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The Impact of Corrective Feedback Timing by Voice-Based AI Tutors on Attentional Engagement and Subsequent Performance

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Résumé

L’essor des tuteurs linguistiques alimentés par l’intelligence artificielle (IA) a transformé l’enseignement des langues, faisant de l’optimisation de la conception de l’interaction homme–IA une priorité urgente. L’une des dimensions critiques de cette conception est le moment de la rétroaction corrective, un facteur reconnu depuis longtemps comme déterminant de l’engagement et des résultats d’apprentissage dans les classes traditionnelles, mais encore peu étudié dans les contextes médiés par l’IA. Cette étude a examiné l’impact d’une rétroaction corrective auditive immédiate versus différée, délivrée par un tuteur vocal en français basé sur l’IA, sur l’engagement attentionnel et la performance post-tâche chez des apprenants adultes de niveau A2. Trente participants ont réalisé des tâches de lecture à voix haute tout en recevant soit une rétroaction immédiate, soit une rétroaction différée, l’oculométrie étant utilisée pour mesurer le nombre de fixations et de saccades en tant qu’indicateurs de l’engagement attentionnel. La performance post-tâche a été évaluée à l’aide d’un test conceptuel de langue. Les résultats montrent que la rétroaction corrective immédiate améliore significativement l’engagement attentionnel et que celui-ci prédit la performance post-tâche. Ce profil de résultats est compatible avec l’hypothèse selon laquelle le moment de la rétroaction pourrait influencer les résultats d’apprentissage en partie via l’attention. Ces résultats prolongent le Student–Feedback Interaction Model révisé dans les contextes médiés par l’IA, en soulignant le rôle de l’attention comme mécanisme central reliant les caractéristiques de conception aux résultats. L’étude apporte une contribution à la fois théorique et pratique, en offrant des pistes pour la conception de la prochaine génération de tuteurs IA : des systèmes adaptatifs capables de suivre et de répondre aux états attentionnels des apprenants pourraient optimiser l’engagement et renforcer l’efficacité de l’apprentissage dans l’éducation linguistique numérique.

Mots-clés : tuteurs IA, rétroaction corrective, moment de la rétroaction, engagement attentionnel, oculométrie, apprentissage des langues, engagement des utilisateurs, technologie éducative, agents conversationnels, interaction homme–IA

Méthodes de recherche : Expérimentation en laboratoire

Abstract

The rise of AI-powered language tutors has transformed language education, making the optimization of human–AI interaction design an urgent priority. One critical design dimension is the timing of corrective feedback, a factor long recognized as shaping engagement and learning outcomes in traditional classrooms but less understood in AI-mediated contexts. This study examined the impact of immediate versus delayed auditory corrective feedback from a voice-based AI French language tutor on attentional engagement and post-task performance among adult A2- level learners. 30 participants completed reading-aloud tasks while receiving either immediate or delayed feedback, with eye-tracking used to capture fixation and saccade counts as indicators of attentional engagement. Post-task performance was assessed through a conceptual language test. Results showed that immediate corrective feedback significantly enhanced attentional engagement, and attentional engagement predicted post-task performance. This pattern of associations is consistent with the idea that feedback timing may influence learning outcomes in part via attentional engagement. These findings extend the Revised Student–Feedback Interaction Model to AI-mediated contexts, underscoring the role of attention as a central mechanism linking design features to outcomes. The study contributes both theoretically and practically, offering insights for the design of next-generation AI tutors: adaptive systems that monitor and respond to learners' attentional states may optimize engagement and enhance learning efficacy in digital language education.

Keywords: AI tutors, corrective feedback, feedback timing, attentional engagement, eye-tracking, language learning, user engagement, educational technology, conversational agents, human–AI interaction

Research methods: Lab experiment

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List of abbreviations and acronyms

AI – Artificial Intelligence

AOI – Area(s) of Interest

CF – Corrective Feedback

CEFR – Common European Framework of Reference for Languages

GPT – Generative Pre-trained Transformer

ITS – Intelligent Tutoring System(s)

SLA – Second Language Acquisition

TOI – Target Object of Interest

Preface

With the authorization of the administrative directors of the Master's of Science in User Experience program, this thesis comprises two articles. The articles are added to the thesis with the written consent of all co-authors.

This research project received approval from HEC's Research Ethics Board (REB) under certificate number 2024-5921, on March 1, 2024.

Both documents can be found in the Appendix.

Acknowledgements

First, I would like to express my sincere gratitude to my co-supervisors, Prof. Sylvain Sénécal and Prof. Pierre-Majorique Léger, for their insightful guidance, rigorous feedback, and steady support from the initial proposal to the final draft. I am deeply thankful for the opportunity and challenge you offered, and for the trust you placed in me throughout this journey.

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Lastly, my heartfelt thanks go to my family and friends for their patience, encouragement, and unwavering belief in me. Your support made this journey possible.

Beyond the many individuals I am grateful to, this research journey deepened my fascination with user experience and the dynamics of human-AI interaction. It strengthened my ability to lead complex, multi-phase projects and sharpened my end-to-end skills in developing AI agents, from prompt design to evaluation and iterative refinement. Most importantly, it sparked a lasting passion for this field, one I am excited to continue exploring and profoundly grateful to have engaged with through this work.

Chapter 1

Introduction

Context and Background

Artificial intelligence (AI) is becoming one of the most transformative forces in education, reshaping how individuals access, process, and internalize knowledge. The market size in the Generative AI sector is projected to reach US$66.89 billion in 2025, with an expected annual growth rate (CAGR 2025–2031) of 36.99%, resulting in a market volume of US$442.07 billion by 2031 (Statista, 2024).

Within this momentum, conversational AI tutors are emerging as particularly powerful tools in education. By simulating natural interactions and providing personalized responses, these systems move beyond static e-learning formats to deliver real-time, adaptive feedback. Such capabilities are especially valuable in second language acquisition, where learners benefit from targeted support that helps them recognize errors, refine their practice, and sustain motivation.

The promise of AI tutors lies not only in their scalability and cost-effectiveness but also in their potential to optimize learner engagement and improve learning outcomes. Unlike traditional classroom settings that are limited by time and instructor availability, AI tutors can operate continuously, personalize guidance at scale, and adapt to the needs of diverse learners. However, realizing this potential requires careful attention to how these systems are designed, particularly how they foster meaningful engagement and enhance learning outcomes.

Research Gap

There is broad agreement in second language acquisition (SLA) research that corrective feedback (CF) enhances learning by helping learners identify and repair linguistic errors (Ellis, Loewen, & Erlam, 2006; Nassaji, 2016). However, scholars remain divided on how to best optimize the conditions under which feedback is delivered. Some studies have argued that immediate feedback maximizes accuracy and learner uptake (Lyster & Ranta, 1997; Goo & Mackey, 2013), while others suggest that delayed feedback may support deeper reflection and longer-term retention

(Butler & Roediger, 2008; Lu et al., 2021). These mixed findings highlight the complexity of feedback as both a cognitive and pedagogical process.

Despite the substantial body of work on CF in classroom-based SLA, there is still a lack of research examining how feedback functions in AI-mediated tutoring environments. Existing studies largely focus on teacher–student or peer–student interactions (Han, 2023; Rassaei, 2023), leaving unresolved questions about how conversational AI tutors, with their ability to deliver scalable, personalized, and multimodal feedback, can shape learner engagement and outcomes. This gap is especially significant given that the effectiveness of AI tutors is contingent not only on the accuracy of their corrections but also on how they sustain user attention and foster meaningful engagement.

This study addresses these gaps by examining how immediate versus delayed auditory corrective feedback from a voice-based AI tutor influences attentional engagement and subsequent post-task performance. By doing so, it contributes both theoretically, extending the Student–Feedback Interaction Model (Lipnevich & Smith, 2022) to AI-mediated learning, and practically, by offering insights into the design of more effective and engaging AI tutoring systems.

Purpose and Objectives

The primary objective of this research is to investigate how the timing of auditory corrective feedback (immediate versus delayed) provided by a conversational AI-tutor influences learners' attentional engagement and post-task performance in a second language learning context.

Thus, the research question guiding this study is:

RQ: How does the timing of corrective feedback (immediate versus delayed) from a voice-based AI tutor affect learner attentional engagement and post-task performance in language learning systems?

Significance of the Study

This study contributes theoretically by advancing the understanding of how feedback timing interacts with attentional engagement in AI-mediated learning contexts. While prior work has examined feedback in traditional classrooms, this research clarifies how immediate versus delayed corrective feedback is associated with attention and subsequent learning performance in a human-AI learning context, thereby extending the Student–Feedback Interaction Model (Lipnevich & Smith, 2022) to digital tutoring environments.

Methodologically, the significance lies in the development of a controlled, in-house AI tutor specifically configured to deliver scripted auditory corrective feedback under both immediate and delayed conditions. This design ensured experimental precision, isolating timing as the key variable while incorporating eye-tracking as a real-time measure of attentional engagement. The resulting framework offers a replicable approach for future studies seeking to combine multimodal feedback with process-level engagement data.

Practically, this research holds important implications for the design of next-generation AI tutors. By examining how feedback timing interacts with attentional engagement and performance, the study highlights a critical design variable that can inform the development of adaptive systems capable of sustaining user engagement and enhancing learning outcomes.

Theoretical Framework

This thesis is grounded in the Student–Feedback Interaction Model: Revised (Lipnevich & Smith, 2022). The model emphasizes the dynamic interplay of feedback characteristics, such as timing, explicitness, and delivery mode, with learner engagement and affective context in shaping learning outcomes. It highlights that the effectiveness of corrective feedback is not determined solely by its content, but by how it interacts with learners' attentional and emotional states in the moment of learning.

Applied to this study, the model provides a conceptual foundation for examining how feedback timing, whether immediate or delayed, delivered by a voice-based AI tutor, can influence learners' attentional engagement during language tasks. Attentional engagement, in turn, is conceptualized as a proximal mechanism through which feedback may impact cognitive processing and post-task performance.

Method

This study used a between-subjects experimental design to examine the effects of corrective feedback timing (immediate vs. delayed) on attentional engagement and post-task performance in an AI-mediated language learning context. Participants were randomly assigned to either an immediate feedback condition or a delayed feedback condition. All participants completed a French reading-aloud task while interacting with a custom-configured AI voice-based tutor. The tutor provided standardized auditory corrective feedback on pre-identified pronunciation errors. In the immediate condition, feedback was delivered directly after the relevant sentence, while in the delayed condition, the same feedback was provided after the full passage was completed. In both cases, learners were asked to repeat the corrected word within its sentence, after which the tutor offered supportive reinforcement. Throughout the reading tasks, eye-tracking data were collected to measure attentional engagement. Key metrics included fixation counts and saccade counts on the text, which served as indicators of visual attention and cognitive processing. After completing the task, participants completed a post-task language test assessing related grammatical and conceptual knowledge to evaluate learning outcomes. Statistical analyses were conducted to compare how feedback timing affected attentional engagement and post-task performance across the two groups, and to test whether attentional engagement predicted performance outcomes.

Scope

This study focuses on how the timing of corrective feedback (immediate versus delayed) in a voice-based AI tutoring system influences attentional engagement and subsequent performance in beginner-level French language learners. The scope is intentionally limited to controlled laboratory conditions, where the AI tutor provided standardized auditory corrections on pre-identified pronunciation errors. This design ensured consistency across participants, allowing the isolated examination of feedback timing as the key variable. Two primary boundaries of scope are recognized. First, the study targeted A2-level adult learners of French, restricting the generalizability of findings to other proficiency levels, age groups, or language contexts. Second, the AI tutor was deliberately constrained in its interactivity, offering only corrective feedback rather than broader conversational exchange. While this level of control was essential for internal validity, it does not fully capture the complexity of naturalistic human–AI tutoring interactions. Despite these boundaries, the scope of the study offers critical insights into the mechanisms by which feedback timing influences attentional engagement and performance in AI-mediated environments. Future research can extend this scope by examining adaptive AI tutors in more ecologically valid settings, with more diverse learner populations and longitudinal designs to explore sustained learning effects.

Thesis Structure

The thesis is structured into four main chapters, followed by a bibliography and an appendix. Chapter 1 introduces the research context, objectives, significance, theoretical framework, scope, and personal contribution. Chapter 2 presents Article 1, the academic research article, providing detailed methodology, data analysis, and findings related to corrective feedback timing, attentional engagement, and post-task performance. Chapter 3 presents Article 2, a managerial article targeted at practitioners, which translates the study's findings into actionable insights for AI tutor developers, educators, and industry stakeholders. Chapter 4 synthesizes the findings from both articles, discusses contributions to theory and practice, acknowledges limitations, and outlines directions for future research. The bibliography includes all references cited throughout the thesis, and the appendix includes supplementary materials relevant to the study.

Personal Contribution

The study was conducted within Tech3Lab at HEC Montréal, where multiple collaborators contributed at different stages. Table 1.1 outlines my individual contributions across each phase of the research process.

Table 1.1. Contribution to the responsibilities of the research project phases

Research Activity	**Contribution**
Research Questions	Formulating appropriate research questions based on the research partner organization's expectations and needs – 70% *Support from the directors and supervisor was provided to determine the research partner's expectations and needs. *Support from the directors and supervisor was provided to formulate appropriate research questions.
Experimental Design	Conceiving and formalizing the experimental protocol – 50% *Members of the Tech3lab conceived the experimental protocol.
Visual Stimuli	Creating the reading passages and feedback scripts – 50% *Visual Stimuli was co-created with a fellow student
AI Tutor Configuration	Configuring and refining the AI tutor to deliver immediate vs delayed feedback – 90% *Support from lab technical staff for troubleshooting occasional system errors.
Ethics	Requesting ethical approval from CER – 50% *Assistance from supervisors in preparing required documentation.
Pretests	Pilot testing the task flow and equipment setup – 50% *Lab assistants contributed during pretesting sessions.
Recruitment	Recruiting participants – 70%
Data Collection	Running experimental sessions in the lab – 50% *Research assistants supported during participant setup and monitoring.
Analyzing	Cleaning and analyzing data – 70% *Statistical guidance provided by the Tech3lab statistician.
Writing	Writing introduction, literature review, and journal/managerial articles – 90% *Supervisors provided iterative feedback and revisions.

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Chapter 2
The Impact of Corrective Feedback Timing on Learner Attentional Engagement and Post-Task Performance in Voice-Based AI Language Tutoring Services

Abstract

The rise of AI-powered language tutors has transformed language education, making the optimization of human-AI interaction design an urgent priority. One critical design aspect is how and when these systems deliver corrective feedback to learners; a factor known to influence engagement and learning outcomes in traditional classroom settings but not yet well understood in AI-mediated contexts. This study investigated the impact of immediate versus delayed auditory corrective feedback from a voice-based AI French language tutor on attentional engagement and post-task test performance among adult A2-level learners. Thirty participants completed reading-aloud tasks while receiving randomized immediate or delayed feedback, with eye-tracking capturing fixation and saccade counts as indicators of attention. Test performance was measured through a post-task conceptual language assessment. Results show that immediate corrective feedback increased attentional engagement, and attentional engagement predicted post-task performance. This pattern of results is consistent with the interpretation that feedback timing may influence outcomes partly via attentional engagement.These findings extend the Student-Feedback Interaction Model to AI-mediated language learning, demonstrating the importance of both feedback timing and real-time engagement monitoring. The study offers actionable insights for the design of next- generation AI tutors: integrating adaptive feedback mechanisms that respond to learners' attentional states may maximize attentional engagement and optimize learning outcomes.

Keywords: AI tutors, conversational AI, feedback timing, attentional engagement, eye-tracking, attentional metrics, language learning, educational technology, chatbot interaction, user performance, Human-AI interaction

2.1 Introduction

The integration of artificial intelligence (AI) into language learning could revolutionize the way individuals learn new languages, offering personalized and interactive experiences that simulate natural language interactions. AI-driven tools such as voice-based conversational agents and virtual tutors provide targeted corrective feedback, which plays a crucial role in second language acquisition (SLA) by helping learners recognize and correct errors in real time (Zhang, 2024). Among the various forms of feedback, the timing of corrective feedback, whether immediate or delayed, has been a subject of extensive research in traditional educational settings (Naeimi et al.,2018; Han, 2023; Goo & Mackey, 2013; Storch & Wigglesworth, 2010; Lyster et al., 2013).

The importance of optimizing these AI tutors is underscored by the rapid expansion of the Generative AI sector, which is projected to reach US$66.89 billion in 2025 and grow at a compound annual rate of 36.99%, resulting in a market volume of US$442.07 billion by 2031 (Statista, 2024). Within this broader transformation, education—and digital language learning in particular—stands out as a critical testing ground for how AI systems can enhance engagement and accelerate learning. The effectiveness of these systems depends not only on their ability to deliver content, but also on how well they sustain learner attention and adapt feedback in ways that genuinely promote long-term learning outcomes.

Previous studies in traditional contexts have yielded mixed results concerning the optimal timing of corrective feedback. Some research suggests that immediate feedback facilitates quicker error correction and prevents the reinforcement of incorrect forms, thereby maintaining a focus on accuracy (Lyster & Ranta, 1997; Ha et al., 2021). Conversely, other studies argue that delayed feedback allows for deeper cognitive processing and self-reflection, which can promote long-term retention (Corral et al., 2020; Dobryakova et al., 2025; Foerde & Shohamy, 2011; Nakata, 2014). However, there is a notable gap in the literature regarding how these dynamics play out in AI-mediated language learning environments, where interaction is mediated by technology and lacks the nuanced social cues of human tutors.

Given this gap, our study addresses the following research question:

How does the timing of corrective feedback (immediate versus delayed) from a voice-based AI tutor affect learner attentional engagement and post-task performance in language learning systems?

To investigate this question, we conducted a controlled experiment with adult A2-level French learners, using a GPT-4-powered AI tutor that provided either immediate or delayed auditory corrective feedback during a reading-aloud task. Eye-tracking was used to measure learners' attentional engagement during the task, and a language test assessed learning outcomes afterward. This design allowed us to directly examine the effects of feedback timing on attentional engagement and learning in an AI-mediated setting.

Our findings show that immediate feedback from an AI tutor leads to greater attentional engagement during a reading task, as indicated by fixation and saccade counts. More importantly, participants who maintained higher attentional engagement performed better on post-task assessments. These results support and refine the Student-Feedback Interaction Model by Lipnevich & Smith (2022), highlighting learner attentional engagement as an important process variable through which AI-delivered feedback may influence language learning outcomes.

2.2 Literature Review and Hypothesis Development

2.2.1 The Student–Feedback Interaction Model: Revised

The Revised Student–Feedback Interaction Model (Lipnevich & Smith, 2022) presents a sophisticated framework for understanding how feedback influences student engagement and learning outcomes. This model emphasizes that the effectiveness of feedback is not merely determined by its content or delivery format, but rather by an interplay of factors including timing, the emotional context of feedback, and learners' own engagement levels.

2.2.2 Corrective Feedback

Corrective feedback (CF) in the context of second language acquisition (SLA) refers to information provided to learners regarding their language use, identifying incorrect forms and offering guidance toward more accurate alternatives (Li, 2023). It is a pedagogical tool that draws attention to gaps between a learner's interlanguage and the target language, fostering linguistic accuracy and development (Ellis, Loewen, & Erlam, 2006; Li, 2023; Wang, 2023). CF is not only corrective but also facilitative, as it encourages learners to notice discrepancies and adjust their output, thereby supporting deeper understanding (Wang & Loewen, 2015; Chu, 2011).

The importance of CF extends beyond error repair. Research shows that well-delivered CF enhances motivation and persistence by providing learners with constructive input that validates their participation (Sun, 2024; Shahid, 2021). Moreover, CF facilitates the negotiation of meaning, prompting learners to reevaluate and restructure their language use (Nassaji, 2016; Shao, 2022). Thus, CF plays a dual role: promoting accuracy while simultaneously creating opportunities for interaction and engagement.

2.2.2.1 Corrective Feedback Timing in Traditional Contexts

In the context of language learning, the comparison between immediate and delayed feedback has garnered significant attention. Studies have shown that immediate feedback often leads to better performance in tasks requiring quick responses, as learners can promptly address and correct their errors, reinforcing correct information while it is still fresh in their minds (Fu & Li, 2023; Corral et al., 2020; Goo, 2020). For example, Corral et al. (2020) found that immediate feedback facilitated better learning outcomes compared to no feedback, particularly in natural learning environments.

Conversely, delayed feedback has been found to enhance higher-order cognitive processes such as reflection, intrinsic understanding, and consolidation of knowledge, especially in complex tasks like language learning. Research indicates that delayed feedback allows learners to engage more deeply with material, fostering a more profound understanding of the concepts involved (Lu et al., 2021). Studies further illustrate that for intricate language tasks, the reflection time afforded by delayed feedback can bolster intrinsic understanding and mastery of the content (Shaofeng et al., 2025).

2.2.2.2 Feedback Timing in AI Tutor Systems

AI tutors, also referred to as Intelligent Tutoring Systems (ITS) or conversational agents, are computer-based platforms that provide adaptive, personalized, and interactive learning support (Alobaidi et al., 2015; Kim & Kim, 2020). Their core characteristics include adaptivity—

modifying content in real time based on learner behavior; feedback provision—delivering constructive input; and personalization—tailoring instruction to individual strengths and weaknesses (Jain et al., 2023; Walker, Rummel, & Koedinger, 2013). Research shows that AI tutors improve learner outcomes by scaffolding gaps in knowledge, reducing educational disparities, and enhancing engagement through timely, personalized feedback (Essel et al., 2022; Nickow, Oreopoulos, & Quan, 2020; Thomas et al., 2024). Their ability to deliver feedback at scale, unconstrained by classroom dynamics, makes them ideal contexts for examining feedback timing.

Recent advancements in AI tutors and their innovative feedback delivery mechanisms raise important questions about feedback timing and its impact on engagement and outcomes. However, the distinct dynamics of AI tutors mean that what works in conventional classrooms may not translate directly to AI-mediated environments (Liu et al., 2024). Alsahli and Meccawy (2022) emphasize the need for systematic studies on these dynamics, highlighting that human–AI tutor interactions differ significantly from traditional classroom settings. Bhatt and Muduli (2022) further argue that effective feedback in AI systems, especially those incorporating natural language processing, can enhance learning experiences by improving motivation and direct engagement, particularly when feedback is immediate.

2.2.3 Attentional Engagement and Corrective Feedback

Attentional engagement is defined as a learner's focus and allocation of cognitive resources toward specific stimuli or information during a task (Li et al., 2019). It reflects the extent to which learners actively concentrate on and interact with instructional materials, influencing both comprehension and retention. In SLA and digital learning contexts, attentional engagement is crucial, as it determines learners' ability to process feedback and integrate new knowledge into cognitive frameworks (McColeman et al., 2014; Li et al., 2019).

Sustained attention to feedback is necessary for improving retention and application of learned material (Ahangari, 2014; Nassaji, 2016). For instance, Jwa's (2025) model of written feedback dialogue emphasizes that students actively construct meaning from feedback, requiring their attentional engagement. This challenges traditional views of feedback as a unidirectional transmission and highlights the importance of attentional involvement in cognitive, affective, and behavioral engagement (Jwa, 2025). Moreover, feedback aligned with learners' attentional focus can activate cognitive processes related to performance control (Mežek et al., 2021). Control over feedback type—peer, self, or teacher—further influences engagement (Ahangari, 2014; Nassaji, 2016). Understanding how attention operates in feedback contexts is, therefore, critical for refining CF strategies. By accounting for feedback–attention dynamics, educators and AI systems can design feedback that is both instructive and engaging (Chen et al., 2023; Arbel et al., 2020).

2.2.3.1 Attentional Engagement and Learning Performance Outcomes

Attentional engagement has been increasingly recognized as a significant predictor of learning performance outcomes, particularly within multimedia and digital tutoring contexts (Liu et al., 2023; Madsen et al., 2021). Studies reveal that enhanced attentional engagement leads to better retention and comprehension of multimedia content (Nkhoma et al., 2014; Serrano & Pellicer-Sánchez, 2022).

For example, Nkhoma et al. (2014) highlight the mediating role of engagement in linking learning processes to outcomes, showing that active, focused learners perform better. Similarly, Roesch et al. (2010) found that attention influences how information is processed, which is vital for learning success. Together, this body of work suggests that attentional engagement is not passive presence but active mental involvement with content, predicting stronger performance.

2.2.3.2 Eye-Tracking as a Measure of Attentional Engagement

Eye-tracking provides a process-level window into attentional engagement by quantifying visual behavior during learning tasks. (Zhang et al., 2021; Li et al., 2019).

Fixation count, defined as the number of times the eyes pause on an element, reflects focused processing and depth of engagement. Higher fixation counts correlate with sustained cognitive effort and improved encoding (Graupner, Pannasch, & Velichkovsky, 2011; Mathôt & Theeuwes, 2011; Zhao, 2018). Saccade count, defined by rapid eye movements between fixations, reflects attentional shifts and active visual search, signaling learners' efforts to monitor and integrate information (Zhang et al., 2021; Fortenbaugh, Robertson, & Esterman, 2017).

In multimodal contexts where learners read text while receiving auditory cues, eye-tracking captures how attention is distributed across modalities. Studies show that auditory prompts increase fixation counts on relevant text segments, facilitating integration of information, while saccade counts reflect strategic transitions between auditory and visual input (Li et al., 2019; Ariasi & Masón, 2010; Chen, Zhang, & Qian, 2022; Barnes et al., 2022). Together, these measures connect moment-to-moment visual attention to comprehension and post-task performance (Gibson, 2018; Peng et al., 2021; Mayer, Rausch, & Seifried, 2023).

2.2.4 Hypothesis Development

The literature on corrective feedback highlights that immediate feedback can capture learner attention more effectively than delayed feedback by providing correction while engagement with the task is still active (Nassaji, 2009; Martínez, 2013; Corral et al., 2020; Goo, 2020). In AI tutoring systems, this immediacy can be delivered consistently and without disruption to task flow, further strengthening attentional engagement (Li, 2023; Bodnar et al., 2011). Based on this, the first hypothesis is proposed:

H1: Learners receiving immediate feedback will show higher attentional engagement during the reading task than those receiving delayed feedback.

Research in multimedia learning and digital tutoring consistently demonstrates that attentional engagement is a strong predictor of comprehension and performance outcomes (Nkhoma et al., 2014; Peng et al., 2021; Wang et al., 2018; Yang, 2025). Eye-tracking studies confirm that learners with higher fixation and saccade counts tend to achieve better retention and post-task performance, supporting the eye–mind hypothesis that attention allocation drives learning success (Gibson, 2018; Mayer, Rausch, & Seifried, 2023). Therefore, the second hypothesis is proposed:

H2: Higher attentional engagement during the reading task will result in better performance on a subsequent test measuring similar language concepts.

2.3. Materials & Methods

2.3.1 Experimental Design

To test the proposed hypotheses, a one-factor between-subjects experimental design was employed. Participants were randomly assigned to one of two conditions: immediate corrective feedback or delayed corrective feedback.

Each participant performed three reading-aloud trials, during which they read a short French text presented on screen. Corrective feedback was provided on a predetermined target word that was identical across all participants. In the immediate feedback condition, the AI tutor delivered auditory corrective feedback directly after the participant completed the sentence containing the target word. In the delayed feedback condition, the AI tutor withheld corrective feedback until the participant had completed the entire passage.

Eye-tracking data were recorded throughout each trial to capture visual attention measures (fixation and saccade counts) within sentence-level Areas of Interest (AOIs). Following each of the three reading trials, participants completed a 15-item conceptual language test on the learning platform, yielding one performance score per trial.

This design allowed for testing H1, whether feedback timing influenced visual attention during reading, and H2, whether higher visual attention predicted better performance on subsequent tests.

2.3.2 Participants

Data were collected from 30 adult English-speaking residents of Quebec, Canada (17 women, 13 men; M age = 30 years, range = 22–58). Eligibility required advanced English proficiency; allophone status (French not a native language); beginner-level French (A2, CEFR-aligned self-assessment). Participants with any self-reported hearing impairment likely to interfere with perception of the tutor's auditory feedback were excluded. Written informed consent was obtained from all participants prior to data collection. Recruitment took place via online outreach and in-person visits to French-language institutes and community centers in Montreal.

2.3.3 Materials

Data for this study was collected using three main components: a voice-based GPT-4 virtual tutor, custom slides with texts for the read-aloud task, and a language learning platform for post-task exercises. All materials were designed for adult A2-level French learners and piloted to ensure clarity and suitability.

2.3.3.1 Virtual Tutor with GPT-4 Voice

The experimental stimulus was a **custom GPT-4 voice tutor** specifically designed and configured for this experiment to deliver oral corrective feedback in French. The tutor was not a generic conversational agent, but a purpose-built research instrument created through extensive prompt engineering, iterative refinement, and stress testing.

The system prompt contained detailed behavioral rules: exclusive use of French; register calibrated for A2-level learners; prohibition against interrupting mid-sentence; and a corrective feedback sequence consisting of (1) identifying the target word, (2) pronouncing it slowly and clearly, (3) re-reading the sentence, (4) prompting the learner to repeat, and (5) acknowledging the effort before continuing.

The final instructional prompt extended to over a page of detailed constraints covering linguistic form, pacing, tone, and contingency instructions to ensure consistent output across participants.

Approximately 30 iterative refinement cycles were conducted. Pilot tests revealed recurrent issues (e.g., accented English infiltrating French, variable phrasing, or inappropriate timing), which were systematically resolved through prompt modifications. This process progressively transformed GPT-4 voice from a flexible conversational model into a standardized and reliable experimental tool.

The tutor was stress-tested with edge-case scenarios to anticipate unpredictable user behaviors (e.g., silence, repeated mistakes, irrelevant utterances, or off-script responses). For each scenario, explicit contingency guidelines were embedded in the prompt, instructing the tutor how to recover gracefully and redirect participants while preserving its corrective role. These measures minimized behavioral drift and enhanced consistency.

Two versions of the tutor were implemented for the between-subjects design: one providing immediate corrective feedback and the other providing delayed corrective feedback. In the immediate condition, the tutor delivered feedback immediately after the designated sentence was read aloud. In the delayed condition, the same feedback was provided only after the participant had finished reading the entire passage. In both cases, the feedback targeted four pre-identified words per trial. Feedback was scripted to be slow, clear, and tailored to A2-level learners. The tutor maintained a polite and supportive tone, delivering only the programmed feedback without any additional conversational content.

2.3.3.2 Visual Stimuli: Slides with Texts to Read Aloud

The experimental reading material consisted of short texts displayed across two slides, each containing five sentences, for a total of ten sentences per trial. Texts were selected and edited to match A2-level grammar and vocabulary requirements, focusing on familiar, everyday themes such as family, daily routines, and local geography. Each sentence ended with a brief pause prompt, standardizing pacing and ensuring clear opportunities for corrective feedback. An example reading screen is shown in Figure 2.1.

For the delayed feedback condition, an additional slide labeled "Correction" appeared after reading, summarizing the designated sentences for feedback (see Figure 2.2).

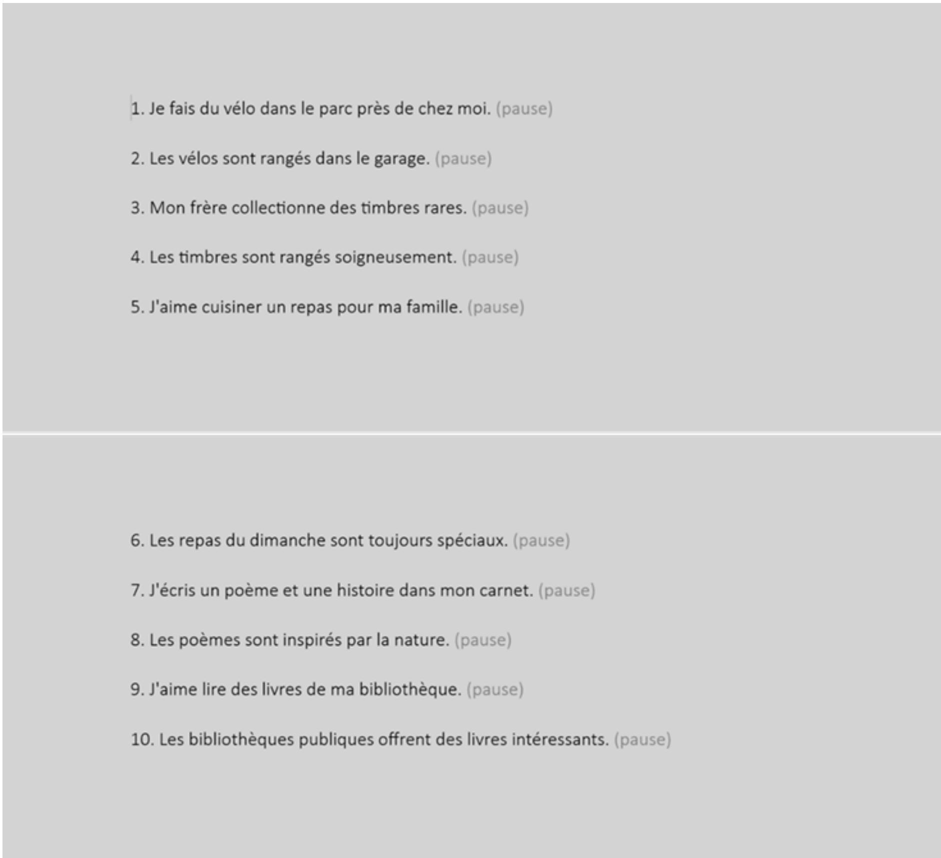

Figure 2.1. Example reading screen slides to read aloud

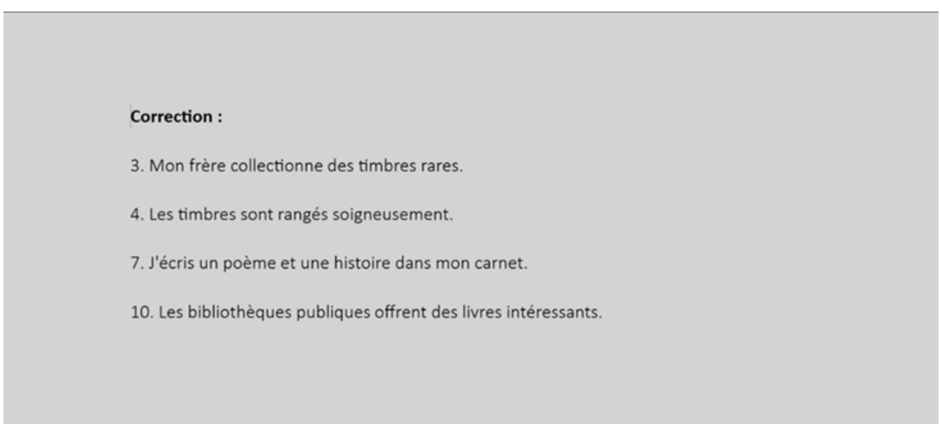

Figure 2.2. Example screen of the correction slide, delayed corrective feedback condition

2.3.3.3 Language Learning Platform

After each reading-aloud trial with the AI tutor, participants were redirected to the industrial partner's web-based platform (LRDG Language Hub) to complete a 15-item conceptual exercise. Each set of 15 items targeted one grammatical domain that had been highlighted in the AI task (e.g., singular vs. plural, contractions, and feminine vs. masculine). Within a given conceptual domain, items were presented through several interactive activity types. For example, in one singular/plural activity, learners listened to a sentence and selected the correct singular or plural noun form to complete it (e.g., choosing sœurs rather than sœur in "Mes ___ sont jolies"). In a contraction-focused activity, they chose between au, à la, à l', aux to complete short noun phrases such as "___ appartement" or "___ édifices." In a gender-focused activity, learners heard isolated nouns (e.g., Madame, appartement, édifice) and indicated their grammatical gender by clicking M, F, or MF. Across these activities, the platform thus assessed transfer of the targeted grammatical concepts to new sentences and vocabulary, rather than recall of the specific wording used in the AI-mediated reading task.

2.3.3.4 Apparatus and Environment

The study was conducted in a quiet laboratory setting. Eye movements were recorded using a Tobii Pro X3-120 eye-tracker (120 Hz sampling rate). All tasks were presented on a desktop computer, and participants listened to feedback via over-ear headphones. Eye-tracker calibration was performed at the start of each session using a nine-point grid. Before beginning the main trials, participants completed a warm-up session with non-experimental text to become familiar with the tutor, the interface, and the reading task.

2.3.4 Procedure

The procedure was designed to ensure standardized data collection and a consistent participant experience. All sessions were conducted in a dedicated laboratory equipped with an eye-tracker. A desktop computer with over-ear headphones delivered all instructions and AI tutor feedback. Each session began with informed consent and a standard nine-point eye-tracker calibration. Participants then completed a warm-up trial using a non-experimental French text to familiarize themselves with the interface, the AI tutor, and the reading-aloud task. This ensured that errors observed in the main experiment reflected linguistic challenges rather than system unfamiliarity. Following the warm-up, participants completed three experimental reading-aloud trials, each consisting of ten French sentences displayed across two slides. In every trial, four target words were pre-selected for corrective feedback. The feedback procedure differed by condition:

Immediate feedback condition: Immediately after the participant finished reading a sentence containing a target word, the AI tutor delivered spoken corrective feedback (i.e., the correct pronunciation) and prompted the participant to repeat the entire sentence with the corrected word before continuing.

Delayed feedback condition: Participants read all ten sentences without interruption. At the end of the passage, a correction slide appeared showing the four target sentences, and the AI tutor then delivered the same spoken corrective feedback, prompting sentence repetition after each correction.

Assignment to conditions was randomized, with 15 participants in the immediate feedback group and 15 in the delayed feedback group. Eye movements were recorded continuously during the reading tasks. Sentence-level Areas of Interest (AOIs) were created for all sentences on the screen, and fixation and saccade counts were extracted as trial-level measures of visual attention. Screen recordings were also collected for verification and further analysis.

Following each of the three trials, participants completed a 15-item conceptual language test on the web-based learning platform. These tests assessed grammatical and lexical concepts related to the reading passages. Raw scores ranged from 0 to 15, providing one outcome score per trial per participant. The whole procedure, including setup, calibration, warm-up, experimental trials with corrective feedback, and post-trial tests, lasted approximately 50 minutes per participant.

2.3.5 Measures

Target Object of Interest (TOI) and Areas of Interest (AOIs): For each reading trial, the Target Object of Interest (TOI) was defined as all sentences presented on the screen. Sentence-level Areas of Interest (AOIs) were created for every sentence in the trial using Tobii Pro Lab. This approach ensured that attentional engagement measures reflected participants' allocation of gaze across the *entire reading and feedback task*, rather than being limited to only the sentence containing the corrected word. In the immediate feedback condition, participants completed 10 sentences per trial, and AOIs were defined for each of these sentences. In the delayed feedback condition, participants read 10 sentences on the initial slides plus 5 correction sentences on the correction slide, resulting in 15 AOIs per trial. By applying this AOI structure consistently across both conditions, attentional engagement measures reflected participants' gaze distribution over the full task experience, supporting valid comparisons between immediate and delayed feedback.

***Visual attention metrics**:* Two standard gaze metrics were computed within the sentence AOIs for each trial. Fixation count, defined as the average number of fixations across all sentence AOIs, and Saccade count, defined as the average number of saccadic eye movements across all sentence AOIs. Both measures were automatically derived using Tobii Pro Lab's velocity–threshold identification algorithm (I-VT) and then averaged across the AOIs to yield one trial-level fixation count and one trial-level saccade count.

Performance: Following each of the three reading trials, participants completed a 15-item conceptual language test administered on the learning platform (maximum score = 15). Thus, every participant contributed up to three post-trial test scores, one corresponding to each reading trial. These test scores served as the performance outcome measure.

2.3.6 Data Analysis

Trials containing technical errors or missing gaze data were excluded from analysis, resulting in 77 valid trials (38 in the immediate feedback condition and 39 in the delayed feedback condition).

Data analysis proceeded in several steps. First, descriptive statistics were calculated for all primary variables: fixation counts, saccade counts, and raw test performance scores (ranging from 0 to 15) within each feedback condition. This provided an overview of attention and learning outcomes across groups.

For inferential analyses, the test performance variable was further dichotomized using a median split to create a binary indicator of high performance (coded as 1 for scores at or above the median, and 0 otherwise). This transformation was implemented because the distribution of test scores was non-normal, allowing for the use of logistic regression models and facilitating clearer interpretation of differences between high and low performers.

Group comparisons were conducted to assess differences in attention and performance between immediate and delayed feedback conditions, using repeated measures ANOVA for continuous outcomes to take into account multiple trials, and logistic regression for the binary performance variable. Finally, predictive modeling was used to evaluate whether attention metrics predicted test performance, with regression models incorporating random intercepts to account for repeated measures within participants. For the tests of H2, feedback timing condition (immediate vs.

delayed) was entered as a fixed-effect control variable, so that the association between attentional engagement and performance was estimated net of any mean differences between conditions. All analyses were conducted using SAS.

2.4. Results

2.4.1 Descriptive Statistics

Descriptive results are displayed in Table 2.1. Descriptive statistics were calculated for attentional engagement metrics, including fixation and saccade counts by feedback condition (Immediate vs. Delayed) and performance scores by condition. Participants in the immediate feedback group showed notably higher engagement during the task.

Table 2.1. Descriptive Statistics for Fixation Counts, Saccade Counts and Performance Score by Feedback Condition

Condition	N	Fixation Count (M ± SD)	Saccade Count (M ± SD)	Performance (M ± SD)
Immediate Feedback	38	57.04 ± 11.52	46.30 ± 11.61	13.05 ± 0.29
Delayed Feedback	39	40.19 ± 7.17	32.76 ± 6.13	12.46 ± 0.41

2.4.2 Hypothesis Testing

Hypothesis 1 (H1): Learners receiving immediate feedback will show higher attentional engagement during the reading task than those receiving delayed feedback.

This hypothesis proposed that learners in the immediate feedback group would demonstrate higher levels of attentional engagement than those in the delayed feedback group. Independent samples t-tests confirmed this prediction: the immediate feedback group showed significantly higher fixation counts ($M = 57.04$, $SD = 11.52$) than the delayed group ($M = 40.19$, $SD = 7.17$), and significantly higher saccade counts ($M = 46.30$, $SD = 11.61$) compared to the delayed group ($M = 32.76$, $SD = 6.13$), with both differences significant at $p < .05$. These results indicate that immediate feedback effectively enhances attentional engagement during task execution, as measured by both fixation and saccade activity.

Hypothesis 2 (H2): Higher attentional engagement during the reading task will result in better performance on a subsequent test measuring similar language concepts.

This hypothesis predicted that greater attentional engagement, as captured by eye-tracking measures, would be associated with higher performance scores on the post-task language assessment. Including feedback-timing condition (immediate vs. delayed) as a control variable, regression analysis confirmed this prediction: both fixation count ($b = 0.55$, $SE = 0.28$, $t(46) = 2.01$, $p = .050$) and saccade count ($b = 0.78$, $SE = 0.31$, $t(46) = 2.54$, $p = .015$) significantly predicted post-task performance scores. Thus, after accounting for condition, learners who maintained higher attentional engagement during the reading task tended to perform better on subsequent language tasks.

These results indicate that learners who maintained higher attentional engagement during the reading task tended to perform better on subsequent language tasks.

Table 2.2. Regression Analysis of Attentional Engagement Measures on Performance Scores

DV	IV	Estimate	Std. Error	DF	t-Value	p-Value
Performance	Fixation Count	0.55	0.28	46	2.01	.050
Performance	Saccade Count	0.78	0.31	46	2.54	.015

2.5 Discussion

This study examined how the timing of auditory corrective feedback in a voice-based AI tutor influences attentional engagement and post-task performance in adult language learners. Results showed that learners in the immediate feedback group displayed higher attentional engagement during the reading task, and that greater attentional engagement predicted higher test performance. Together, these findings are consistent with a process in which corrective feedback timing may influence performance outcomes through its impact on attentional engagement.

Mechanistically, immediate feedback appears to function as a salient orienting signal that redirects learners' gaze toward the critical word at the moment of error. This gaze reallocation, evidenced through increased fixation and saccade counts, likely facilitates error recognition and in-situ correction. In contrast, delayed feedback preserves task flow but may miss the opportunity to capture learners' visual attention at the precise moment when errors are most salient. Thus, while both timing strategies have theoretical benefits, our results highlight the attentional advantage of immediacy in controlled AI-tutoring contexts.

The finding that attentional engagement, rather than feedback timing alone, predicted test performance suggests that attention is the proximal driver of learning in AI-mediated language tutoring. This pattern is consistent with the eye–mind hypothesis, which posits that what learners fixate on reflects the information they actively process (Just & Carpenter, 1980). In this study, higher fixation and saccade counts were associated with better post-task outcomes, providing process-level evidence that attention allocation is a plausible mechanism through which feedback may support learning, in line with the eye–mind hypothesis.

2.5.1 Theoretical contributions

These findings extend the Revised Student–Feedback Interaction Model (Lipnevich & Smith, 2022) by highlighting a potential attentional pathway: feedback timing appears to be associated with performance in part through its relationship with attentional engagement. This helps reconcile mixed results in the SLA literature, where some studies favor immediate CF while others support delayed CF. Our data suggests that it is the attentional engagement that determines when timing policies are most effective. In multimodal contexts such as listening-while-reading, this attentional mechanism is particularly critical, since auditory input and visual gaze must be integrated in real time.

2.5.2 Design implications for AI tutoring systems

For designers and decision-makers in educational technology, these results highlight attention as a design lever. Immediate, in-context corrective feedback can effectively sustain attentional engagement, thereby improving downstream performance. However, rather than adopting a one-size-fits-all approach, AI tutors could adapt timing dynamically: providing immediate CF when attention wanes, while strategically delaying CF to encourage reflection when engagement is already high. Features such as real-time eye-tracking integration, engagement analytics, and adaptive feedback policies may maximize both user experience and learning efficacy in commercial platforms.

2.5.3 Limitations and future research

This study has several limitations. First, the controlled lab setting involved feedback on predetermined target words and restricted two-way interaction, which may not fully capture naturalistic language learning. Second, the post-task performance test assessed grammatical concepts rather than pronunciation, the focus of the corrective feedback, which may limit direct transfer of effects. Nonetheless, this design provided a conservative test of transfer, strengthening confidence in the attentional pathway. Third, the sample consisted of adult beginner French learners in Quebec, which restricts generalizability to other age groups, proficiency levels, or linguistic backgrounds. Finally, while eye-tracking provides robust measures of visual attention, it cannot capture off-screen attention or fully account for emotional and cognitive engagement.

Future research should explore adaptive feedback timing in more interactive, conversational tutoring scenarios, examine long-term retention effects through delayed post-tests, and incorporate multimodal engagement measures such as pupillometry, galvanic skin response, or self-reported affect. Expanding to diverse learner populations and real-world learning contexts will further clarify how timing and engagement interact to shape language learning outcomes.

2.5.4 Conclusion

In sum, this study shows that corrective feedback timing influences performance indirectly by modulating attentional engagement. Immediate feedback captures attention at the point of error, but it is the quality of attentional engagement,rather than timing itself,that drives learning outcomes. These results extend theoretical models of feedback and provide practical guidance for the design of AI tutors: systems that adaptively monitor and optimize learner attention are best positioned to maximize both engagement and achievement in digital language education.

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Chapter 3
Designing AI Agents That Keep Users Engaged: What Eye-Tracking Teaches Us About Feedback Timing

Executive Summary

AI agents are no longer experimental add-ons; they are fast becoming the frontline of customer service, onboarding, and employee training. But one design choice is consistently underestimated: *when the AI delivers feedback*.

Our study with a GPT-4–powered French language tutor, using eye-tracking to track attentional engagement, showed that immediate feedback increased attention, and higher attention predicted better performance on follow-up tasks. The results highlight a crucial mechanism: timing influences outcomes indirectly through attention.

For designers and decision-makers in educational technology and beyond, this underscores attention as a design lever. Immediate, in-context feedback can sustain engagement and improve downstream performance. Yet the next step is adaptivity: AI systems that monitor engagement and adjust timing dynamically, immediate when focus wanes, delayed when reflection is possible, will set the standard for high-performing AI experiences.

Study Context

This study involved 30 adult A2-level French learners in Quebec, randomly assigned to receive either immediate or delayed auditory corrective feedback from a GPT-4 voice tutor during read-aloud tasks. Immediate feedback followed each target sentence, while delayed feedback was presented afterward on a “Correction” slide. Learner gaze was tracked with eye-tracking technology, and 77 valid trials were analyzed.

A Small Design Choice with Outsized Impact

AI agents are rapidly becoming the frontline of digital interaction, from Duolingo's gamified language coaches to corporate onboarding assistants and employee training bots. They are designed to be smart, scalable, and always available.

Yet one design lever remains consistently underestimated: when the AI delivers feedback.

In our study with a GPT-4-powered French language tutor, we used eye-tracking to compare immediate versus delayed corrective feedback. The results were clear:

- Immediate feedback boosted attentional engagement.
- Learners who sustained higher attention achieved better test performance.

The insight: feedback timing appears to shape outcomes in part by modulating attention. This suggests that attention is not a secondary engagement metric, but a key process through which AI agents can influence performance.

Why Leaders Should Care

Business leaders face a paradox. Many invest heavily in AI technologies that can analyze language, personalize experiences, or generate human-like responses, yet still see user engagement plateau or drop off before task completion. The missing piece is not intelligence; it is **attention**. Our study demonstrates that timing is not simply about efficiency. When an AI agent provides feedback immediately, it captures user attention at the exact moment of relevance. Eye-tracking data showed learners redirecting their gaze to the corrected word and sustaining higher attentional focus. This heightened attention, in turn, predicted stronger performance on a follow-up test.

For managers, the implication is clear: attention is the currency of digital engagement. AI systems that capture and maintain it will consistently outperform those that fail to recognize when users are drifting.

In customer service, acknowledging input instantly keeps users engaged long enough to reach a resolution. In training, correcting errors in the moment helps the lesson "stick." Across industries, attention-aware design is the difference between a system that feels intelligent and one that feels frustrating.

Three Design hypotheses and A/B-testable practices

1. Use Immediate Feedback to Anchor Attention

Immediate corrective feedback acts like a spotlight. In our experiment, it redirected learners' gaze at the precise moment of error, keeping their focus where it mattered most.

- **Customer service:** Acknowledge input instantly to prevent disengagement.
- **Training:** Deliver corrections while mistakes are still fresh.
- **Onboarding:** Intervene at high drop-off points (e.g., during form completion) to keep users on track.

Pro Tip: Use immediate feedback at critical moments to sustain attention and prevent drift.

2. Monitor Engagement in Real Time

Attention fluctuates. Eye-tracking was our research tool, but real-world systems can use proxies like pause length, scrolling patterns, or voice hesitations. These signals provide a window into when users are focused and when they are slipping.

- **Customer service:** Detect long pauses and prompt with clarifying questions.
- **E-learning:** Identify skim behavior and insert interactive checkpoints.
- **Retail chatbots:** Escalate to a human agent when repeated queries signal disengagement.

Pro Tip: Treat disengagement as an event you can detect and correct. Embed lightweight attention monitoring to ensure timely intervention.

3. Adapt Timing Dynamically

Our study showed that immediate feedback increases attention and thereby improves performance. But not every situation requires the same timing. Once a learner is already highly engaged, delaying feedback may encourage reflection and deeper processing.

For designers, this points to a new frontier: adaptive timing policies.

- Provide immediate feedback when attention wanes, to re-anchor focus.
- Offer delayed feedback when engagement is already high, to allow reflection.

Pro Tip: Build adaptive systems that choose timing based on engagement signals—delivering the right kind of feedback at the right moment.

The Competitive Advantage of Attention-Aware AI

The next wave of AI adoption will not be decided by raw model power, but by user engagement. A technically sophisticated AI system that fails to hold attention will underperform against a simpler, well-designed system that keeps users engaged through completion.

Our study suggests that attention is a central process connecting design choices such as feedback timing, to measurable outcomes. This has direct implications for business leaders: attention-aware systems will consistently outperform attention-blind systems.

- **Higher task completion rates:** Customers are more likely to finish onboarding flows or service requests when attention is actively maintained.
- **Improved learning outcomes:** Employees retain more when corrective feedback aligns with attentional state.
- **Stronger trust in AI:** Users perceive attentive systems as more responsive, increasing adoption and loyalty.

The Bottom Line

- Immediate corrective feedback sustains attentional engagement.
- Attentional engagement drives downstream performance.
- Adaptive timing policies represent the next design frontier.

For designers and decision-makers, the message is simple: don't just ask *"What should the AI say?"* Ask *"When should it say it—and how will timing sustain user attention?"*

Chapter 4
Conclusion

4.1 Reminder of Research Context and Objectives

This article-based thesis explored the role of corrective feedback timing in voice-based AI language tutors,a critical yet underexplored design dimension in human–AI interaction for second language acquisition (SLA). While prior research has extensively examined immediate versus delayed feedback in traditional classroom settings, less is known about how these timing strategies translate to AI-mediated, voice-based learning environments.

The primary objective was to examine how the timing of oral corrective feedback (immediate vs. delayed) from a GPT-powered, French-speaking AI tutor influences attentional engagement and learning performance in adult A2-level learners. We aimed to generate insights not only about outcomes but also about the attentional mechanisms that mediate these outcomes, using a combination of eye-tracking metrics (fixations, saccades) and conceptual language testing.

To investigate this, we developed a custom AI tutor capable of delivering controlled, consistent auditory feedback and designed a laboratory experiment incorporating Tobii Pro eye-tracking, controlled timing protocols, and conceptual grammar assessments. The study employed a between-subjects design with two groups: one receiving immediate feedback after the target sentence and the other receiving delayed feedback at the end of the task. The goal was to isolate the impact of feedback timing on learner attention and subsequent performance, thereby informing design decisions for next-generation AI tutors.

This work contributes to the growing field of human-centered AI in education by addressing a gap in both the empirical and theoretical understanding of how feedback timing can influence learner–AI interaction, engagement, and learning outcomes.

4.2 Reminder of Research Questions and Main Findings

This thesis was guided by a central objective: to assess how the timing of corrective feedback from a voice-based AI tutor affects user attention and learning performance in language learning systems. The research question was:

RQ: How does the timing of corrective feedback (immediate versus delayed) from a voice-based AI tutor affect learner attentional engagement and post-task performance in language learning systems?

To answer this, we conducted a controlled laboratory experiment with 30 adult A2-level French learners randomized to immediate or delayed feedback conditions. Participants completed read-aloud tasks while receiving oral corrective feedback from a GPT-powered tutor. Attentional engagement was indexed via eye-tracking (fixation and saccade counts), and post-task performance was assessed with a conceptual grammar test.

The main findings are as follows:

• Immediate feedback heightened attentional engagement. Participants in the immediate condition exhibited significantly more fixations and saccades during the task, indicating greater on-task focus. This suggests that real-time auditory feedback can serve as a salient attentional cue in AI-tutored environments.

• Greater attentional engagement was associated with stronger post-task performance. Learners who showed higher attentional engagement tended to score better on the follow-up conceptual test, linking sustained attention to subsequent learning performance.

Taken together, these results are compatible with an indirect pathway in which immediate feedback operates primarily by amplifying attention, while performance gains are associated with the learner's sustained engagement.

4.3 Theoretical Contributions and Practical Implications

This thesis advances the theoretical understanding of corrective feedback in AI-mediated learning by extending the Revised Student–Feedback Interaction Model (Lipnevich & Smith, 2022) to suggest that feedback timing may influence performance partly through attentional engagement, positioning engagement as a key process variable.

Using eye-tracking, the study provides process-level evidence: fixation and saccade patterns index this attentional pathway, offering concrete support for how AI-delivered feedback fosters learning. In doing so, the findings help reconcile mixed results in SLA research—some favoring immediate, others delayed feedback—by demonstrating that the effectiveness of timing policies depends on the quality of attentional engagement they elicit.

The managerial article translated these insights into actionable guidance for AI-driven systems. It argues that attention is not merely a cognitive by-product but a strategic design lever. By integrating timing-sensitive corrective feedback and monitoring attentional signals, AI tutors—as well as customer-service agents, onboarding systems, and training bots—can maximize engagement and improve downstream outcomes.

These findings have direct implications for educational technology and AI design: immediate, in-context corrective feedback sustains attention at critical moments and indirectly enhances performance. To amplify this effect, prioritize attention-aware system design, integrating signals such as response latency, scrolling patterns, and voice hesitations to detect disengagement. Building on this, AI tutors can apply dynamic timing strategies—providing immediate feedback when attention wanes and delaying feedback to encourage reflection when engagement is strong. Attention-driven design is both pedagogically valuable and commercially advantageous, enabling higher task completion, better learning outcomes, and deeper trust in AI systems.

4.4 Limitations and Future Work

Several limitations should be acknowledged. First, the experimental environment was highly controlled, involving predetermined target words and limited interaction with the AI tutor. While this control increased internal validity, it may reduce ecological validity compared to naturalistic learning scenarios. Second, the alignment between the task (pronunciation feedback) and the post-task test (grammar concepts) was not perfect, though conceptually related. This conservative test design may have underestimated the true effect size of feedback timing on directly aligned outcomes. Third, the sample consisted of adult A2-level French learners in Quebec, restricting generalizability to other languages, proficiency levels, or learner populations. Finally, while eye-tracking provided robust indicators of visual attention, it cannot capture off-screen attentional shifts or fully reflect affective and motivational dimensions of engagement.

Building on these findings, future research should investigate adaptive AI feedback timing systems that dynamically adjust when corrective feedback is delivered based on learners' real-time attentional states, alternating between immediate and delayed feedback to optimize engagement. In addition, integrating multimodal engagement measures such as eye-tracking, pupillometry, galvanic skin response, and self-reports would provide a more holistic picture of learner engagement. Expanding the scope to include diverse populations, such as children and advanced learners, will help assess the generalizability of these effects. Finally, exploring feedback timing in ecologically valid, longitudinal contexts such as mobile applications and online platforms will strengthen the applicability of these insights to real-world educational environments.

This thesis provides evidence that attention is an important process linking feedback timing to learning outcomes in AI-mediated language tutoring Immediate corrective feedback enhances attentional engagement, and attentional engagement, in turn, predicts post-task performance. By advancing theoretical models, offering practical design guidance, and pointing toward adaptive, attention-aware systems, this work contributes to both the scholarly understanding of corrective feedback and the applied design of next-generation AI learning technologies.

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Annexes

HEC MONTRĒAL

Comité d'éthique de la recherche

ATTESTATION D'APPROBATION ÉTHIQUE COMPLÉTÉE

La présente atteste que le projet de recherche décrit ci-dessous a fait l'objet des approbations en matière d'éthique de la recherche avec des êtres humains nécessaires selon les exigences de HEC Montréal.

La période de validité du certificat d'approbation éthique émis pour ce projet est maintenant terminée. Si vous devez reprendre contact avec les participants ou reprendre une collecte de données pour ce projet, la certification éthique doit être réactivée préalablement. Vous devez alors prendre contact avec le secrétariat du CER de HEC Montréal.

Nom de l'étudiant(e) : Elham Rashidi Ranjbar

Titre du projet supervisé/mémoire/thèse : Titre du projet de recherche : The impact of voice-based conversational agent (VCA) feedback on language learning experiences and outcomes

Titre du projet sur le certificat : Etude de l'impact de la rétrocation d''un agent conversationnel à base vocale (VCA) sur les expériences d'apprentissage des langues et sur leurs résultats

Projet # : 2024-5921

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Date d'approbation initiale du projet : 31 mai 2024

Date de fermeture de l'approbation éthique pour l'étudiant(e) : 09 septembre 2025

Maurice Lemelin
Président
CER de HEC Montréal

Signé le 2025-09-10 à 08:45

NAGANO Fin de participation d'un étudiant à un projet
Comité d'éthique de la recherche - HEC Montréal

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Request for authorization to submit in the form of articles

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Title : The Impact of Corrective Feedback Timing on Learner Attentional Engagement and Post-Task Performance
Journal or book:
Current status of article: ☐ published ☐ submitted for publication ☑ in preparation

Author(s) : Elham Rashidi Ranjbar, Sylvain Sénécal, Pierre-Majorique Léger
Title : Designing AI Agents That Keep Users Engaged: What Eye-TrackingTeaches Us About Feedback Timing
Journal or book:
Current status of article: ☐ published ☐ submitted for publication ☑ in preparation

Author(s) :
Title :
Journal or book:
Current status of article: ☐ published ☐ submitted for publication ☐ in preparation

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4. Student's signature

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5. Approval by Research Director/Co-Directors

Sylvain Sénécal		10-09-2025
Director's name	Signature	Date
Pierre-Majorique Léger		10-09-2025
Co-Director's name (if applicable)	Signature	Date

6. Decision and signature of Program Director

Decision: ☐ Accepted ☐ Refused

Program Director	Signature	Date

Declaration on the Use of Generative Artificial Intelligence Tools

In line with HEC Montréal's guidelines, generative artificial intelligence was used only to support writing and language revision in the preparation of this thesis.
More specifically, these tools were used to suggest alternative phrasings to improve clarity and flow, and to assist with stylistic and grammatical revision of text originally written by the author. These AI tools were not used to generate or alter experimental data, perform statistical analyses, produce results, tables, or invent bibliographic references.