and widely applicable system may pose challenges, but addressing this challenge could yield beneficial results. In this study, we focused on developing a MALL tool, which prioritizes contextual information based on the situational learning approach and contextual information [4], such as the learner's real-world surroundings and ubiquitous learning time, to create an immersive, contextual learning experience.

2.3 Artificial Intelligence in Language Learning

AI-enabled learning is concerned with integrating AI technologies into learning platforms to deliver tailored content, guidance, pathways, feedback, or interfaces that cater to individual learner needs and preferences [21]. A thorough examination of AI technologies has highlighted that AI-based modelings possess the potential to augment the intelligence and functionality of real-world applications; AI-based solutions can be more extensively utilized in real-world applications for language learning [42].

Recent reviews on AI-based language learning tools have shown that the majority of these tools adopted machine learning (e.g., intelligent tutoring systems) and natural language processing, most of which focus on the cognitive aspects of language acquisition, and some consider affective or psychological aspects [28, 52]. For instance, Shazly integrated AI chatbots into the speaking practices of English learners, with findings indicating promising improvements in linguistic output gains [6]. Chen et al. used AI to develop a personalized, collaborative digital reading annotation to reduce reading anxiety in English learners [3]. In addition to the research field, software applications like Babbel [1] and Duolingo [2] utilize AI technologies to enhance language learning experiences. Babbel provides immediate feedback on learners' inputs, addressing issues like mixed tenses and verb forms [43], while Duolingo employs an AI model called "Birdbrain" to ensure exercises are at the optimal difficulty level based on learners' strengths and weaknesses [11].

However, the potential of AI in language learning extends beyond these examples. AI facilitates immersive language learning by integrating data such as images, voice, and text into learning environments, enabling context understanding and enhancing interaction during the learning process. One innovative example is the AI-based English language learning system (AIELL) developed by Jia et al. [15], which employs image recognition in mobile learning to aid lower-grade learners in improving vocabulary and grammar skills. This demonstrates AI's positive impact on learners' motivation in real and ubiquitous language learning environments.

3 DESIGN AND IMPLEMENTATION

3.1 Overview

We designed AIlingo, a MALL tool that provides contextual and immersive language learning experiences. Different from the traditional MALL tool, which relies on static content, AIlingo uses the user's smartphone camera and state-of-the-art AI models to collect contextual information from the users' real environments. Our tool aims at offering a dynamic and versatile learning platform that seamlessly integrates real-world contexts, AI technology, and personalized learning experiences.

The design concept of AIlingo caters to learners at all proficiency levels, based on the principles of Bloom's Taxonomy [18]. It encompasses a blend of memorization, recognition, translation, and interpretation activities. Even though the learning experience consists of several iterative steps and spans a longer period, AIlingo focuses on the following key steps: (1) capturing a scene from real-world contexts using the smartphone camera, (2) providing a verbal description of the captured scene generated with a vision AI model [38], (3) receiving a verbal description of the scene from AIlingo and (4) verbally repeating the description provided by AIlingo.

3.2 Implementation

The core tasks of AIlingo include object detection, image captioning, caption rewriting, and text-to-speech. Figure 2 illustrates the system pipeline, depicting the flow of data and four AI techniques used in AIlingo.

The system uses user-captured images from real-world environments as the primary input. The captured image is first processed by YOLOv8, a CNN-based image classification model. It is the latest version of YOLO (You Only Look Once), a highly efficient real-time object detection system [38]. This model was deployed using Supervision [40], an open-source library for computer vision tasks. YOLOv8 acts as a feature extractor, identifying and encoding the prominent visual elements within the image. Simultaneously, the same image is fed into a transformer-based model called BLIP [26]. BLIP excels at image captioning. It analyzes the visual data and generates a textual description of the image content. This study

[1] https://www.babbel.com/
[2] https://www.duolingo.com/

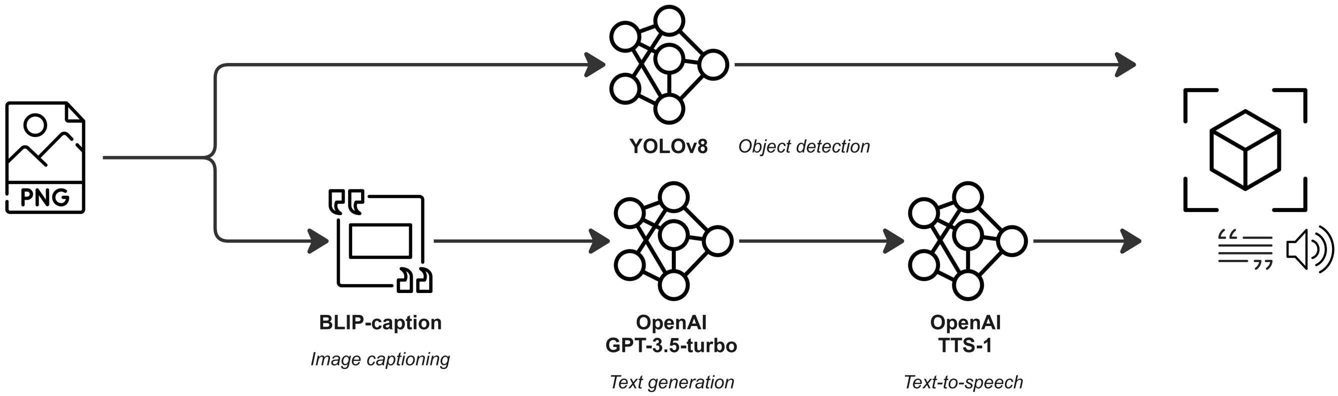


Figure 2: The overall pipeline of AIlingo.

utilizes the BLIP-caption model, accessible through the open-source LAVIS library [25]. BLIP-caption effectively encodes the image and decodes it into a natural language sentence describing the scene.

While BLIP-caption provides a useful starting point, the captions it generates may not be ideally suited for language learning due to their potentially static nature. As users progress in their language proficiency, captions with increasing complexity would be beneficial. Therefore, the system utilizes OpenAI's GPT-3.5-turbo model [32] via its application programming interface (API). GPT-3.5-turbo is a powerful language model capable of text generation and manipulation, which is employed to dynamically rewrite the captions generated by BLIP-caption. This rewriting process is guided by a specific prompt that instructs GPT-3.5-turbo on how to modify the caption for optimal language learning purposes. An example prompt used in this study is: "Rewrite the following sentence in beginner level dutch: ...". Subsequently, the rewritten caption is inputted into OpenAI's TTS-1 text-to-speech (TTS) model [33] via the same API. TTS-1 converts the textual caption into an audio file. This audio file can then be played back to the user, allowing them to practice their speaking.

3.3 Interactive Prototype of AIlingo

An interactive prototype was developed using Figma for experimental purposes. AIlingo is intended to function with any combination of target and source languages, yet this particular prototype teaches Dutch to English speakers.

Figure 3 shows the workflow of the interaction process with AIlingo. The process begins when users tap the camera icon, which opens a full-screen camera page that allows them to take and upload photos of their immediate surroundings. After taking an image, users come to the selection page, where they can define specific areas of interest within the image for AI recognition. It is done by adjusting the corners of a white box, filtering out irrelevant objects. Once users select the desired area, they simply tap the "select" button to proceed. Next, users are prompted to verbally describe the scene, while the AI model processes the image to generate captions. By tapping the 'Show Results' button, users receive the AI-generated description, which is displayed in a central box, along with audio, in the central box. Users can choose to engage with follow-up exercises by tapping "continue exploring." Alternatively, users can go back to the camera page by tapping the camera icon to capture new scenes and continue their learning.

4 User Study

We conducted a user study to evaluate the user experience of AIlingo, which was approved by the university's Ethical Review Board.

4.1 Participants

Through purposive sampling, 7 participants (4 males and 3 females, aged between 24 and 26, marked as P1 - P7) who are international students from a university in the Netherlands, where English is the official language, took part in the study. All participants are in the early stages of learning Dutch (aiming to reach the Common European Framework of Reference for Languages level A1: beginners) and have prior experience using other language applications, such as Duolingo. Participation was voluntary.

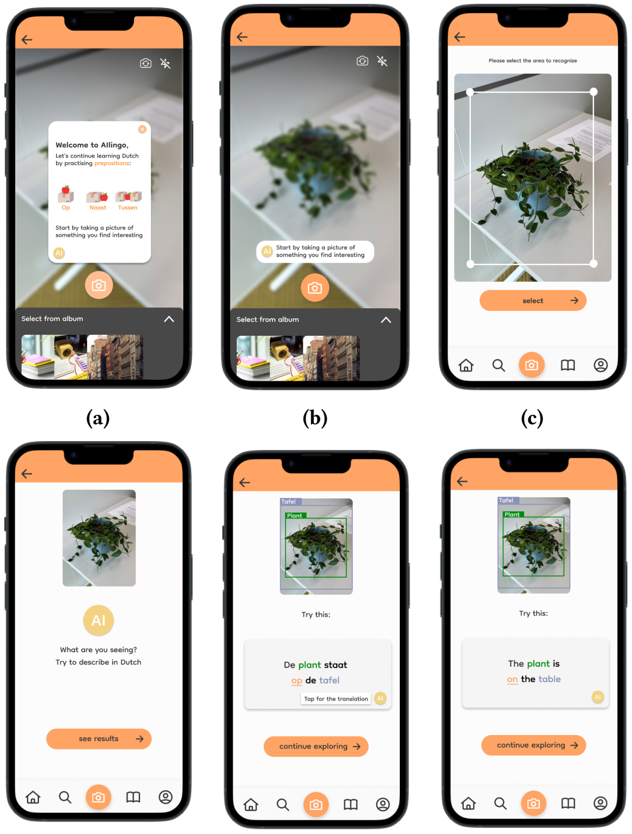
4.2 Materials

We arranged three scenarios; each had a set of physical objects that served as the learning materials for participants, see Figure 4.

These scenarios were designed for participants to interact with the AIlingo prototype. One scenario was developed to accommodate different difficulty levels by varying the number of objects described in a single sentence (Figure 4c). Participants selected between one to three objects, and descriptions were subsequently generated based on their selection (Figure 5).

4.3 Measures

The User Experience Questionnaire (UEQ) was used to assess the usability of AIlingo. UEQ facilitates a rapid and direct evaluation of user experience, using 7-point semantic differentials ranging from −3 (indicating complete agreement with negative conditions) to +3 (indicating complete agreement with positive opinions), with a midpoint of 0 representing neutrality [23, 44]. This questionnaire yields results on six dimensions with 26 items. These dimensions are attractiveness, perspicuity, efficiency, dependability, stimulation, and novelty.



(a) (b) (c)

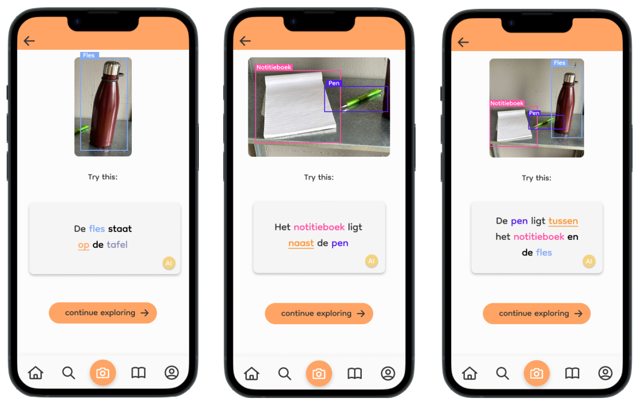
(d) (e) (f)

Figure 3: Screenshots of the interaction process: The user starts at the welcome screen (a), where they can tap the camera icon to capture the scene (b). Then the user can select an area of interest and tap "select," leading to a prompt for verbal Dutch description (c). Selecting "see results" displays the scene description in Dutch provided by AIlingo (d), while opting for "tap for translation" gives the English translation of the description (f). By tapping "continue exploring," the user can further explore the current scene. The user can start a new turn by tapping the camera icon, returning them to the camera page (b).

Direct behavior observation was used to observe participants' real-time interactions with AIlingo. A semi-structured interview was conducted to delve deeper into participants' experiences with AIlingo and to help interpret the quantitative data collected from UEQ. It included comparisons with a widely used language learning application, Duolingo. We also evaluated AIlingo's contextual learning and immersion features, explored customization options, and discussed future implications. Additionally, participants were asked for their opinions on memorable features, descriptions of usage scenarios, discussion about the integration of these features into their language learning habits, and the ability to raise any concerns.

(a) (b) (c)

Figure 4: We organized three scenarios for the user study: (a) a plant on a table, (b) a chair against the window, and (c) a notebook, a pen, and a bottle on a shelf.



(a) (b) (c)

Figure 5: Descriptions of objects in a single scenario with varying selections. (a) The bottle is standing on the table. (b) The notebook lies next to the pen. (c) The pen lies between the notebook and the bottle.

4.4 Procedure

The study was carried out in a dedicated study room, which was set up with three aforementioned scenarios. The participant was required to sign consent forms prior to participation. They were briefed on the purpose of the study and the data that were collected. Pre-study questions were asked to collect demographic information, participants' proficiency in Dutch, and their previous experiences with language learning applications.

The participant was then clearly instructed on how to use the AIlingo prototype, which was prepared and opened on a smartphone provided by the researcher. They were guided to position themselves properly in the study room to ensure that the angles to capture pictures of the learning materials matched those programmed in the prototype. Subsequently, the participants were tasked with using the AIlingo prototype to interact with the three scenarios one by one while thinking aloud, which lasted approximately 10 minutes. An on-site researcher took notes on participants' confusion levels, facial expressions, and interactions with the prototype throughout this process. At the end of the task, participants completed the printed UEQ, followed by a 20-minute individual semi-structured interview.

4.5 Data Analysis

The data collected from UEQ, semi-structured interviews, and observation includes quantitative and qualitative data. Quantitative data obtained from UEQ was analyzed using the UEQ Excel Analysis Tool, downloaded from http://www.ueq-online.org (accessed on 5 April 2024).

The qualitative data from the interviews and observations followed the thematic analysis method [30]. All interviews were transcribed using Whisper Web[3], a machine learning-powered speech recognition tool. Three researchers independently reviewed transcripts and observation notes, identifying common topics and generating initial codes. Subsequently, they convened to resolve any discrepancies through discussion until a consensus was achieved on the coding. The coded text segments were then categorized into overarching themes. These initially identified themes were further discussed and refined to establish representative key themes. Subthemes were discerned to offer a deeper understanding. The team systematically reviewed the candidate themes in relation to the dataset, refining them through iterative discussion until consensus was attained.

5 Results

5.1 Quantitative data results

According to the standard interpretation of UEQ, the range extends from -0.8 to +0.8, representing a neutral evaluation of the corresponding scale. Values above +0.8 indicate a positive evaluation, while those below -0.8 indicate a negative evaluation. Figure 6 shows mean scores of the UEQ scales. All results surpass the 0.8 threshold, indicating positive evaluations on all dimensions. Statistical results for mean and variance are outlined in Table 1.

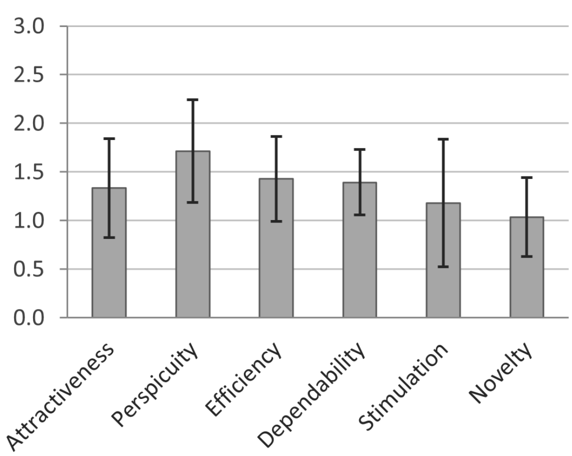


Figure 6: Mean scores of UEQ with error bars indicating standard errors.

The highest rating was given to perspicuity, with a mean of 1.71, which indicates that the process of interaction was perceived as clear and easy to understand. Although the variance is 0.51, which may indicate some variety in perceptions of clarity, the overall trend

[3]https://huggingface.co/spaces/Xenova/whisper-web

Table 1: Summary of mean and variance of the UEQ scores

Dimensions	Mean	Variance
Attractiveness	1.33	0.47
Perspicuity	1.71	0.51
Efficiency	1.43	0.35
Dependability	1.39	0.21
Stimulation	1.18	0.79
Novelty	1.04	0.30

is positive. Especially remarkable is the item related to clarity versus confusion (item 21) within perspicuity, which obtained the highest rating, with a mean score of 2.0 (variance = 0.7), thus underlining the clarity of the interaction process.

Pragmatic quality aspects, efficiency, and dependability focused on goal-directed usability received positive evaluations as well (mean = 1.43 and 1.39, respectively), with relatively low variance (0.35 and 0.21). This indicates stable consensus among participants about how good AIlingo was in supporting them in performing the task and in being a reliable and consistent system to trust.

Despite attractiveness receiving a moderately positive mean score (1.33), its variance (0.47) indicates variability in users' perceptions of the prototype's aesthetic appeal. Nonetheless, the design aesthetics of the prototype have an overall positive impact on the user experience.

Stimulation (mean = 1.18, variance = 0.79) and novelty (mean = 1.04, variance = 0.30), which are categorized as aspects of hedonic quality, were rated lower on average. This suggests a variation in user opinions regarding what they found stimulating, engaging, and challenging about AIlingo, while evaluations of its innovativeness were consistently low. This can be attributed to AIlingo's application of AI technologies that have commonly been used in other various software programs, thereby not being considered innovative. This is further evidenced by the low mean (0.4) of the 'usual/leading edge' item (item 15) on novelty (variance = 1.0).

5.2 Qualitative results

Five themes were identified from the qualitative data.

5.2.1 Contextual learning experience. Participants expressed that the contextual learning experience offered by AIlingo positively contributed to their motivation to use this MALL tool. The approach of taking pictures in real-world contexts as input was highlighted as a fun aspect of AIlingo that fosters user engagement. As P6 commented, this experience "is definitely more vivid." The active engagement with environmental elements and objects increased the depth of the learning experience, making it more immersive. This is noted by P4: "To learn in another language then it makes you more aware of your surroundings..." Besides that, participants noted that learning from objects in familiar environments helped them better remember what they learned using AIlingo.

However, some participants did not find that using their real-life environment as learning material was relevant to their everyday lives, especially if they were not actively attempting to learn a new language. This shows that the effectiveness of AIlingo may differ among different goals and situational conditions.

5.2.2 Adaptation and personalization. Participants offered diverse perspectives on AIlingo's adaptability for users with different language levels. P6 suggested its potential for beginner or intermediate learners, noting its focus on object recall as beneficial for vocabulary and foundational language skills. However, participants observed a lack of adaptability to users' proficiency levels which was expected. A primary concern emerged regarding the prototype's limited variation in generated descriptions. They underlined the importance of congruence with personal learning goals and interests, therefore supporting the idea of personalization. They also suggested increasing engagement by offering multiple descriptions for a single input image.

The participants also pointed out the necessity of having basic linguistic knowledge before using AIlingo, a point brought out by P1, in order to facilitate understanding and identification of the language elements introduced.

5.2.3 Role of AI: now and future. Some participants were concerned about the accuracy of image detection performed by AI in AIlingo; for example, the objects detected sometimes did not match what they had expected, which would be frustrating. However, they saw such a possible error as a positive aspect in that it would increase their curiosity and aid in learning new vocabulary. The participants also suggested other ideas for AI functions, including the idea of P5 to integrate a chatbot that can enable users to guide system-generated descriptions.

Furthermore, participants expressed a desire for further personalization in AIlingo, suggesting that the approach should be designed based on human input in addition to AI functionalities. For example, P4 suggested a model in which users can give general directions on AI learning, which could then suggest scenes or pictures for interaction. In addition, the role of AI was outlined in achieving adaptation to various levels of users. Participants suggested the use of AI to track their strengths and weaknesses, automatically adjusting content complexity as in Duolingo [11], to optimize learning outcomes and appropriate challenge levels.

5.2.4 Comparisons and use cases. Participants drew interesting comparisons between AIlingo and other language learning tools, such as Duolingo. While appreciating the contextual focus of AIlingo on everyday situations, participants wished for gamification elements in a similar vein to Duolingo.

Besides, there were concerns about the practical utility of AIlingo in real-life settings. P1 compared AIlingo with the use of Google Translate in the supermarket, questioning how effective AIlingo is in comparison to the more stable and reliable translation service offered by Google Translate. P1 mentioned, "I need to give input, which may not make everyone comfortable in public, especially if their language skills are not so good."

In general, the participants expressed that they would use AIlingo regularly for casual or passive language learning, especially during their free time. They valued the flexibility of the tool and its ease of use in different physical contexts, which made customized learning possible anywhere. Commonly mentioned use cases included getting to know new objects, performing translation tasks, and engaging in leisure activities. Participants further envisioned that AIlingo could support current language courses by helping increase motivation in users and giving a different and immersive experience adapted to users' preferences.

5.2.5 Intuitive user interface. While the UI was not the primary focus, AIlingo's UI played an important mediating role in communicating the idea of the tool and shaping users' experiences. Despite the occasional confusion that was caused by the limitation of the prototype as a mockup, the clarity and intuitiveness of the UI had been well appreciated by participants. They liked how the UI helped in effective interaction with the system, and especially appreciated the color of the bounding boxes and quick switching between translated and non-translated descriptions, enhancing the overall usability and flexibility.

6 Discussion

AIlingo offers a unique approach to language learning by integrating real-world surroundings into the learning materials. Overall, the positive ratings across the UEQ dimensions reflect the success of the design in providing a user-friendly and appealing language learning tool. This agrees with previous MALL research, as highlighted by Huang [14], which has pointed out the strengths of MALL in terms of flexibility and ease of use. These aspects are further supported by qualitative feedback, where participants remarked on the clarity of the interactions and the effectiveness of the system in supporting the completion of the tasks. Moreover, users perceived AIlingo as suitable for casual learning. Our study further expands on this by further investigating user experience and the role of AI in such environments.

The novelty score of 1.04 in UEQ indicates areas for improvement to make the application innovative. Participants praised the fun and engaging nature of AIlingo, while a desire was expressed to complement it with further functionalities related to the integration of other AI technologies and gamification elements, indicating its potential to be integrated into already existing language learning platforms rather than as an independent solution. By this, AIlingo can enhance the tool's versatility and also ensure that users get to experience a comprehensive language learning experience by combining the strengths of multiple resources.

Participants enjoyed the contextual learning experience provided by AIlingo, which is in line with the established importance of real-world contexts in language acquisition [50]. Unlike translation tools, AIlingo captures real-world objects and transforms them into learning material. However, some found its relevance to daily needs limited, highlighting gaps in research regarding user autonomy and individual learning goals. Some participants also wanted an adaptation to different proficiency levels. Limitations of variation of generated descriptions were also pinpointed. The future scope could thus involve refining functionalities of AIlingo and embedding it with features like variant descriptions, adaptive proficiency, and collaboration.

While previous research on using AI in language learning focused on cognitive aspects and language proficiency, our results showcase the potential of AI to provide added value for user experiences and increase user motivation and engagement. Although the participants expressed some doubts about the accuracy of AI, they acknowledged that it created curiosity and helped them to learn vocabulary; thus, this suggests a trend toward AI that is more user-centered and adapted to the needs of the individual. The desire for more intelligent features to enhance personalized learning experiences increases the demand for further research into AI technologies.

Another interesting finding is the fact that while the perceived attractiveness and novelty of AIlingo varied among users, its efficiency and dependability were consistently rated positively. This would hint that users are more concerned with practical aspects, such as the ability of the tool to complete tasks and be reliable, when evaluating language learning tools, which underscores functionality over aesthetic appeal or novelty. This finding underlines that basic user needs and expectations should be met in the design and development of language learning tools.

6.1 Limitations

While this study provides a valuable insight into the usability and potential of AIlingo for language learning, several limitations have to be noted. First of all, the samples used in this study consisted mostly of a few international students, which made the pool of participants small and homogeneous; thus, generalizability and depth were limited.

Moreover, in the user study, an interactive prototype, a Figma mock, was used to simulate how AIlingo would be used in a controlled environment with users acting upon pre-defined objects. However, participants' experiences and performance of tasks within this simulated environment cannot fully capture the real-world usage scenario. A fully functioning application should be developed to allow users to use AIlingo as it was intended, whereas our settings imposed a limit on this. Such an application should support multiple languages and be able to accommodate a broader range of learning objectives. Therefore, it will allow further comparison studies to be conducted for the effective definition of the effectiveness of AIlingo in comparison with other existing language learning applications.

Meanwhile, we recognize that the process of addressing ethical issues that may arise from AI-generated content is crucial to user safety, especially for younger audiences. While this study did not examine these ethical considerations, this is a risk that must be addressed with intensive content screening and moderation protocols. Future work could include the implementation of advanced AI filters that proactively detect and exclude sensitive or biased information to help create a safe learning environment.

Lastly, the evaluation of AIlingo focused on the usability within beginner-level language learners and thus limited insights into the adaptability across proficiency levels. Future development could use AI to automatically adjust learning materials, including vocabulary and sentence structures, according to the proficiency level of users, and further test AIlingo across different user groups. Besides, the actual learning results were not measured in the study because they could be affected by several factors, including studying conditions and participants' preliminary mastery of Dutch vocabulary. Our evaluation instead focused on moderating factors like attractiveness and enjoyment via UEQ. Future research should, therefore, include measures that can assess aspects such as vocabulary retention, language proficiency, and comprehension skills to obtain a full understanding of how AIlingo influences language learning.

7 Conclusion

This paper introduces AIlingo, an AI-enabled MALL tool that provides real-world contextual language learning. We developed an interactive prototype using Figma for experimentation and demonstrated the usability of this concept in a user study with the potential to create an immersive learning experience. Using AI and real-world contextualization, AIlingo exemplifies the potential of such an AI-enabled MALL tool to transform traditional educational paradigms and offer learners more engaging and effective learning experiences. Further development efforts should prioritize user engagement, personalization features, and refinement of more AI-enabled functionalities to reach its full potential. We hope this work will support future expeditions exploring the seamless integration of language learning into people's everyday lives and the integration of more advanced AI into language education.

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