

FretMate: ChatGPT-Powered Adaptive Guitar Learning Assistant

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Abstract

Learning to play the guitar poses significant challenges for beginners, who often choose to practice alone to avoid the embarrassment of making mistakes in front of others. This isolation leads to a lack of timely feedback and encouragement, resulting in frustration and decreased motivation. Traditional learning methods fail to provide personalized and immediate support. To address these issues, we propose a GPT-powered guitar learning assistant, FretMate, that provides immediate error correction, personalized learning paths, and emotional support. The design was informed by formative interviews with six guitar instructors and six learners. We evaluated our assistant against the traditional self-guided practice in a controlled two-week study with 16 participants. Results showed that participants using FretMate improved in skill acquisition, engagement, and motivation compared to the control group. We discuss the potential of integrating conversational AI into instrument learning to provide personalized instruction and emotional engagement.

CCS Concepts

- Human-centered computing → User interface programming.

Keywords

Guitar Education, AI-driven Feedback, Personalized Learning, Music Theory Integration, Emotional Support, ChatGPT

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1 Introduction

Learning to play the guitar is a difficult trip, especially for beginners who frequently make mistakes, receive delayed feedback, and feel isolated [30, 36]. These difficulties can frustrate trainees and may ultimately cause them to discontinue their practice.



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However, traditional means of learning, such as private classes or self-study through textbooks and videos, fall short in assisting students to overcome these obstacles [12, 18]. In private lessons, while personalized feedback is a significant advantage, scheduling constraints often delay this feedback, hindering continuous progress [38]. Additionally, the high cost of private instruction can be prohibitive for many learners. Teachers may also struggle to consistently address the emotional challenges students face during independent practice sessions [23], potentially leading to decreased motivation. Self-study methods heavily rely on static resources that fail to provide personalized and adaptive feedback or adjust to a learner's specific weaknesses [30]. This absence of interactivity can result in learners struggling to assess their progress, leading to confusion and frustration [24]. Without adaptive elements to maintain engagement and motivation, learners may lose interest and discontinue their efforts to learn the instrument.

To tackle these problems, we introduce FretMate, an AI-driven guitar learning assistant for beginners, aimed at delivering an extensive learning experience through incorporating immediate technical feedback, customised learning trajectories, and responsive emotional support [9, 22]. FretMate leverages recent advancements in artificial intelligence, including natural language processing and conversational AI, to meet the cognitive and emotional requirements of guitar learners. Specifically, FretMate builds on the abilities of large language models like ChatGPT, to provide sympathetic advice and technical support throughout the learning process [51].

To inform the design of FretMate, we conducted formative interviews with six guitar teachers and six guitar students, which highlighted the critical importance of immediate feedback, personalized content, and emotional support in the learning process. Correspondingly, we design FretMate to include three main functions: 1) *immediate correction* that utilizes audio and gesture detection to offer timely feedback on chords, scales, rhythm, and hand positioning, allowing learners to rectify mistakes instantly and ensuring effective practice; 2) *personalized learning paths* that are generated by feeding the above-mentioned performance errors to ChatGPT and providing customized suggestions of songs and exercises that match the learner's current skill level and musical preferences; 3) *emotional support* offered by ChatGPT through timely encouragement and positive reinforcement tailored to the learner's emotional state, backed by the analysis of interaction patterns and error frequency. Finally, we evaluated our system in a controlled two-week study involving 16 participants, comparing the effectiveness of FretMate against the traditional self-directed practice.

Our contributions include:

- **Developing an adaptive feedback system:** This system incorporates both technical analysis and emotional support, integrating state-of-the-art AI tools to provide a holistic learning experience.
- **Enhancing engagement and learning outcomes:** We demonstrate how AI tools like ChatGPT can significantly enhance learner engagement and improve learning outcomes through personalized strategies and encouragement.

2 Related Work

Our proposed guitar learning assistant builds upon prior work in music education, AI-powered music learning tools, and emotionally adaptive learning systems.

2.1 Guitar Learning

Traditional approaches to guitar learning include face-to-face lessons and self-study using static materials. Face-to-face lessons, such as those provided by experienced instructors, offer personalized feedback on technical aspects like hand positioning and rhythm [18, 30]. However, these lessons are often expensive, require consistent scheduling, and do not provide immediate feedback during independent practice. This delayed feedback can lead to inefficient learning and the reinforcement of bad habits [32]. In contrast, our approach integrates immediate corrective feedback into an AI-powered guitar learning assistant, ensuring that learners receive immediate guidance during practice sessions.

Self-study methods, relying on resources such as textbooks and online tutorials, offer flexibility but lack adaptability to individual learning needs [16, 20, 21]. Learners often struggle to identify and correct mistakes without expert input, resulting in frustration and stalled progress [24]. Intelligent guitar learning systems, such as Yousician [11] and Rocksmith [19], have sought to address some of these limitations by providing interactive immediate feedback through audio analysis. These systems allow learners to correct mistakes on elements such as pitch and rhythm during practice, enhancing technical skills.

Despite this technical feedback, these tools still lack emotional intelligence, which is critical for maintaining learner motivation during challenging learning phases. In contrast, our assistant incorporates emotional support powered by ChatGPT, providing empathetic guidance alongside technical feedback to foster motivation and sustained engagement.

2.2 AI-Powered Music Learning

The use of artificial intelligence in music education has brought significant improvements to personalization and learning efficiency. Audio analysis is a key technology in this field, allowing learners to receive immediate feedback on their performance, which prevents incorrect habits from forming [6, 37]. Moreover, Arai et al. [5] proposed TimToShape that supports instrument practice by visualizing timbre played by the learners with 2D shapes using the variational autoencoder, offering insights for timbre improvement. Our approach builds upon this by integrating both audio and gesture analysis, providing comprehensive feedback that includes

auditory and visual guidance, such as chord accuracy and hand positioning.

AI-based personalized learning systems adapt content to match the learner's progress and specific weaknesses [33, 51]. By dynamically adjusting the difficulty of exercises and offering targeted guidance, these systems keep learners engaged without overwhelming them [9]. For example, X5Learn [41] employs AI-driven personalisation that emphasises intuitive interfaces and usability principles to ensure the learning platform remains accessible and engaging. It delivers adaptive lessons in mathematics, language arts, and science, significantly boosting learner engagement. Regarding music learning, Xu [53] targeted musical instrument practice specifically by analyzing pitch and timing errors and automatically adjusting difficulty, thereby improving accuracy and sustaining motivation through adaptive feedback. Meanwhile, other AI systems, such as conversational AI systems in language learning [45] and collaborative AI systems in educational discussions [28] have demonstrated how AI can provide personalized and interactive feedback, fostering adaptive learning environments [25].

Our assistant extends these concepts by incorporating ChatGPT to facilitate in-depth, personalized interactions. This approach enables recognizing learners' emotional cues and responding with motivational reinforcement, thus providing a more holistic and supportive learning experience. By addressing both cognitive and emotional challenges, our system ensures sustained engagement and meaningful progress.

2.3 Emotion Support in Learning

Emotion plays a critical role in the learning process, particularly in skill-based activities like learning an instrument, where frustration can easily lead to disengagement [40]. Emotion-aware learning systems leverage emotion detection techniques to better understand learners' needs and adapt feedback accordingly [3, 14, 56]. Pérez-Rosas et al. [42] demonstrated the effectiveness of emotion detection in improving AI's responsiveness to learners' emotional states. Moreover, Ahn and Picard [2] investigated emotion detection in educational contexts, showing how such systems enhance adaptability by recognizing emotional content in interactions.

Motivation and engagement are also influenced by the emotional climate created by learning systems. Research emphasizes the need for emotional intelligence and support to foster persistence and success. Lazarus [29] discussed the role of emotions in adaptation and learning, highlighting their impact on motivation. Similarly, St. George [48] explored how positive reinforcement sustains learner engagement, while Baker et al. [8] demonstrated that managing emotions like frustration significantly improves learning outcomes. Building on these insights, Zawacki-Richter et al. [55] and Edgar [17] highlighted the value of integrating emotional intelligence into learning systems to create supportive environments. These works collectively show that providing timely emotional support enhances learner engagement and persistence [27, 39]. Leveraging these principles, our assistant is designed to recognize signs of frustration and offer encouragement, ensuring learners remain motivated during challenging periods.

In addition, many research works on affective computing emphasize the critical role of advanced emotion models and recognition

techniques in enhancing human-computer interactions. Their work highlights how affective computing enables systems to perceive and interpret human emotions through various modalities such as facial expressions, speech, and physiological signals [43, 50]. By integrating these sophisticated emotion recognition algorithms, applications can respond more empathetically to users' emotional states, leading to improved engagement and effectiveness in learning environments [4, 31, 52]. Similarly, collaborative AI systems [28] highlight the potential for AI to address both cognitive and emotional challenges through interactive engagement. Our assistant incorporates similar principles by utilizing immediate performance data and learner interaction patterns to provide contextually appropriate emotional feedback. Specifically, we employ emotion recognition techniques to assess learners' frustration or disengagement levels during practice sessions. This allows the system to adapt its responses—offering encouragement, adjusting task difficulty, or providing motivational prompts—thereby creating a more adaptive and empathetic learning environment.

Meanwhile, Choi et al. [10] raised ethical considerations regarding the transparency and reliability of AI in educational contexts, highlighting the need for clear and supportive AI interactions. Our research addresses these concerns by ensuring that all feedback from ChatGPT is understandable, supportive, and designed to build learner confidence, thus fostering a positive learning experience that promotes both technical and emotional growth.

3 Formative Interviews

To inform the design of our AI-powered guitar assistant, we conducted formative interviews with six guitar instructors (T1-T6) and six students (S1-S6) from China and the UK. We aimed to understand their roles, challenges in guitar education, and attitudes toward AI assistance. Instructors were selected to have at least two years of teaching experience, with three Chinese instructors having worked as guitar teaching assistants. Students included four self-taught learners and two receiving formal instruction. All students had regular access to a guitar and a minimum of five months of practice experience. The interviews were conducted online and lasted around 45 minutes each. Participants were compensated with a £20 gift voucher.

Overall, both instructors and students expressed a cautious yet positive view on AI's potential to enhance practice sessions. Below, we summarize key findings related to instructor roles, student challenges, and perspectives on AI in guitar education.

3.1 Instructors' Perspectives on Guitar Learning and AI Assistance

The role of teaching assistants in guitar learning. Three Chinese instructors with experience as guitar teaching assistants shared that their primary role was to supervise student practice, correct mistakes, and provide encouragement. They viewed their role as crucial yet less intensive than that of a full teacher, primarily focusing on maintaining course correctness without overwhelming the students.

"As assistants, we mainly watched for incorrect technique and offered encouragement when students struggled. It's about keeping them on track without overwhelming them." – T2

This experience underscores the importance of positive reinforcement and corrective feedback during practice, particularly for younger or beginner students prone to repetitive mistakes.

Feedback and motivational support. All six instructors emphasized the importance of immediate feedback in correcting mistakes during practice sessions, noting its essential role in preventing the formation of bad habits.

"Students need to know when they're doing something wrong, and it's best if they get that correction immediately." – T1

Additionally, they highlighted the necessity of motivational support during practice, especially for students facing challenges from repetitive tasks or slow progress.

"Kids need encouragement to keep going. Sometimes, a little positive feedback is all it takes to keep them motivated." – T3

Challenges with traditional learning materials. The instructors identified challenges with outdated or unengaging learning materials, which often do not resonate with current students' musical tastes or learning preferences.

"We would find popular songs online, simplify them, and tailor them to the student's level to make practice more relevant." – T2

The potential for AI tools. Instructors recognized the potential of AI-driven tools to provide immediate, precise feedback and track progress effectively between lessons, although they cautioned against the replacement of the human element in teaching.

"AI can correct technical mistakes, but it cannot replace the relationship or deeper musical insights that a human teacher provides." – T6

3.2 Students' Perspectives on Learning and AI Assistance

Discomfort with being observed during practice. Five students shared their discomfort with being observed while practicing, particularly when they made repetitive mistakes.

"I get really embarrassed if someone's watching me practice and I keep making the same mistake." – S4

This sentiment underscores the potential benefits of AI systems that offer private, non-judgmental feedback.

Self-taught students value practical learning over theory. Four self-taught students interviewed, a clear preference for practical learning over in-depth music theory was evident. One student noted:

"I know theory is important, but I'd rather learn it while playing, not separately." – S3

“If I could learn theory while practicing a song, I’d be much more interested.” – S2

These students typically engage in learning by selecting songs and practicing repetitively, often lacking structured guidance. Nevertheless, there was an expressed willingness to engage with theoretical aspects if they were integrated seamlessly into the practical learning process:

Structured learning paths prioritized by students with formal instruction. Students receiving formal instruction appreciated the structured learning paths tailored to their needs by their teachers:

“I prefer to follow my teacher’s path because it’s tailored to my needs. They know what I should work on next.” – S6

Despite this structured approach, these students expressed a need for additional support between lessons, especially a lack of feedback during individual practice sessions.

Desire for systematic and guided learning. Both self-taught and formally instructed students stressed the importance of systematic learning for making progress:

“I usually just find a song and practice, but it would be better if I had a clear path.” – S3

Structured learning was deemed essential for long-term improvement, with AI-assisted platforms seen as potentially beneficial in providing such structure.

Difficulty in finding enjoyable and suitable learning materials. Several students expressed frustration with the challenge of finding practice materials that are both enjoyable and suited to their current skill level. One student mentioned:

“When I hear a song I like, I try to practice it, but sometimes it has techniques I don’t know, so I end up spending a lot of time searching online for simplified sheet music. Sometimes I find an easy version, but other times, I spend hours and still don’t get what I need.” – S3

Another student, who primarily follows instructional books and videos, noted a similar challenge:

“I follow along with the songs in the books, but I don’t always like them. I wish I could practice songs I enjoy that also help me work on the chords or techniques I’m learning, but I know that’s hard to find.” – S5

Both students highlighted the need for customized practice materials that balance skill development with personal musical preferences. They often struggle to find songs that are both engaging and suitable for their level of expertise.

4 Design Goals

Guided by insights from our formative interviews with guitar instructors and students, as well as prior literature, we established three primary design goals for the development of the AI-powered guitar assistant. These goals aim to address key challenges in both self-guided and formal guitar learning, by integrating technical feedback, personalized learning paths, and emotional support.

DG1: Provide immediate technical feedback and error correction. Guitar learners often struggle with technical aspects like chord accuracy, rhythm, and hand positioning during practice. To ensure learners do not reinforce bad habits, the assistant should provide immediate and personalized feedback during practice sessions. This timely feedback allows learners to identify and correct mistakes in the moment, without the anxiety of being observed, fostering a more effective practice environment. Research has shown that immediate feedback is critical in improving the learning process, particularly in music education, by enhancing practice efficiency and skill development [34, 54].

DG2: Generate dynamic and personalized learning paths. Learners often experience difficulties with generic learning materials that do not align with their unique skill levels and learning goals. The assistant should support dynamically adjusting learning paths based on learners’ performance data, focusing on individual challenges while progressing toward defined learning objectives. This adaptive system can keep learners motivated by tailoring content to their current needs and abilities. The use of AI for personalized learning has been shown to improve engagement and skill acquisition by creating focused and efficient practice routines [46].

DG3: Provide adaptive emotional support and motivation. Instrument learning can be a frustrating and isolating process, especially during self-guided practice. The assistant should monitor learners’ emotional states by analyzing interaction patterns and error frequency, offering encouragement and emotional support when needed. Providing positive encouragement during challenging moments helps reduce frustration, enhance confidence, and maintain motivation. Recent studies have shown that emotional support is crucial in boosting learner engagement and achievements [44, 47]. Such emotional support helps learners maintain a balanced and positive learning attitude, especially when they encounter difficulties.

5 FretMate

To satisfy the design goals, we design FretMate that provides an interactive guitar learning experience by combining immediate performance analysis, personalized feedback, and emotional support.

Figure 1 shows an overall workflow of FretMate. Learners begin by selecting a song from FretMate’s built-in library for practice or uploading a custom music sheet with the accompanying audio file. Then, FretMate records their practice, capturing both audio and video data for analysis upon completion. The analysis identifies errors the learners make, such as rhythm deviations, pitch inaccuracies, chord mismatches, and gesture mistakes (Section 5.2). Based on these errors, FretMate leverages ChatGPT to provide textual feedback, including technical corrections, personalized learning paths tailored to the user’s progress, and motivational support (Section 5.3). Both feedback is immediately delivered to the learners through FretMate’s interface, e.g., the highlighted mistakes on the tablature and fretboard diagrams (Figure 2-left). They can further interact conversationally with ChatGPT to seek clarification, request additional exercises, or adjust their practice focus (Figure 2-right). This integrated workflow ensures that users receive timely and

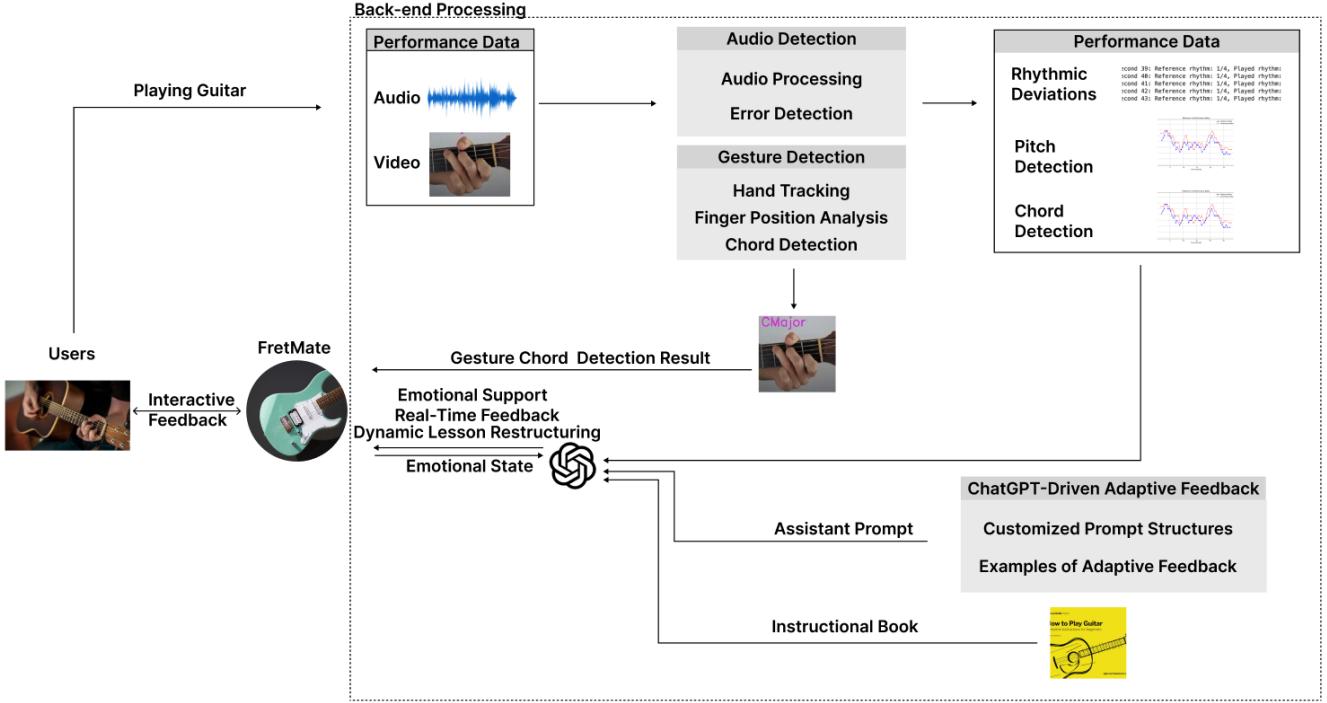


Figure 1: FretMate: Interactive feedback framework for adaptive guitar learning

actionable guidance, creating a continuous and engaging guitar learning experience that adapts to individual needs and goals.

We introduce the user interface and underlying modules that drive FretMate's functionality as follows.

5.1 User Interface Overview

As shown in Figure 2, the FretMate user interface consists of two primary panels: a visual feedback panel on the left and a conversational assistant panel on the right.

The left panel shows visual feedback to learners, which is composed of three main elements. At the top displays a guitar tablature with the performance feedback focusing on pitch accuracy, with green denoting correct notes and red indicating pitch errors. In the middle, a dynamic guitar fretboard diagram, inspired by YouSician's design [11], uses bouncing balls to guide learners. The ball's position indicates the string to pluck, the number shows the fret to press, and its speed and amplitude reflect the rhythm. Red and green markers further provide real-time feedback on finger placement accuracy. At the bottom, the recorded practice video allows users to review their performance and navigate specific sections via the video progress bar. This interface integrates pitch analysis, rhythm guidance, and performance review, offering a comprehensive and intuitive practice experience.

The right panel consists of a conversational interface to provide interactive feedback. Users can chat with FretMate through voice or text, asking for tips on challenging sections or requesting easier songs. In response, FretMate provides tailored guidance and

clarifications. FretMate also delivers motivational and encouraging feedback by sending supportive messages, suggesting breaks, or celebrating milestones. These insights are derived from analyzing user performance data, such as frequent errors, time spent on challenging sections, and repeated practice attempts, as well as interaction patterns during the session. For example, a high frequency of mistakes or prolonged practice on a single segment may indicate frustration, while consistent improvement over time reflects positive progress. By integrating this analysis with conversational AI, FretMate fosters a more engaging and personalized learning experience that blends technical assistance with emotional support.

5.2 Error Detection

FretMate collects and processes user performance data after each practice session or upon completion of a specific segment of a song. This is achieved through two key modules: the audio detection module and the gesture recognition module. This enables comprehensive error detection and performance analysis.

Audio Detection Module. The Audio Detection Module analyzes the user's guitar performance in terms of three key areas: rhythm, pitch, and chord accuracy. Errors are mapped to the corresponding notes within the performance, enabling targeted corrections for technical growth.

The rhythm analysis identifies discrepancies in timing and tempo by comparing the user's performance to a reference track. The reference track is a pre-recorded, accurate audio performance provided by an instructor to serve as the benchmark for evaluation. This

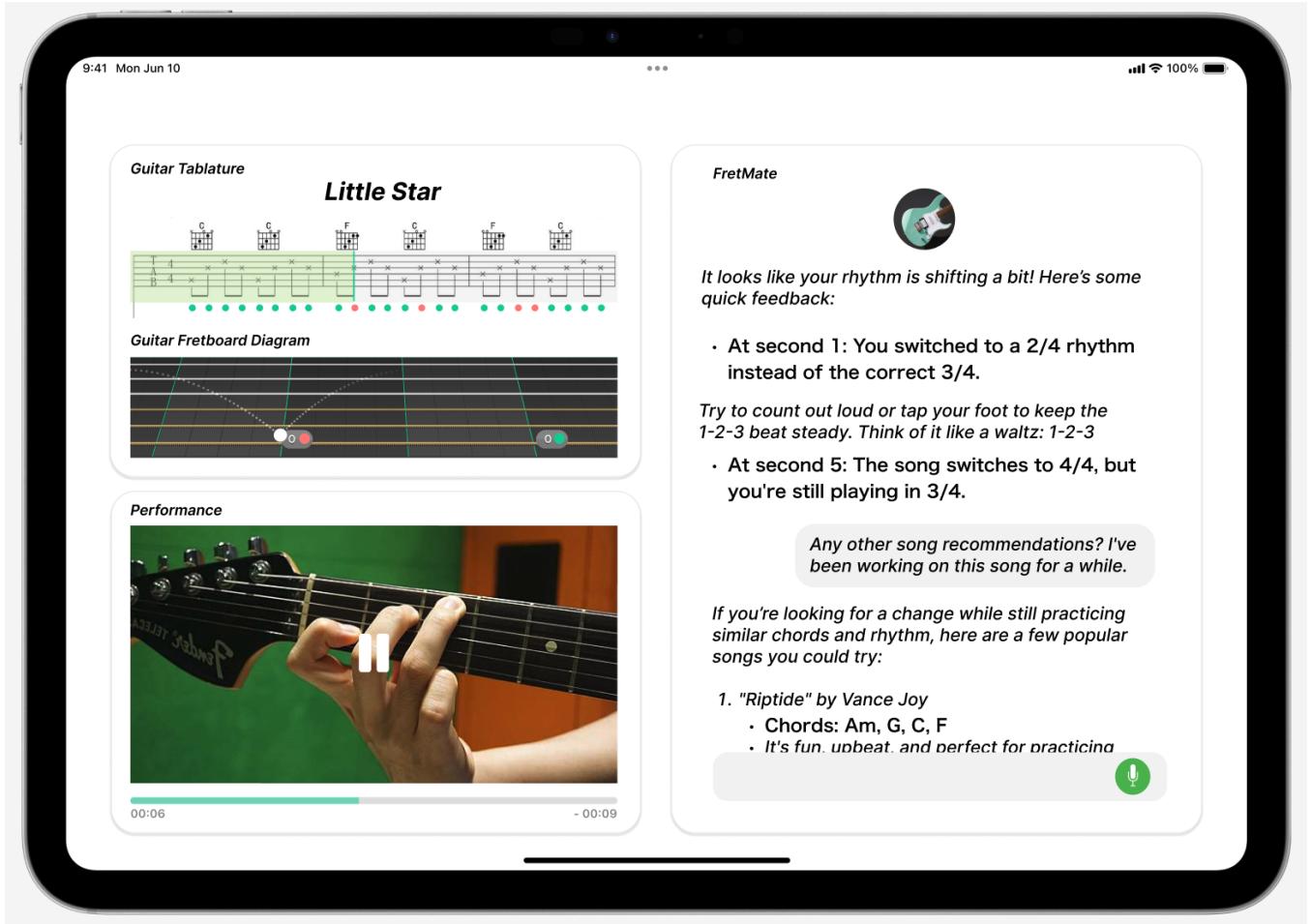


Figure 2: The FretMate user interface. FretMate performs audio and gesture recognition to provide personalized feedback (Pitch Accuracy, Rhythm Consistency, Chord Visualization, Gesture Correction) and dynamic lesson restructuring (Learning Path Adjustment, Music Theory Integration) along with emotional support powered by ChatGPT.

is achieved by processing two WAV audio files: one for the reference track and the other for the user’s performance. Both files are preprocessed for time alignment to ensure comparability. Using the librosa library and its beat_track function [35], beats are detected in both files and segmented into beat frames. These are then converted into temporal markers to create a time-rhythm map. Deviations between the user’s performance and the reference track are calculated, highlighting areas where the rhythm was rushed, delayed, or inconsistent. This detailed analysis helps learners refine their timing and tempo.

Pitch analysis evaluates the tonal accuracy of the user’s performance by comparing the detected pitch of each note against the reference track. The system employs the CREPE (Convolutional Recurrent Neural Network for Pitch Estimation) model to extract pitch data from both WAV audio files [26]. The extracted pitch data is converted into MIDI note values using the music21 toolkit [13], enabling precise identification of pitch deviations. This allows the

system to map incorrect notes to specific points in the performance, providing actionable feedback for improving tonal accuracy.

Chord analysis assesses harmonic accuracy by examining the chord structures in the user’s performance and comparing them to the reference track. Frequencies extracted during pitch analysis are processed using music21’s Pitch objects to identify chords, including major and minor triads as well as seventh chords [13]. Detected chords in the user’s performance are then aligned with the reference track to evaluate correctness and fluency in chord transitions. Errors, such as missing notes in a chord or incorrect finger positioning, are identified and linked to specific sections of the performance, offering learners targeted insights for refining harmonic proficiency.

Figure 3 showcases the results of a learner’s practice of *Jingle Bells*, in terms of the three key performance metrics, i.e., pitch deviations, rhythmic inaccuracies, and chord errors. For example, a 30-second audio segment typically requires 2-3 seconds for processing across all modules, including rhythm analysis, pitch analysis,

and chord analysis. These processing times are optimized for simple melodies with a duration of less than 2 minute. As our system primarily focuses on beginner-level pieces, this design ensures that feedback is generated quickly and efficiently, enabling timely and actionable insights for learners.

Gesture Recognition Module. The Gesture Recognition Module leverages computer vision techniques to track and analyze hand movements and finger positions during guitar practice, enabling real-time feedback on chord accuracy and technique. This module consists of two key components: hand tracking and finger position analysis.

The hand tracking system utilizes computer vision algorithms, implemented using TensorFlow [1], to detect and monitor the position, orientation, and movement of the user's hands across the guitar fretboard. Video data captured during practice sessions is processed to analyze wrist positioning, hand posture, and transitions between chords. By identifying these details, the system ensures learners maintain optimal hand posture and perform efficient chord transitions. This feature is particularly beneficial for identifying issues such as awkward hand angles or inefficient movements, enabling learners to improve their technique in real time. The tracking system builds upon methods implemented in related projects [7].

Finger position analysis focuses on evaluating the accuracy and precision of finger placements on the fretboard. The system employs a deep learning model based on the EfficientNetV2 architecture [49], which is fine-tuned using transfer learning. The model classifies chords such as C Major, D Major, and G Major by analyzing video data to detect which strings and frets are being pressed. A dataset of 208 augmented images was used to train the model, achieving an accuracy of 89.9% on the test set. This analysis provides immediate feedback on chord accuracy, including errors like insufficient finger pressure or incorrect placements, and suggests adjustments to improve performance. By integrating data from hand tracking and finger position analysis, the system offers a comprehensive solution for refining playing technique in real time.

5.3 ChatGPT-Driven Adaptive Feedback

After analyzing the user performance data, FretMate inputs the detected errors into ChatGPT to generate dynamic and personalized guidance across three key dimensions: technical feedback, adaptive learning paths, and emotional support. These features ensure a comprehensive and engaging learning experience by analyzing user performance and tailoring interactions.

Technical Feedback. FretMate leverages ChatGPT to deliver technical feedback by prompting

"This GPT is a personalized guitar learning assistant that helps users improve their guitar skills through real-time feedback, customized learning paths, and tailored guidance. By analyzing their performance data, including pitch, rhythm, and chord accuracy, the GPT provides adaptive learning experiences. It restructures traditional lesson content to suit the learner's individual pace and goals. The feedback provided will be concise, offering one or two sentences of advice per interaction, focusing on key points for improvement or praise to keep the user engaged without overwhelming them." We showcase an example of feedback regarding rhythm below:

*"At second 3, you switched to 2/4 rhythm instead of 3/4.
Let's try tapping your foot to keep the beat steady."*

Adaptive Learning Paths. The FretMate system personalizes learning paths by analyzing user performance and preferences. This dynamic learning path is continuously adjusted to accommodate changes in the learner's abilities and goals.

Profile-Driven Customization: The system begins by gathering essential data from the learner, including their skill level, learning objectives (e.g., mastering chord transitions or improving rhythm), and practice habits. Inspired by the prompt, *"Generate an initial learning path based on the user's profile and adjust dynamically based on real-time performance data."* This ensures the lessons align with the learner's style, such as step-by-step or challenge-based approaches.

Dynamic Content Adjustment: As the learner progresses, FretMate adapts the difficulty of lessons in real time. If certain areas (e.g., rhythm accuracy or chord transitions) are flagged as weak, the system rearranges lesson content to emphasize these areas before advancing to more challenging topics. Similarly, if the user demonstrates proficiency, the system introduces new techniques or increases complexity to keep the learner engaged. This approach aligns with the design prompt, *"Reorder traditional lesson content based on detected areas of difficulty or progress to ensure a personalized learning experience."* For example:

"You've made great progress on chord transitions—let's challenge you with some rhythm variations and finger-picking patterns!"

Interactive Queries: Users can ask the system specific questions, such as requesting further explanations or tips on difficult sections. The system provides interactive feedback based on user queries, aligning with the design prompt, *"Offer detailed, interactive feedback based on user queries (e.g., 'I'm having trouble with G chord transitions; can you help?'). Provide deeper explanations when users request more insight on specific mistakes or concepts."* For instance:

"This song is so childish, I want to learn a pop song instead"

The system responds: *"Sure! A super popular song that also uses C and F chords is "Let It Be" by The Beatles. It's a great, well-known tune, and it sticks to simple chord progressions like C, F, G, and Am. Perfect for practicing your chord transitions!"*

Emotion Detection and Support. Emotion detection is a core part of the FretMate system, allowing it to provide motivational support based on the learner's emotional state during practice sessions. By analyzing conversation cues and performance data, the system adjusts its tone and feedback to support the learner emotionally, aligning with the design prompt, *"Before each practice session, FretMate will engage the user in a brief conversation to assess their mood and readiness."*

Conversation-Based Emotion Detection: Before each practice session, FretMate engages the user in a brief conversation to assess their mood and readiness. Based on the user's responses, the system adjusts the tone of the feedback to suit their emotional state:

*"Hi! How are you feeling about practicing today?"
"I'm a bit tired, but I'll give it a shot!"*

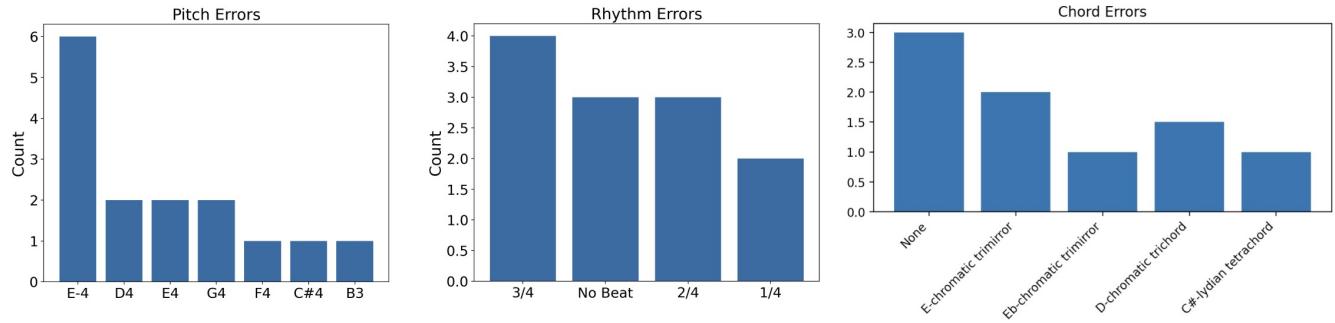


Figure 3: User performance error analysis. The figure summarizes pitch errors (left), rhythm errors (center), and chord errors (right) identified during user practice sessions.

The system might respond: “*Let’s take it easy today. We’ll focus on small goals—every bit of practice helps!*”

Performance-Based Emotion Detection: The system tracks the user’s performance metrics (e.g., frequency of mistakes, time spent on difficult sections) to detect frustration or confidence levels. By analyzing these metrics, FretMate adjusts its feedback to align with the user’s emotional state, as described in the prompt: “*During practice sessions, FretMate will also recognize emotional cues such as frustration, motivation, or disengagement and provide tailored responses.*” For instance, if the learner is repeatedly making the same mistakes or spending too long on a difficult section, the system provides empathetic feedback to ease frustration:

“I see you’ve been working hard on this part. It’s okay to take a break if you need it—sometimes stepping away helps!”

By combining technical feedback with adaptive learning paths and emotional support, FretMate ensures that learners not only improve their skills but stay motivated and engaged throughout their practice sessions.

6 Evaluation

To assess the effectiveness of our ChatGPT-powered guitar learning assistant, we conducted a controlled study comparing its impact on learners against traditional self-guided practice methods. The evaluation focused on measuring improvements in skill acquisition, engagement, and motivation through both quantitative and qualitative analyses.

6.1 Participants

We recruited 16 guitar learners (P1-P16) aged between 18 and 45 years old (Mean age = 20.5, SD = 7.2), with diverse representation in terms of gender and background. Participants were required to have their own guitars and access to a computer or smartphone. They were randomly assigned into two groups:

- **Experimental Group (Assistant Users):** 8 participants (4 beginners, 4 intermediate).
- **Control Group (Traditional Learners):** 8 participants (4 beginners, 4 intermediate).

All participants agreed to practice for at least 30 minutes daily over a two-week period.

6.2 Procedure

The study comprised three phases, each designed to evaluate different aspects of the learning process when using a guitar learning assistant compared to traditional self-guided methods.

Phase 1: Pre-study Assessment. The initial phase involved evaluating the participants’ baseline skills and motivations. Participants performed a standardized set of exercises, including chord transitions, scale runs, and rhythm patterns, which were recorded for error analysis. Additionally, pre-study questionnaires were used to collect data on their prior experience, practice habits, and motivation levels, assessed using a 7-point Likert scale.

Phase 2: Study Period (2 Weeks). During the study period, participants were divided into two groups. The experimental group used the guitar learning assistant during their practice sessions, benefiting from immediate error correction, personalized learning paths, and emotional support provided by the system. In contrast, the control group continued their usual self-guided practice without additional tools and manually logged their practice activities. Both groups maintained practice logs and completed weekly motivation questionnaires to track their progress and engagement throughout the two-week period.

Phase 3: Post-study Assessment. In the final phase, participants underwent reassessment and provided feedback on their learning experiences. They repeated the initial set of exercises to enable a comparative analysis of skill improvement. Additionally, post-study questionnaires and interviews were conducted to gather insights into their perceived improvements, overall satisfaction, and reflections on the learning process.

6.3 Metrics Collected

We employed a combination of quantitative and qualitative measures to comprehensively evaluate the impact of the guitar learning assistant on participants’ skills and experiences.

Quantitative Metrics. The quantitative metrics focused on three key areas: skill improvement, engagement, and motivation.

Skill improvement was assessed through two primary measures. The first was error rate reduction, which quantified the decrease in the number of mistakes participants made per exercise. The second was performance accuracy, evaluated through improvements in chord accuracy, scale fluency, and rhythm consistency, reflecting participants' overall technical proficiency.

Engagement metrics captured participants' practice habits. This included practice frequency, measured as the number of practice sessions completed per week, and practice duration, calculated as the average time spent per session. These metrics provided insights into how consistently and intensively participants engaged with their practice routine.

Motivation levels were evaluated using self-reported scores collected weekly through a 7-point Likert scale. These scores tracked changes in participants' motivation throughout the study, offering a deeper understanding of the emotional and psychological impact of the learning process.

Qualitative Metrics. Qualitative metrics provided deeper insights into the user experience, learning satisfaction and emotional impact. For user experience, feedback focused on the assistant's usability, helpfulness, and the perceived impact of emotional support. Learning satisfaction was assessed through participants' reflections on their progress and practice enjoyment. Emotional impact was explored to understand how the learning approach influenced participants' feelings toward practicing guitar.

7 Results and Analysis

This section presents both quantitative and qualitative analyses to demonstrate the impact of the guitar learning assistant on the participants' performance and experience.

7.1 Quantitative Analysis

The quantitative results were analyzed using independent samples *t*-tests to compare the means of key metrics between the experimental and control groups. Prior to conducting the *t*-tests, the data were tested for normality using the Shapiro-Wilk test. The results indicated that all metrics approximately followed a normal distribution (e.g., practice frequency: $W = 0.938$, $p = 0.592$ for the experimental group; $W = 0.849$, $p = 0.061$ for the control group).

Table 1 presents the comparison of skill improvement metrics between groups, while Table 2 summarizes engagement metrics.

Skill improvement was assessed through error rate reduction, chord accuracy, scale fluency, and rhythm consistency. The experimental group showed a mean error reduction of 35%, compared to 15% in the control group. Performance accuracy improved significantly in chord accuracy (40% vs. 18%), scale fluency (25% vs. 10%), and rhythm consistency (30% vs. 12%). Engagement metrics focused on practice frequency and duration. The experimental group practiced an average of 6 days per week with 45 minutes per session, compared to 4 days and 30 minutes in the control group.

As shown in Figure 4, motivation levels were evaluated using self-reported scores on a 7-point Likert scale. The experimental group showed a significant increase in motivation, with final scores increasing from 4.5 to 5.7, compared to an increase from 4.7 to 5.0 in the control group.

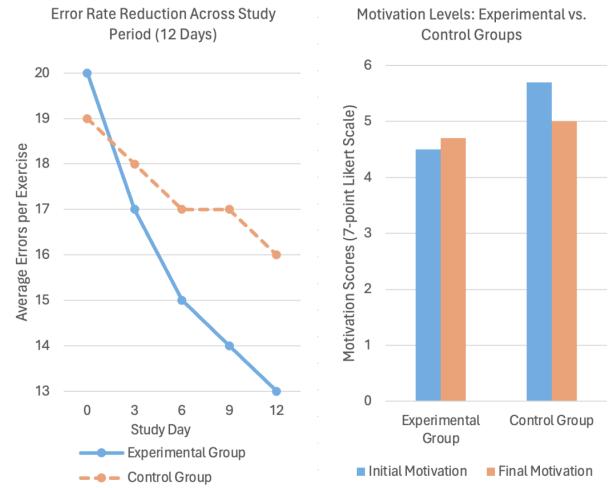


Figure 4: Motivation Levels and Error Rate Reduction: Experimental vs. Control Groups.

7.2 Qualitative Analysis

Qualitative feedback from participants further supports the quantitative findings, providing insights into the user experience and emotional impacts of the assistant.

User Experience: Participants in the experimental group found the assistant intuitive and easy to navigate, with positive comments on the seamless integration of feedback during practice.

"In the past, it was hard to know if I was making progress or repeating mistakes because there was no feedback, but now he can point out my mistakes in a timely manner, which I think is great."

Participants appreciated how ChatGPT explained their mistakes and provided actionable suggestions.

"When I made the same mistake repeatedly, ChatGPT would rephrase its feedback in a simpler way, which made it easier to understand and apply."

Learners valued the encouraging messages, reporting that emotional support reduced frustration and increased enjoyment.

"When I'm struggling with a tricky chord transition, ChatGPT's messages do sometimes give me something I want to keep practising, but I think it would be better if it was spoken to me through a more animated voice."

Learning Satisfaction: Participants in the experimental group expressed higher satisfaction with their progress and enjoyed practicing customized songs adapted to their skill level.

"Having songs tailored to my skill level made practice feel achievable yet challenging."

Participants highlighted ChatGPT's role in dynamically adapting learning paths.

"It felt like ChatGPT understood my struggles and adjusted the practice routine to help me overcome them."

Table 1: Comparison of skill improvement metrics between groups

Metric	Experimental Group	Control Group	p-value
Error Rate Reduction	35%	15%	< 0.01
Chord Accuracy Improvement	40%	18%	< 0.01
Scale Fluency Increase	25%	10%	< 0.05
Rhythm Consistency Improvement	30%	12%	< 0.05

Table 2: Engagement metrics comparison

Metric	Experimental Group	Control Group	p-value
Practice Frequency (days/week)	6	4	< 0.05
Practice Duration (minutes/session)	45	30	< 0.05

"I don't know if it's because I trust ChatGPT so much that when ChatGPT gives me some feedback I'll feel it's kinda in line with my expectations."

Emotional Impact: Participants in the experimental group appreciated the encouraging messages, reporting that emotional support reduced frustration and increased enjoyment

"The assistant's encouragement made me look forward to practicing."

"I felt like I had a personal tutor guiding me, but I don't need to worry about my embarrassment being seen when I made a mistake."

Users reported that ChatGPT's empathetic feedback played a significant role in boosting their motivation.

"Even though ChatGPT it occasionally makes mistakes or sometimes doesn't phrase things exactly right, the fact that it was able to explain why the mistake I just made happened and advise me on how to correct it made me feel good."

8 Discussion and Future Work

Our study demonstrates that the ChatGPT-powered guitar learning assistant significantly improves the learning experience compared to traditional self-guided practice. The assistant effectively addressed key challenges in guitar education by providing immediate feedback, personalized learning paths, and emotional support.

In terms of skill acquisition, participants in the experimental group showed notable improvements in error reduction and performance accuracy. The immediate feedback allowed for immediate correction of mistakes, preventing the reinforcement of incorrect techniques. This aligns with previous research [6, 37], which emphasizes that immediate feedback is crucial for improving learning outcomes, especially in motor skill development.

Engagement and motivation were also significantly higher in the experimental group. Learners practiced more frequently and for longer sessions, with the assistant's ability to provide emotional support and personalized content contributing to this increased motivation. This finding highlights the importance of emotional support in education, especially for learners practicing independently, where frustration and isolation can hinder their progress. By

offering encouraging feedback and personalized song adaptations, the assistant helped learners remain engaged and confident, even during more challenging exercises.

Another key feature was the personalized learning paths. By tailoring exercises and adapting songs to each learner's skill level, and incorporating some teaching of music theory into the process of learning this practice guitar, FretMate allows learners to learn at their own pace, balancing challenge with fun. This approach effectively prevented learners from feeling overwhelmed while ensuring steady skill development. In particular, the integration of music theory into practical lessons was highly appreciated by learners, who often find learning theory in isolation boring and difficult, but when music theory is added to the practice repertoire it can be learned deeply and easily.

Despite the promising outcomes, several limitations need to be addressed. The sample size was relatively small, and participants were self-selected, which may introduce bias. Additionally, the two-week study duration may not fully capture long-term learning trajectories or skill retention. Future studies should consider larger, more diverse participant pools and extended timeframes to better assess sustained improvements.

In terms of technical challenges, while the assistant performed effectively in many areas, the accuracy of gesture recognition and audio error detection requires further improvement, even though this was not the primary focus of the current study. Instances of incorrect feedback due to misinterpreted gestures or pitch errors occasionally occurred, indicating the need for refinement of the underlying algorithms. Future iterations of the assistant should prioritize improving the accuracy of these recognition systems, potentially by leveraging more advanced machine learning models or integrating additional data sources, such as video analysis, for better interpretation of user input.

While emotional support was beneficial, it was limited in accurately adapting to individual learners' emotional states. The current system relies on basic contextual cues, which may not fully capture learner frustration or satisfaction. Future work should explore integrating more advanced emotional recognition, such as voice tone analysis or facial expression detection, to provide more nuanced support. This could lead to more personalized emotional guidance, further enhancing the user experience.

Future developments will focus on expanding the assistant's capabilities, conducting longer-term studies, and exploring its applicability in broader educational contexts. By extending the scope to other instruments and enhancing multi-sensory inputs, FretMate can provide even more comprehensive and adaptive learning experiences. Additionally, AI-powered music learning systems, such as Piano Genie [15], demonstrate how AI can be utilized to facilitate music creation by mapping simple inputs to plausible sequences. While Piano Genie focuses on improvisation, integrating similar approaches could expand FretMate's functionality to include creative music-making, offering learners a pathway not only to technical improvement but also to artistic expression.

9 Conclusion

This study demonstrates the effectiveness of a ChatGPT-powered guitar learning assistant in addressing key challenges faced by learners, such as a lack of immediate feedback, structured guidance, and emotional support. Through immediate error correction, personalized learning paths, and motivational reinforcement, FretMate significantly enhances skill development, engagement, and learner confidence. The positive results observed highlight the assistant's potential as an impactful and scalable tool for music education, providing a holistic learning experience that combines technical precision with emotional encouragement.

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