PressurePick: Muscle Tension Estimation for Guitar Players Using Unobtrusive Pressure Sensing

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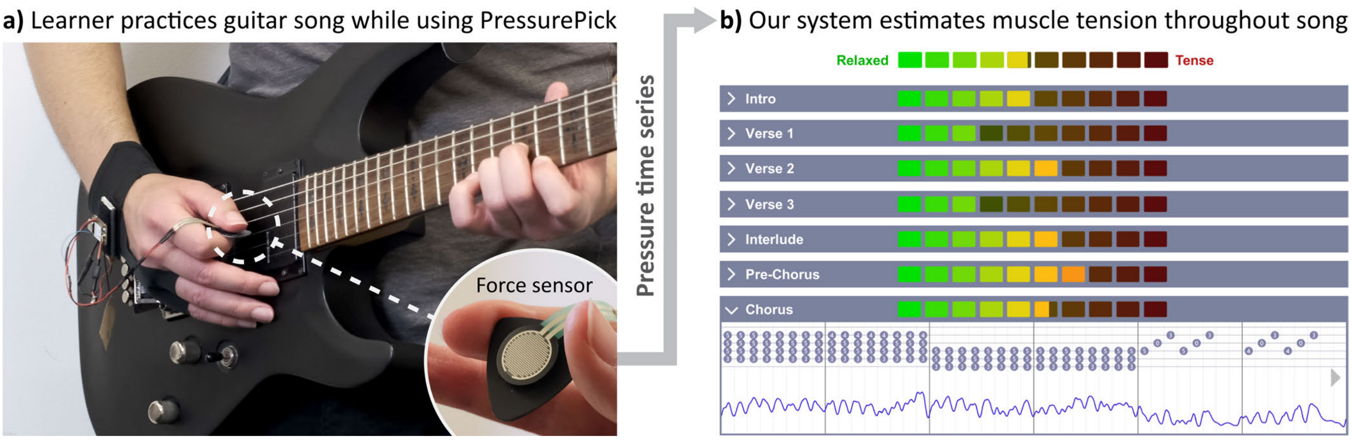

Figure 1: We present PressurePick, a wearable device that unobtrusively records pressure on a guitar pick in order to estimate muscle tension. a) First, the learner uses our PressurePick device while practicing a song. b) Based on the recorded pressure time series of the guitar pick, we estimate the learner's muscle tension. Our front end visualizes the estimated muscle tension for the whole song and for each part. In the UI, the learner can click on a part for detailed inspection.

ABSTRACT

When learning to play an instrument, it is crucial for the learner's muscles to be in a relaxed state when practicing. Identifying, which parts of a song lead to increased muscle tension requires self-awareness during an already cognitively demanding task. In this work, we investigate unobtrusive pressure sensing for estimating muscle tension while practicing songs with the guitar. First, we collected data from twelve guitarists. Our apparatus consisted of three pressure sensors (one on each side of the guitar pick and one on the guitar neck) to determine the sensor that is most suitable for automatically estimating muscle tension. Second, we extracted features from the pressure time series that are indicative of muscle tension. Third, we present the hardware and software design of our PressurePick prototype, which is directly informed by the data collection and subsequent analysis.

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CCS CONCEPTS

• **Applied computing** → *Sound and music computing*; • **Computing methodologies** → *Learning from implicit feedback*.

KEYWORDS

Guitar, muscle tension estimation, guitar pick, instrument learning

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1 INTRODUCTION

The guitar has long been present in western music and culture at large. Although musical genres not driven by the guitar have increased in popularity, acoustic and electric guitars are still capturing people's interest. Especially during the Covid-19 pandemic, many people started exploring new hobbies including guitar playing [8]. Apps and platforms can complement professional guitar lessons or facilitate learning to play the guitar as a hobby without a teacher. For instance, Yousician [33] can record the learner's performance and assess whether the correct notes were hit. However, besides the sound, there are additional important aspects when learning an instrument–like the correct execution of specific playing techniques. This is why many researchers explored using sensing technologies to automatically assess and report the learner's execution while playing [34, 35, 45]. Importantly, a learner also needs to maintain a relaxed state while practicing in order to increase the learning outcome [29] and to prevent injuries [4, 12, 29, 46]. While a guitar teacher can observe the student directly in order to remind them to relax and to possibly slow down, this type of feedback is not available when practicing between lessons or when self-teaching. Therefore, researchers have also investigated how to measure muscle tension during instrument practice in order to provide automatized biofeedback. Systems that use Electromyography (**EMG**) [5, 6, 39, 54] are very common, as the biofeedback is based on directly measuring the muscle activity. However, since EMG can be cumbersome to set up and challenging to analyze, researchers investigated other means of providing biofeedback by using sensors, such as accelerometers and pressure sensors. Those approaches are less obtrusive and often specialized for the instrument [20, 23, 24, 26, 36, 43]. For these instrument-specific setups, it is crucial to understand the patterns generated by the sensors and how they are related to increased muscle tension.

In this paper, we present an approach for estimating a guitar player's muscle tension based on unobtrusive pressure sensing[1]. In our data collection with twelve participants, we recorded the pressure that participants exerted on the guitar neck as well as on both sides of the guitar pick using Force Sensing Resistors (**FSR**s). From the data, we identified the features that are most useful for estimating subjective muscle tension. Based on this, we present the PressurePick prototype that integrates pressure sensing in its hardware (Figure 1 a). Our front end (Figure 1 b) allows learners to practice a song and receive automatized feedback about their muscle tension levels for each of the song's parts[2]. The PressurePick device as well as the muscle tension estimation method used in the front end are directly informed by the results of the data collection. Taken together, we contribute:

- A data collection containing various distinct electric guitar exercises, from which we extracted a data set of pressure time series together with subjective muscle tension ratings.
- An analysis of the data to identify the best features and models for estimating perceived muscle tension.
- A wearable device called PressurePick and a front end to demonstrate automatized muscle tension feedback for guitar learners.

2 RELATED WORK

Using technology for learning instruments has been a topic within different research communities. One focal point within HCI is to make the instrument learning process more visual and engaging. Example interfaces range from conventional screen-based UIs [55], to tutorial systems based on Augmented Reality [10, 31, 32, 41, 48]. While those output-focused and visually rich interfaces have been proven effective for learning and practicing without supervision as well as to internalize music theory, an often overlooked aspect in such systems is the learner's state of relaxation to avoid wrong muscle memory or even negative health effects [4, 12, 29, 46]. Within musical interface research, e.g., the *New Interfaces for Musical Expression* (NIME) community, many researchers have investigated the use of pressure sensing or other implicit input to build models that detect high levels of muscle tension. In this section, we discuss works from both fields. We first focus our attention on previous methods and systems for measuring the learner's state of relaxation and biofeedback (using EMG or alternative sensing methods). Then, we discuss previous sensing systems that focus on augmenting the performance of musicians.

2.1 EMG-based biofeedback

Measuring muscle tension has been a research interest for a long time–also with use cases other than learning instruments [1]. As early as 1969, Budzynski and Stoyva [5] built an analogue feedback system to achieve deep muscle relaxation. Their system continuously tracked the muscle action potential in subjects and gave auditory feedback in the form of a tone which varied in pitch. The results indicate a 50% mean decrease of muscle tension when using biofeedback. Even though they did not focus specifically on musical performance, the goals are closely related to ours and their results indicate the effectiveness of biofeedback in general. Many works that followed and focused on musical instrument learners also used EMG as the primary means of implicit input [6, 54], as this is a direct way of measuring muscle tension.

It is particularly common to use *surface* EMG (**sEMG**) as it only requires electrodes attached to the skin without direct muscle contact. For instance, Cattarello et al. [6] measured the muscle activity of 17 violin players (in addition to force sensors on the instrument) while playing specific notes. Morasky et al. [38] investigated muscle tension in the left forearm extensors of string instrument players. Subjects had EMG electrode sets placed on their forearms and performed a series of musical exercises on their instruments, while the system played a tone whenever EMG levels exceeded 90% of pretest mean levels. The results indicated reduced muscle tension. To test whether the positive effects generalize to no-feedback scenarios, Morasky et al. [39] compared EMG levels measured in the forearm extensors of clarinet players performing exercises on their instruments. They divided participants into two groups. The first group used conventional practice and the second group utilized biofeedback. Alterwards, all participants of both groups played the instrument without biofeedback. Participants, who practiced with biofeedback before (the second group) showed decreased muscle tension (even when not receiving biofeedback anymore) compared to participants who practiced conventionally. Similarly, the results of Cutietta [9] showed that feedback training was sufficient to reduce muscle tension during performance in many cases. They further showed that lowered levels were maintained one week after training. Karolus et al. [25] use a small number of electrodes with a relatively simple setup to assist the guitar learning process by adjusting the tempo depending on the muscle tension.

While our solution does not utilize EMG, previous research that used EMG showed the effectiveness of biofeedback for instrument performance in general.

[1]In this paper, we use 'Force' and 'Pressure' interchangeably even though they have different meanings.
[2]We use excerpts from the guitar melody of *Wake Me Up When September Ends* by Green Day (Warner Music) as examples for showcasing the front end

2.2 Alternative sensing methods

Even though sEMG setups are not as invasive as intramuscular EMG, accurate medical devices can still be cumbersome and expensive, especially with *high-density* sEMG setups that use matrices of many electrodes instead of individual pairs. Furthermore, professional devices require expertise and a dedicated operator. Even setting up only few electrodes [25] can reduce spontaneity when practicing at home. Hence, researchers also investigated low-cost unobtrusive alternatives for automatically assessing different aspects of performance [20, 23, 24, 26, 36, 43] in order to enable everyday-use without complicated setups [17].

The most related commercial product is *Pickatto* [42], which fully integrates a pressure sensor and wireless transmission into a guitar pick. The two purposes of the device are counting plucks (to facilitate practicing with the picking hand) and measuring pressure levels to warn learners when they squeeze the pick too hard[3].

Specific sensor setups can not only measure muscle tension, but also other indicators of performance or even stage fright [28]. Grosshauser et al. [18] equipped a violin and the bow with sensors to analyze whether the (asymmetric) tasks of the two hands are executed synchronously. *LetsFrets* by Marky et al. [34] uses LEDs along the frets as guidance (similar to the *Fretlight* guitar series [27, 49]). In addition, their prototype enables the accurate capture of finger positions via integrated, 3D-printed touch sensors to adjust the feedback based on the performers input. Similarly, Guaus et al. [21] used aluminium foil attached to the frets to detect different playing techniques. Shin et al. [47] approached the problem of detecting which string was played by placing piezo sensors in the saddle of the guitar to sense the vibration of the strings. Matsushita [35] developed a system that estimated the wrist's angular velocity while playing the rhythm of heavy metal songs. This approach provided accurate picking timing information and enabled beginner-level participants in a user study to significantly increase their down-picking speed. Grosshauser [16] measured the absolute pressure on the bow of a violin to provide visual feedback. Later, Grosshauser and Tröster [19] attached sensors to various instruments (violin, acoustic guitar and piano) in order to sense the finger position and the exerted pressure. Reboursière et al. [44] attached several sensors to an electric guitar to detect the current playing technique. Their aim was to detect a wide range of techniques (including palm muted, bend, slide and so on) using audio signals (one channel per guitar string using commodity RMC pickups). Subsequent research showcased how playing techniques can even be recognized from a single recorded audio track [7, 50], meaning that the guitar does not need to be equipped with additional pickups.

2.3 Augmenting instrument performances

Equipping instruments with sensors can not only be useful for unobtrusive performance measurements, but also enhance the performance itself. Often times, those two purposes (assessing performance and augmenting performance) go hand-in-hand when using sensors [37]. For instance, Frisson et al. [15] defines the purpose of physically enhancing instruments along two axes: adaptive learning (as previously discussed) and augmenting guitar performances. The latter is a not a goal of our work. However, some of the previous works that aim to augment performances are nevertheless relevant because of their sensor setups. *Magpick* by Morreale et al. [40] is a guitar pick that can sense the motion relative to the electric guitar by using electromagnetic induction. This extra input can be used to subtly manipulate the sound generated by the performer (e.g., manipulating the volume for a tremolo-like effect). Many previous works enhanced a guitar pick similar to our device. Yoshida and Matsuyama [56] attached a pressure sensor to a guitar pick and an IMU to a ring around the index finger. They implemented a heuristic for classifying playing techniques. They did not focus on biofeedback and instead used the real-time data for generating live visualizations matching the guitar performance. The *MIDI pick* by Vanegas [52] aims to replace the guitarist's foot pedal, making it possible to switch modes with the pick instead. Vets et al. [53] enhanced the pick and the guitar strings with sensing capabilities to sense motion, gestures and more for live performances.

Augmenting the guitar performance is an inherent additional capability enabled by sensors. While the physical design of our PressurePick prototype is related to such works and our device could in principle support simple augmentations, our work revolves around estimating muscle tension.

[3]At the time of writing, the Pickatto product is not released, i.e., there is limited information about the exact capabilities.

2.4 Summary and positioning in literature

Previous research showcased the effectiveness of biofeedback, but many approaches require sophisticated setups. Indirectly measuring muscle tension, e.g., via pressure sensing, is a promising approach for providing feedback to learners in an unobtrusive way. Equipping a guitar or a guitar pick with pressure sensors has the potential of detecting inappropriate amounts of muscle tension. However, we need to understand the patterns emerging in the pressure time series and in which way they can be indicators for muscle tension. This also includes understanding how the employed technique and the number of strings being hit (single strings, chords etc.) changes the way in which the signal needs to be treated. Building upon prior knowledge from music-performance research, we focus on an unobtrusive solution for estimating muscle tension when playing the guitar. Some of the previous works discussed in this section directly inspired our approach. Others are focusing on aspects of instrument learning orthogonal to our pressure-based approach (e.g., previous research based on motion sensing or audio processing). Thus, our solution can be complementary to many previous guitar learning interfaces.

3 DATA COLLECTION STUDY

We first conducted a data collection as a basis for our analysis, which had three goals: (1) Find out, which pressure sensing location (guitar neck or guitar pick) yields the most promising signal. (2) Investigate, what patterns emerge in the pressure time series when playing the guitar. (3) Identify the features in the pressure time series that are most suitable for estimating muscle tension.

We equipped the neck of an electric guitar and a guitar pick with pressure sensors. Using this setup, participants did twelve exercises and played three songs. After each exercise, participants provided a subjective muscle tension rating. The study was approved by the local ethics commission of ETH Zürich.

3.1 Participants

We recruited participants via word of mouth and flyer advertisements on the university campus, as well as at instrument stores and music schools. The main requirement for participation was to have at least basic guitar skills and being able to use a guitar pick. Concretely, participants had to be able to play the most common open chords and basic strumming patterns. Furthermore, participants had to be familiar (though not necessarily proficient) with the hammer-on and pull-off techniques and had to be able to play the standard E- and A-shaped bar chords. In total, we recruited 12 participants (1 female). Their age ranged from 22 to 35 ($M = 26.3$). All participants played the guitar right-handed (one participant was left-handed, but was able to play the guitar right-handed).

3.2 Apparatus

We provided a *Fender Stratocaster*, which is a common electric guitar design and a *Dunlop Max Grip 1.0* guitar pick. We video-recorded the session with a camera that pointed to the guitar (i.e., without capturing the participant's face).

Our sensor setup consisted of three FSRs in total (Figure 2). One was a strip (*SF15-600*), attached to the back of the guitar's neck. It measured the pressure the participant's left hand applied to the instrument (Figure 2 top). We attached two circular FSRs (*Bolsen Tech FSR402*, about two centimeters in diameter) to both sides of the guitar pick (Figure 2 bottom). All FSRs were connected to an ESP32 micro-controller, which streamed the sensor values to a PC.

The guitar was connected to a *Focusrite* digital audio interface, which in turn was connected to the PC to record the electric guitar without the need for an amplifier or specialized microphones. Connected to the digital audio interface, headphones allowed the participants to hear the sound they produced with the guitar while playing, as well as a metronome.

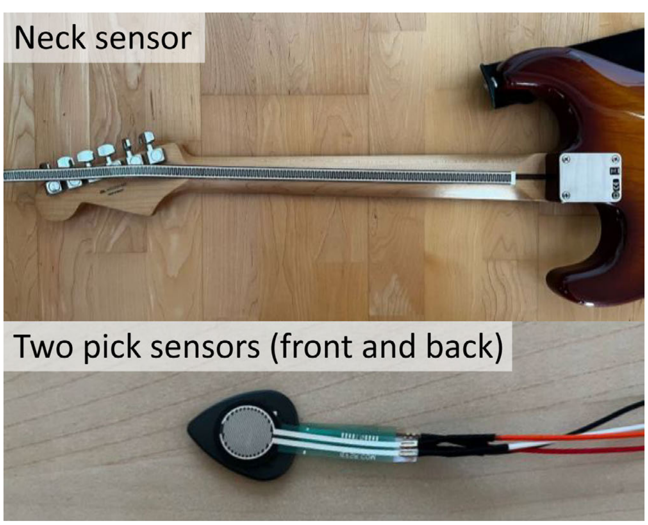

Figure 2: Sensor arrangement of our data collection. Top: A long FSR strip along the neck of the guitar. Bottom: Two circular FSRs attached to a guitar pick (front and back).

3.3 Procedure

The experimenter greeted the participant and explained the purpose of the study. The participant filled out a consent form and had the opportunity to ask questions. Afterwards, the participant filled out a pre-questionnaire containing questions about demographics and previous experiences with the guitar. Each experiment session lasted for about 90 minutes and consisted of two blocks.

3.3.1 Block 1: Exercises. We designed three types of exercises with each type containing four exercises, leading to a total of twelve exercises. All exercises of this block are showcased in *Video Figure A* in the supplemental materials and described in the following.

Picking exercises. Exercises 1 to 4 focused on hitting single strings using two different picking techniques. In general, with down-picking (**DP**), the guitarist plays every note by striking the guitar string in a downward motion. With alternate-picking (**AP**), the guitarist alternates between hitting the string in a downward motion and an upward motion. The participant played each technique while hitting the same string versus switching between two adjacent strings. In sum, the picking exercises were:

E1: DP on the same string
E2: AP on the same string
E3: DP on two adjacent strings
E4: AP on two adjacent strings

Chord strumming exercises. Exercises 5 to 8 consisted of playing a common progression of open chords (G C D), a simple progression of power chords (F Bb G# C#) with two strumming techniques, and an unusual progression of bar chords (Gm C A Dm). For the open chord, the participant used alternate-strumming (**AS**), which, analogous to AP, alternates between down-strokes and up-strokes when playing the chords.For the power chords, participants used both, alternate-strumming and down-strumming (**DS**). Lastly, the bar chords were played with AS. In sum, the chord exercises were:

E5: AS with open chords
E6: DS with power chords
E7: AS with power chords
E8: AS with bar chords

Hammer-on and pull-off exercises. Exercises 9 to 12 involved only the left hand. With hammer-on and pull-off (**HOPO**), a guitarist plays notes by hammering onto and pulling off from the guitar string with any finger of their fretting hand, the thumb excluded. For the HOPO exercises, the participant used their index finger as an anchor, leaving the middle, ring and little finger free to perform the technique. Specifically, the exercises of this type were:

E9: HOPO with the middle finger
E10: HOPO with the ring finger
E11: HOPO with the little finger
E12: HOPO with cyclical use of the middle, ring and little finger

The participant had to perform each of the twelve exercises for two cycles of three different tempi, leading to six *sections* per exercise (120 BPM → 150 BPM → 180 BPM → 120 BPM → 150 BPM → 180 BPM). The tempo was indicated to the participant via a metronome track heard through headphones. The participant was instructed to play eighth notes, i.e., they hit one note on the metronome click and one in between two clicks. Each section lasted

20 seconds. After completing an exercise, the participant rated their perceived muscle tension for each of the six sections on a scale from 1 (low tension) to 10 (high tension).

Instead of explaining all exercises at once, the experimenter provided instructions for each exercise right before it started. During the whole block, we configured the system to apply no effects to the output signal of the guitar (e.g., no distortion or reverb).

3.3.2 Block 2: Free-playing. After the structured exercises concluded, the participant was asked to play three songs (or sections of songs) of their choice, each between one and two minutes in length. During recruitment, they were encouraged to think about which songs they wanted to play. The songs were required to match the following descriptions:

(1) Easy song: The participant can play this comfortably, and mistakes are very unlikely to occur.
(2) Medium song: This song displays the participant's current skill level, and a few mistakes are likely to occur.
(3) Difficult song: This song is slightly beyond the participant's current skill level, and mistakes are very likely to occur.

The following guidelines applied to the choice of songs:

- The participant needed to be able to play the song with a guitar pick on a 6-string electric guitar.
- As opposed to the first block, the participant could choose to play with a distorted or high gain sound, as well as some reverb if they wished. We used the audio workstation *REAPER* [22] to apply the effects to the output. However, tonal effects were limited. If a song relied on more elaborate effects, the participant was instructed to chose a different song.
- Using a capo was not possible.
- Changing the tuning of the guitar (e.g., Drop-D) was allowed.

3.3.3 Post-questionnaire and end of session. After both blocks concluded, the participant was asked to reflect on whether they encountered any states of high muscle tension while they were performing the exercises or the songs. Additionally, they were given the option to express any closing thoughts they might have had. This also included possible thoughts about the twelve exercises or the apparatus (e.g., in terms of intrusiveness). After the study concluded, the participant received a small assortment of guitar picks as a gratuity for their time and was then dismissed.

4 DATA ANALYSIS

The main goal of the data collection was to gather an understanding of the relationship between pressure patterns and subjective muscle tension. This also entails understanding the pressure patterns depending on the number of strings hit in one motion and the technique. The free-playing block allowed us to visually inspect the pressure signals recorded while playing songs. All plots of both blocks can be found in the supplemental materials. The majority of our analysis revolved around Block 1, which contained the twelve structured exercises. We pre-analyzed our data by first inspecting it visually and by calculating descriptive statistics. We then identified the sensors and features that are most promising for estimating muscle tension. This section reports the different steps and the results of our analysis.

4.1 Previous guitar experiences of participants

We first summarize the responses of the pre-questionnaire about the participants' previous experiences. We report descriptive statistics using mean (**M**), median (**m**), and standard deviation (**SD**). The participants' playing experience ranged from 5 to 18 years ($M = 11.8$, $SD = 4.5$). The average playing time per week in the last three months ranged from 30 minutes (or less) to 8 hours ($M = 3.6$, $SD = 3.2$). On a scale from 1 (beginner) to 10 (expert), participants rated their skill level between 2 and 7 ($m = 5.5$). The responses of the most relevant pre-questionnaire items can be found in Table 1.

4.1.1 Previous muscle tension experiences. We specifically asked participants to comment on their previous experience with muscle tension. Except for Participants 8 and 9, all participants reported that they generally experience muscle tension to different degrees. Participants 2, 5, 7 and 10 reported the most common muscles to get tense to be those in their left hand involved in playing bar chords and power chords, specifically the muscles in their thumb and index finger. Participant 3 has also experienced tension in their left hand when playing chords with wide finger placements. Participant 12 stated that high muscle tension in their left hand was most likely to arise while they used hammer-on and pull-off techniques. Participant 2 states that, whenever feasible, they substitute bar chords with other fingerings of the same chords which require less force in order to alleviate tight muscles. Participant 3 has encountered muscle tension in the elbow region of their right arm while Participant 4 faces tightness in their right hand when they are focusing very intently. Participant 6 initiates the picking movement with the thumb and index fingers (pinching motion) of the right hand instead of with their wrist. This causes the participant to feel tense in the thumb of their right hand. Strategies to deal with tension employed by most participants include shaking the hands, massaging the muscles, and playing something less taxing for the muscles.

Participant	Years exp.	Time / week	Skill est.	Tension
1	5	45 min	3	2
2	18	4 h	7	3
3	6.5	2.5 h	7	6
4	5	6 h	7	6
5	15	1 h	4	2
6	13	< 30 min	6	3
7	13	2 h	6	3
8	15	< 30 min	2	1
9	10	8 h	4	1
10	16	< 30 min	5	4
11	17	8 h	7	7
12	6	30 min	5	5

Table 1: Previous experiences of participants. 'Years exp.' refers to the number of years that the participant played the guitar. 'Time / week' is the average aggregated weekly practice duration. 'Skill est.' is the estimated skill of the participant (self-assessed), ranging from 1 (beginner) to 10 (expert). 'Tension' is the regularity of uncomfortable muscle tension when playing, ranging from 1 (never) to 10 (very often).

4.2 Pressure patterns on the guitar pick

Before investigating muscle tension estimation, we visually inspected and pre-analyzed the patterns in the pressure time series that emerge depending on the number of strings that are hit (e.g., single strings versus chords) and the playing technique (e.g., down-picking versus alternate-picking). As a representation of typical pressure time series, Figure 3 shows the raw pressure data of a test recording with the two pressure sensors that are attached to the pick. The figure shows different combinations of techniques (DP & DS versus AP & AS) and numbers of strings (1, 3 or 4).

All pressure patterns are oscillating in multiples of the beats per minute. When comparing down-picking and alternate-picking (or down-strumming and alternate-strumming), a large difference can be seen in the oscillation patterns. In the case of DP & DS, the pressure increases when approaching the string and is lower between hits (Figure 3 left). Our frequency analysis across all DP & DS data points indeed identified the number of eighths hit per second as the most dominant frequency. In contrast, AP & AS exercises led to frequencies that are half as high as the frequencies of the DP & DS exercises. This difference in mean is statistically significant with a $p < 0.0001$ according to a Wilcoxon signed rank test. This can also be seen in Figure 3 with a single oscillation roughly taking up two hits in the AP & AS examples. However, there was more variation in the frequency spectrum (7.19 Hz versus 5.48 Hz, respectively). While the high-frequency oscillations are still present when the individual strings are hit, it is clear that down-strokes and up-strokes cannot be treated in the same way when analyzing the performance. As a side effect, this clear difference also implies that, while down-strokes and up-strokes generate almost the same sound, the pressure time series can likely be used to distinguish between those techniques in many cases.

Based on our recordings it seems like the pressure sensors are precise enough to capture the moments in which every individual string is hit. Specifically, small high-frequency oscillations corresponding to the number of strings hit can be seen in the plots of Figure 3. While this can be a useful signal for various purposes (e.g., estimating number of strings hit), those high-frequency oscillations do not serve a purpose for our goal of estimating muscle tension. Therefore, we use a low-pass filter on all signals in order to focus on the lower-frequency oscillations. The smoothed signal is also visualized in our front end (e.g., Figure 1 right).

Another observation is that the base pressure (or mean) does not necessarily increase depending on the number of strings that are hit (i.e., single strings versus chords). In fact, in our data, the amplitude of the oscillation decreases as more strings are hit at once. When hitting a chord (**E5** - **E8**), the average oscillation amplitude is lower compared to hitting a single string (**E1** - **E4**). This difference in mean is significant with a p-value smaller than 0.05 (Wilcoxon signed rank test).

The pressure patterns of the two sides of the pick are very similar, yet not fully identical. This was also reflected in the collected data. Across all collected samples, we observed a cross-correlation of 0.77 between the signals of the two pressure sensors on the pick. This provides a first indication that a second pressure sensor on the pick does not add much information compared to a single sensor. We evaluate this in more detail later in subsection 4.5.

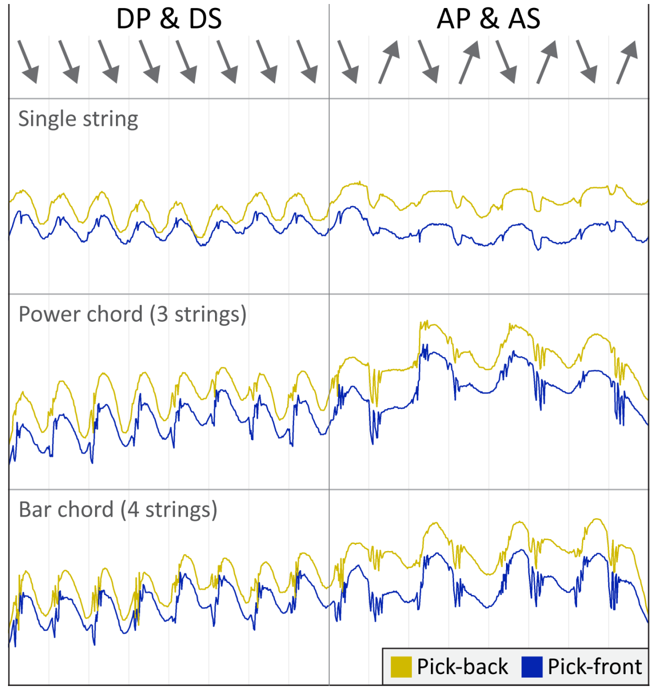

Figure 3: Pressure time series on the two sensors of the pick to visually compare down-picking and alternate-picking (or strumming in the case of chords) each with 1, 3 or 4 strings hit. The x-axis is time and the y-axis is pressure in all plots.

We also observed oscillations and vibrations with varying amplitudes in the data of the pick sensors during the HOPO exercises, even though the pick hand was technically inactive. Upon video inspection, those can be explained by participants tapping to the beat or small movements of the guitar when performing HOPOs. Interestingly, for some participants who held the pick firmly while performing the HOPOs, we observed a slight increase in pressure over time as the exercise became more demanding for the left hand. Therefore, there are indications that a pick sensor can be used for measuring tenseness during HOPOs. However, since participants did not hold the pick persistently during the HOPO exercises, a dedicated data collection would be needed to confirm this effect.

4.3 Base pressure and subjective ratings

There were individual differences in terms of base pressure levels and variation. Figure 4 shows the box plots of the mean pressure of the pick's front FSR for all exercises and tempos for each participant together with the variation in the pressure signal. This is not surprising as similar individual differences were also found in previous works, particularly works that found individual muscle activation differences with sEMG [6, 13, 25].

Figure 5 shows how the standard deviation of the peaks relates to subjective muscle tension ratings for the different BPM in **E1**. Within each play speed, we observed an almost identical relationship to subjective muscle tension ratings. This indicates that the variation in the amplitude of oscillation peaks is likely linked to muscle tension ratings and not just the BPM.

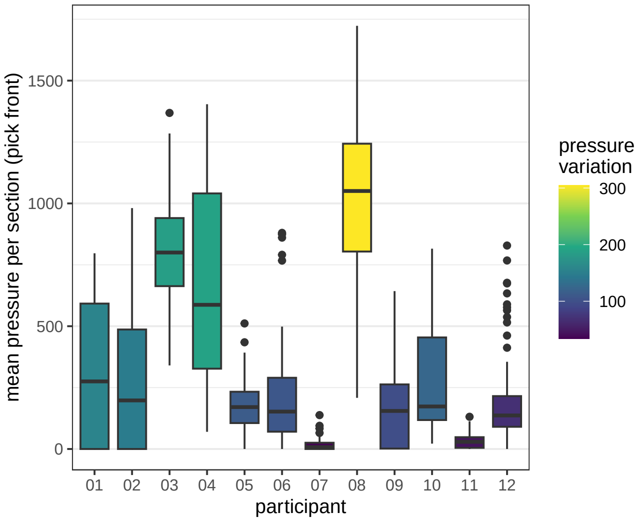

Figure 4: The distribution of pressure per participant recorded from the pick's front sensor across all exercises. The box plots are colored based on the average standard deviation of the pressure signal in each section per participant.

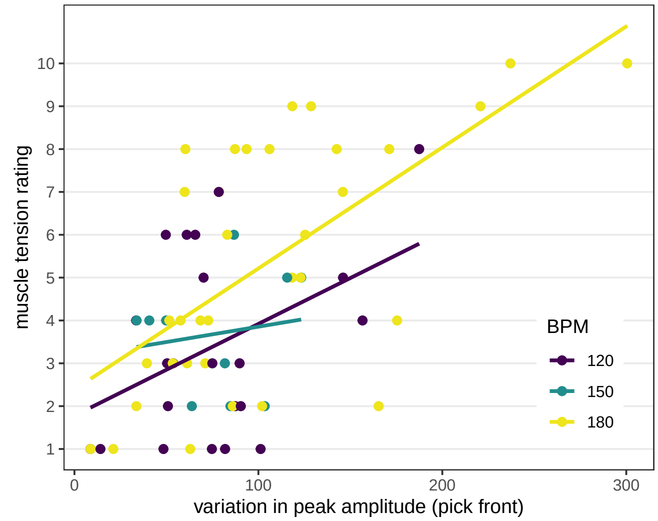

Figure 5: SD of pressure peaks (variation) against muscle tension ratings at three different tempi for the first exercise (DP on one string) across all participants. The trend lines within each tempo (BPM) indicate that sections with increased variation tended to have higher muscle tension ratings.

4.4 Feature extraction

A simple global pressure threshold or integral cannot be used to assess muscle tension because (1) there were individual differences in the base pressure, and (2) the pressure peaks depend on the number of strings that are hit. Therefore, we need to identify different features that can estimate muscle tension and general performance. We computed the following four features for all three sensors (pick-front, pick-back and neck) in each exercise section.

- M: Mean pressure
- SD: Variation in amplitude at the peak of an oscillation
- Δ SD: Variation in the pressure difference of the valley to the consecutive peak of an oscillation
- M+SD$_n$: The variation in oscillation peaks after normalizing the pressure signal (dividing by the maximum to make them lie between 0 and 1) plus the mean amplitude of peaks (to incorporate base pressure levels).

4.5 Estimation models

Since we cannot assume linear relationships between the measured FSR signals and the subjective muscle tension ratings, we need to choose a model that can handle nonlinearities. We use Proportional Odds Logistic Regression (**POLR**) to assess the explanatory power of the four features. Compared to standard regression techniques, POLR (a generalized linear model) does not assume a linear relationship between the different levels of muscle tension. For ordinal responses, POLR models are a common choice and preferable over many (non-linear) regression techniques [2, 3], because POLR models do not make assumptions about the spacing between the response levels. Cut-off points are optimized as part of the fitting process. Hence, with their simplicity and flexibility to model ordinal data, POLR models perform well for ordered categorical responses and often outperform more complex regression techniques [2].

For each combination of sensor, feature and exercise, we fitted a model across all participants and calculated the explained variance as the squared Pearson correlation coefficient between fitted muscle tension ratings and true muscle tension ratings. The explained variance ($R^2 \in [0, 1]$) indicates how much of the variation in muscle tension ratings is captured by the structural part of the POLR model [11]. A higher R^2 indicates a stronger correlation between predictions and true observations. In the following, we discuss the results shown in Table 2, which contains the model performance in terms of explained variance of the four features with each of the three sensors in each exercise.

We observe that for five of the picking or strumming exercises, one of the four feature combinations achieves to explain more than 10% of the variance in subjective muscle tension ratings for at least one of the three sensors. In **E1**, 40% of the variance in muscle tension ratings is explained with M+SD$_n$. The sensor located at the front of the pick achieves or matches the best performance in seven out of the twelve exercises, and performs best for all picking exercises (**E1**–**E4**). Notably, mapping the mean pressure (M) to model muscle tension ratings is always outperformed by a model using an alternative feature. The feature M+SD$_n$ achieves or matches the best performance for **E1**, **E4**, and **E6** (see Table 2). The feature Δ SD, however, achieves or matches the best performance for **E2**, **E4**, **E5**, and **E6**. The neck sensor generally performed worse than any of the pick sensors and some sections of time series had to be removed when fitting the model, as the pressure signals were too weak. The tension in **E8** was generally challenging to estimate even with the neck sensor, which supposedly receives most pressure in this exercise. Only in **E5** (open chords) and **E8** (AS bar chords) did it outperform the pick sensors, but it is only marginally better than the second best model in both cases. We conclude that the pick sensors generally performed best for estimating muscle tension.

	Pick-front (thumb)				Pick-back (index finger)				Guitar neck			
	M	SD	Δ SD	M+SD$_n$	M	SD	Δ SD	M+SD$_n$	M	SD	Δ SD	M+SD$_n$
E1: DP single	0.09	0.3	0.31	**0.4**	0.06	0.12	0.27	0.1	-	-	-	-
E2: AP single	0.03	0.15	**0.17**	0.16	0.08	0.09	0.15	0.1	-	-	-	-
E3: DP adjacent	0.04	0.1	0.07	**0.21**	0.06	0.09	0.19	0.19	-	-	-	-
E4: AP adjacent	0.07	0.03	**0.09**	0.07	0.01	0	0.03	0.03	-	-	-	-
E5: AS open chords	0	0.12	0.03	0.25	0.02	0.16	0.16	0.07	0	0.2	**0.26**	0.18
E6: DS power chords	0.02	0.03	0.04	**0.06**	0.02	0.04	**0.06**	**0.06**	0.03	0	0.04	0.04
E7: AS power chords	0	0.05	0	0.09	0	0.15	0.02	**0.21**	0	0	0.02	0
E8: AS bar chords	0.03	0.06	0.04	0.04	0.03	0.03	0.08	0.05	0	0	**0.09**	0.02
E9: HOPO middle	0.12	**0.26**	0.06	0.17	0.04	0.09	0.1	0.24	0.04	0	0	0.02
E10: HOPO ring	0	0	0	0.07	0	**0.19**	0	0.12	0	0.02	0	0.09
E11: HOPO pinky	0	0.05	0.09	0.16	0.09	0.05	**0.35**	0.15	0.13	0.09	0.07	0.1
E12: HOPO multi	0.14	**0.4**	0.28	0.37	0.12	**0.4**	0.27	0.27	0	0.05	0.16	0.02

Table 2: Models with different combinations of features with each of the three pressure sensors. Bold numbers indicate models that worked best for the respective exercise (sometimes multiple for the same exercise). In the first four exercises (picking) the neck sensor did not receive enough pressure (denoted as dashes in cells). The pick sensors provided signals in many cases within the HOPO exercises, but the pick was technically not part of those exercises. Hence, those cells are grayed out.

5 FINAL PROTOTYPE

Based on the findings from the analysis of our data collection, we created the PressurePick prototype device and a simple guitar tutorial front end specifically for muscle tension estimation (Figure 1). We encourage the reader to watch the supplemental video to see the final prototype hardware and software in motion.

5.1 Device

Figure 6 shows our final prototype device. As reported in the data collection, the pressure time series on the pick can be used to estimate perceived muscle tension. Furthermore, the two pressure sensors on the pick that we used in the data collection provide very similar signals. As shown in the data, the pick sensors provided more reliable models for most techniques compared to the neck sensor. For those reasons, we only use a single pressure sensor on the pick without attaching a sensor to the guitar.

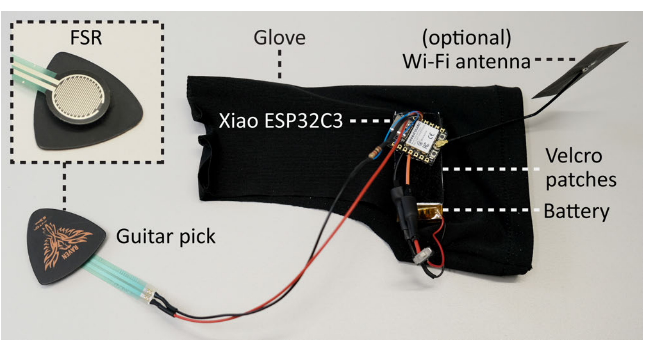

Figure 6: Hardware of our PressurePick prototype device. We use an FSR on the guitar pick. The remaining components are attached to a drawing glove (all fingers exposed). A battery can be attached between the glove and the device (when using the device wirelessly).

Instead of integrating all electronic components into the pick, we aimed to minimize changes to the weight and form factor of the pick. Therefore, only the pressure sensor is attached to the pick and all other components are attached to a glove. We repurposed a *Wacom* drawing glove (leaving the thumb and fingers exposed) to make the prototype wearable. To easily attach and detach the components, we sewed Velcro to the glove. We connected the pressure sensor to a small *Xiao ESP32C3*. The micro controller can transmit the pressure time series data via a serial USB connection, via Wi-Fi, or via Bluetooth Low Energy (BLE). A battery with Velcro on both sides powers the device when untethered.

5.2 Software

The software part of our prototype allows to record performances of specific songs in order to estimate and visualize the muscle tension.

5.2.1 Song format. Our prototype is based on guitar tabs (or 'tablatures'), which is a common notation for the guitar parts of songs. For instance, various websites allow musicians and hobbyists to upload tabs so that they can be used for practicing interactively (e.g., *Ultimate Guitar* [30]). Tabs directly communicate which strings to push down at which fret and at what time. Another advantage compared to sheet music notation is that they uniquely specify, on which string to play a note (on the guitar, the same notes can be played on multiple strings except for very low or very high notes). More concretely, for sequences of notes, it is fully specified in the tabs when the same string is hit multiple times and when different strings are hit. This can be advantageous in the analysis, as pressure patterns differ when hitting the same versus different strings.

Our software also supports 'stress accents', e.g., notes or chords, which are supposed to be played louder and hence with more pressure. For instance, parts of the fourth bar in the 'Bridge' of Figure 7 are marked as accents (those tabs are darker than the rest). Defining accents ensures that playing some notes and chords intentionally louder is not penalized when analyzing the variance in pressure.

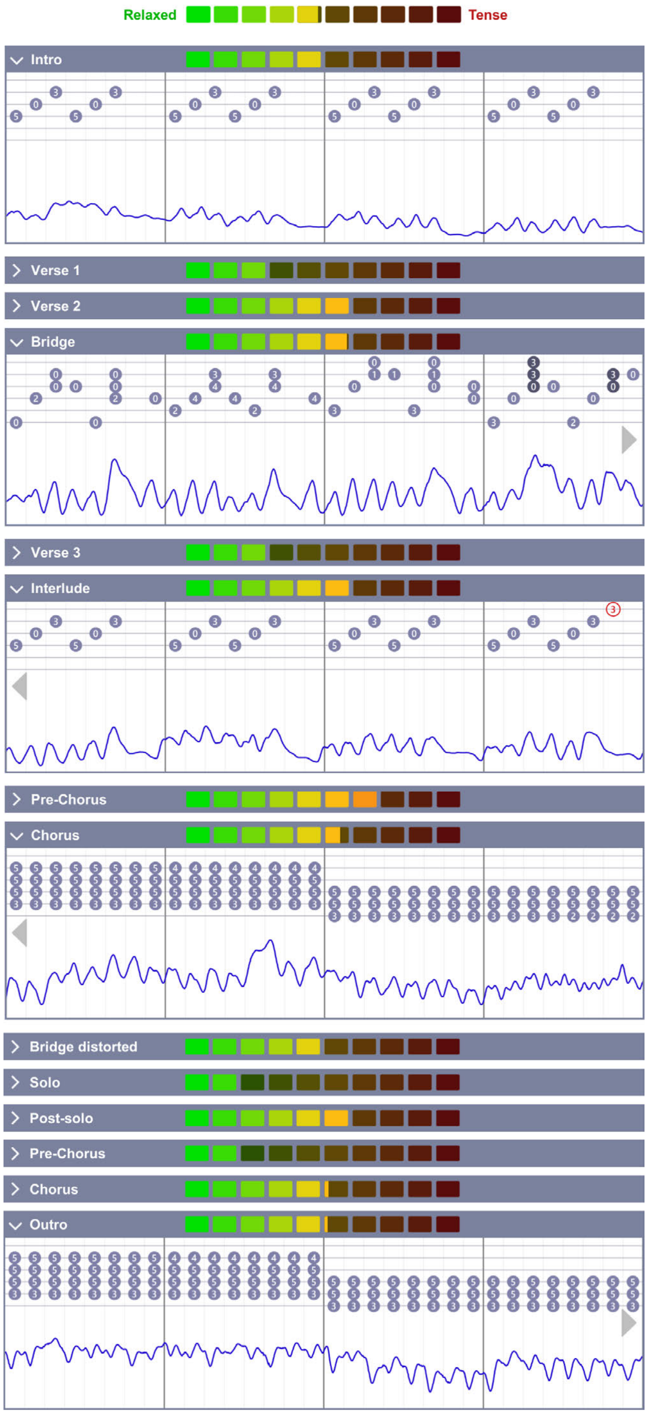

Figure 7: The user interface of our prototype. The top shows the overall estimated muscle tension ranging from green (Relaxed) to red (Tense). We also visualize the estimations for each part of the song. In addition, each song part can be expanded to closely inspect the recorded pressure time series synchronized with the tabs of the song. Red circles in the tablatures indicate missed notes. For instance, the last hit of 'Interlude' is detected as missing.

5.2.2 User interface. After the learner is done playing, the system analyzes the pressure time series and generates visual feedback (Figure 7). As high-level feedback, the front end displays the overall estimated muscle tension throughout the song (Figure 7 at the very top). A number from 1 to 10 indicates the overall estimated muscle tension, where 1 means almost no tension (relaxed) and 10 means very high tension, meaning that the lower the number, the better. The front end visualizes this number using 10 boxes arranged from left to right with the number of filled boxes corresponding to the estimation. Additionally, the boxes form a color-gradient ranging from green (left-most box) to red (right-most box).

Besides the overall estimation, every part contains a separate muscle tension estimation (in the same format as the overall estimation). The reason is that it is often the case that some song parts lead to more muscle tension than others. Sometimes the same repeated part even can have different muscle tension levels depending on where in the song it reoccurs. For instance, a part can be easy to play the first time, but as tension builds up throughout the song, there could be a different level of muscle tension the second time the same riffs are played.

Each part can be expanded by clicking on it (e.g., 'Intro' and 'Chorus' in Figure 7). This reveals the tabs and the plots of the smoothed pressure time series, making it possible to inspect each individual hit. Furthermore, if there is no peak detected even though there is a note in the tabs, the front end flags the note as a missed hit (e.g., at the end of 'Interlude' in Figure 7).

The muscle tension output can be interpreted as the estimated subjective answer that the learner would give when reflecting upon muscle tension when playing. In addition, they could be interpreted as their general pressure consistency. This means that using the muscle tension feedback together with the low-level plots, learners can monitor their progress in terms of consistency when playing.

5.2.3 Implementation. We used the Velt Framework [14] for the overall dataflow and the UI. To create the muscle tension feedback, we use the POLR models with the features and weights as optimized in subsection 4.5. This means, we first categorize the different techniques and number of strings hit (single string, power chords, open chords and bar chords). For instance, for each part of the song, all power chords are assessed with the POLR model that worked best for the power chord exercises in the data collection. If a part contains mixes of single notes, chords and so on, we simply average the estimations for each type. Hence, some parts in Figure 7 have partially filled boxes. While averaging the estimations is not completely accurate, we consider this a simple way of providing a single estimation instead of visualizing every estimation of each type. Similarly, the overall estimation is the average of the estimations of each type of notes and chords throughout the song.

6 LIMITATIONS AND FUTURE WORK

This work primarily aims to understand how pressure patterns relate to muscle tension. There are many possible future directions that can build upon our approach and results.

Our final prototype is wireless and unobtrusive, but our study apparatus was tethered. It became clear from the post-questionnaire that many participants initially had issues with the many sensors and cables of the study apparatus. Participants generally got used to the setup eventually. For instance, Participant 4 said that it was less intrusive than they initially thought and Participant 5 said that the setup was ok, once everything was settled. However, a data collection that uses a simple wireless device could provide additional insights. In connection to this, a long-term deployment with multiple learners using the final prototype could provide insights about the broader effectiveness of the approach, also in the context of a more fully realized tutorial system that also incorporates other types of feedback for learners, e.g., based on audio processing.

In this work, we focused on collecting data with specific structured exercises. As we could see in the data, even with the same tempo and technique, playing the same string repeatedly generates different patterns compared to playing different strings. Capturing a larger variety of pairs of strings or transitions from a single string to chords might improve the models. For this, a future undertaking could use a crowd sourcing approach, in which guitar players play songs with different combinations of string transitions to train a model with many combinations of notes and chords.

The captured signal from the FSR is near linearly dependent on the physically applied force and so far we did not apply a correction to make it fully linear. POLR is in principle able to handle such non-linear inputs and features. However, in the future, we would like to explore different mappings from the raw signal to the model input, e.g., to make the input linear with regards to the actual applied pressure or pre-processing it in other ways that can potentially improve the model's output.

Our current front end is designed around practicing specific songs akin tutorial software like *Rocksmith* [51]. This allows detailed assessment of individual parts of pre-defined songs. To also enable free-playing, our approach could be complemented with a classifier that first detects the technique that is being employed and then chooses the appropriate estimation model on the fly.

7 CONCLUSION

We presented PressurePick, a pressure sensing pick for predicting muscle tension aimed at guitar learners. Our device complements audio feedback and can be used to ensure that a moderate amount of pressure is applied when practicing guitar songs. This is particularly useful for self-taught learners or between guitar lessons when there is no teacher present to ensure that the learner's muscles are relaxed. We conducted a data collection and analysis to investigate the pressure patterns that emerge when practicing with the guitar and particularly its connection to muscle tension. We extracted features that predict subjective levels of muscle tension only using pressure time series. Based on the insights from the data collection and analysis, we built the PressurePick device and user interface. We believe that our approach can improve the learning outcome of guitar practice sessions in an unobtrusive way and can be complementary to existing practicing methods.

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REFERENCES

[1] Neusa R Adão Martins, Simon Annaheim, Christina M Spengler, and René M Rossi. 2021. Fatigue monitoring through wearables: A state-of-the-art review. *Frontiers in physiology* (2021), 2285.

[2] Alan Agresti. 2012. *Categorical data analysis*. John Wiley & Sons, Chapter Logit Models for Multinomial Responses.

[3] Christopher R Bilder and Thomas M Loughin. 2014. *Analysis of categorical data with R*. CRC Press.

[4] Bráulio Bosi. 2017. Building an effective right-hand guitar technique around injury prevention methods. *Revista Musica Hodie* 17, 2 (2017), 121–133.

[5] Thomas H Budzynski and Johann M Stoyva. 1969. An Instrument for Producing Deep Muscle Relaxation by Means of Analog Information Feedback. *Journal of Applied Behavior Analysis* 2, 4 (1969), 231–237.

[6] P. Cattarello, R. Merletti, and F. Petracca. 2017. Analysis of High Density Surface EMG and finger pressure in the left forearm of violin players. *Problems of Performing Artists* (2017).

[7] Yuan-Ping Chen, Li Su, Yi-Hsuan Yang, et al. 2015. Electric Guitar Playing Technique Detection in Real-World Recording Based on F0 Sequence Pattern Recognition. In *ISMIR*. 708–714.

[8] Fender Musical Instruments Corp. Christina Stejskal. 2021. 16 million Americans learned how to play guitar in the last two years: Why and who are they? https://spotlight.fender.com/newsroom/news/844. Accessed: 2023-01-24.

[9] Robert Cutietta. 1986. Biofeedback training in music: From experimental to clinical applications. *Bulletin of the Council for Research in Music Education* (1986), 35–42.

[10] Marta Sylvia Del Rio-Guerra, Jorge Martin-Gutierrez, Vicente A Lopez-Chao, Rodolfo Flores Parra, and Mario A Ramirez Sosa. 2019. AR Graphic representation of musical notes for self-learning on guitar. *Applied Sciences* 9, 21 (2019), 4527.

[11] Alfred DeMaris. 2002. Explained variance in logistic regression: A Monte Carlo study of proposed measures. *Sociological Methods & Research* 31, 1 (2002), 27–74.

[12] Rita de Cássia dos Reis Moura, Graziela Bortz, and Patrícia Aguiar. 2012. Proposal for Treatment of Focal Dystonia in a Guitar Player: A Case Study. In *Proceedings of the 12th International Conference on Music Perception and Cognition and the 8th Triennial Conference of the European Society for the Cognitive Sciences of Music*. 23–28.

[13] Dario Farina, Corrado Cescon, and Roberto Merletti. 2002. Influence of anatomical, physical, and detection-system parameters on surface EMG. *Biological cybernetics* 86, 6 (2002), 445–456.

[14] Andreas Fender and Jörg Müller. 2018. Velt: A Framework for Multi RGB-D Camera Systems *(ISS '18)*. Association for Computing Machinery, 73–83. https://doi.org/10.1145/3279778.3279794

[15] Christian Frisson, Loïc Reboursière, Wen-Yang Chu, Otso Lähdeoja, John Anderson Mills III, Cécile Picard, Ao Shen, and Todor Todoroff. 2009. Multimodal guitar: Performance toolbox and study workbench. *QPSR of the numediart research program* 2, 3 (2009), 67–84.

[16] Tobias Grosshauser. 2008. Low Force Pressure Measurement: Pressure Sensor Matrices for Gesture Analysis, Stiffness Recognition and Augmented Instruments. In *NIME*. 97–102.

[17] Tobias Grosshauser, Alberto Calatroni, David Bannach, and Gerhard Tröster. 2015. Connected musicians-examples of new supportive technologies for musician's performance analysis and daily routine. *Proceedings of the Third Vienna Talk on Music Acoustics* (2015), 141–145.

[18] Tobias Grosshauser, Victor Candia, Horst Hildebrandt, and Gerhard Tröster. 2012. Sensor Based Measurements of Musicians' Synchronization Issues.. In *NIME*.

[19] Tobias Grosshauser and Gerhard Tröster. 2013. Finger Position and Pressure Sensing Techniques for String and Keyboard Instruments. In *NIME*, Vol. 13. 27–30.

[20] Tobias Grosshauser and Gerhand Tröster. 2014. Musical instrument interaction: development of a sensor fingerboard for string instruments. In *Proceedings of the 8th International Conference on Tangible, Embedded and Embodied Interaction*. 177–180.

[21] Enric Guaus, Tan Ozaslan, Enric Palacios, and Josep Lluís Arcos Rosell. 2010. A left hand gesture caption system for guitar based on capacitive sensors. (2010).

[22] Cockos Incorporated. 2023. REAPER. https://www.reaper.fm/. (Accessed: July 25, 2023).

[23] Fumiyoshi Kamo and Soichiro Matsushita. 2021. Interactive Diagnosis System for Electric Guitar Strumming Using Wrist-worn Real-time Wireless Motion Tracking Device. In *2021 IEEE 10th Global Conference on Consumer Electronics (GCCE)*. IEEE, 619–622.

[24] Fumiyoshi Kamo and Soichiro Matsushita. 2022. Evaluating Electric Guitar Strumming Form as Musically Correct Rhythm And Sharpness Using Wrist-Wom Inertial Motion-Tracking Device. In *2022 IEEE International Conference on Consumer Electronics (ICCE)*. IEEE, 1–6.

[25] Jakob Karolus, Hendrik Schuff, Thomas Kosch, Paweł W Wozniak, and Albrecht Schmidt. 2018. EMGuitar: Assisting guitar playing with electromyography. In *Proceedings of the 2018 Designing Interactive Systems Conference*. 651–655.

[26] Yoshitaka Kashiwagi, Youji Ochi, Yasuo Miyoshi, Yuichiro Mori, and Ryo Okamoto. 2015. A study of performance detection method for a guitar skill learning using

kinect sensor. In *2015 IEEE 4th Global Conference on Consumer Electronics (GCCE)*. 343–345. https://doi.org/10.1109/GCCE.2015.7398550

[27] Joseph R Keebler, Travis J Wiltshire, Dustin C Smith, and Stephen M Fiore. 2013. Picking up STEAM: educational implications for teaching with an augmented reality guitar learning system. In *Virtual, Augmented and Mixed Reality. Systems and Applications: 5th International Conference, VAMR 2013, Held as Part of HCI International 2013, Las Vegas, NV, USA, July 21-26, 2013, Proceedings, Part II 5*. Springer, 170–178.

[28] Martin Kusserow, Gerhard Tröster, Victor Candia, Gerd Folkers, Oliver Amft, and Horst Hildebrandt. 2010. Wearable monitoring of stage fright in professional musicians. In *International Symposium on Wearable Computers (ISWC) 2010*. 1–2. https://doi.org/10.1109/ISWC.2010.5665852

[29] David Leisner. 2018. *Playing with ease: a healthy approach to guitar technique*. Oxford University Press.

[30] Ultimate Guitar USA LLC. 2023. Ultimate Guitar. https://www.ultimate-guitar.com/. (Accessed: July 25, 2023).

[31] Markus Löchtefeld, Sven Gehring, Ralf Jung, and Antonio Krüger. 2011. guitAR: supporting guitar learning through mobile projection. In *CHI'11 Extended Abstracts on Human Factors in Computing Systems*. 1447–1452.

[32] Markus Löchtefeld, Sven Gehring, Ralf Jung, and Antonio Krüger. 2011. Using mobile projection to support guitar learning. In *Smart Graphics: 11th International Symposium, SG 2011, Bremen, Germany, July 18-20, 2011. Proceedings 11*. Springer, 103–114.

[33] Yousician Ltd. 2022. Yousician. https://yousician.com/. (Accessed: July 25, 2023).

[34] Karola Marky, Andreas Weiß, Andrii Matviienko, Florian Brandherm, Sebastian Wolf, Martin Schmitz, Florian Krell, Florian Müller, Max Mühlhäuser, and Thomas Kosch. 2021. Let's Frets! Assisting Guitar Students During Practice via Capacitive Sensing. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. 1–12.

[35] Soichiro Matsushita. 2019. A wrist-worn motion evaluation system for fast and powerful down picking of heavy metal guitar. In *Proceedings of the 23rd International Symposium on Wearable Computers*. 145–149.

[36] Soichiro Matsushita and Fumiyoshi Kamo. 2022. Interactive Training System for Electric Guitar Strumming Form by Using Inertial Motion Sensors. In *2022 IEEE 11th Global Conference on Consumer Electronics (GCCE)*. IEEE, 97–100.

[37] Jaydev Mistry. 2012. *The Mistry-Hyper Guitar*. Ph. D. Dissertation. University Of Huddersfield.

[38] Robert L Morasky, Creech Reynolds, and George Clarke. 1981. Using biofeedback to reduce left arm extensor EMG of string players during musical performance. *Biofeedback and Self-regulation* 6 (1981), 565–572.

[39] Robert L Morasky, Creech Reynolds, and Larry E Sowell. 1983. Generalization of lowered EMG levels during musical performance following biofeedback training. *Biofeedback and Self-regulation* 8, 2 (1983), 207–216.

[40] Fabio Morreale, Andrea Guidi, Andrew McPherson, et al. 2019. Magpick: an augmented guitar pick for nuanced control. New Interfaces for Musical Expression.

[41] Yoichi Motokawa and Hideo Saito. 2006. Support system for guitar playing using augmented reality display. In *2006 IEEE/ACM International Symposium on Mixed and Augmented Reality*. IEEE, 243–244.

[42] Michael Murawski. 2023. Pickatto. https://pickatto.com/. (Accessed: July 25, 2023).

[43] Laurel S Pardue, Christopher Harte, and Andrew P McPherson. 2015. A low-cost real-time tracking system for violin. *Journal of New Music Research* 44, 4 (2015), 305–323.

[44] Loïc Reboursière, Otso Lähdeoja, Thomas Drugman, Stéphane Dupont, Cécile Picard-Limpens, and Nicolas Riche. 2012. Left and right-hand guitar playing techniques detection. In *NIME*.

[45] Chris Rhodes, Richard Allmendinger, Caroline Jay, and Ricardo Climent. 2023. Towards Developing a Virtual Guitar Instructor through Biometrics Informed Human-Computer Interaction. In *Extended Abstracts of the 2023 CHI Conference on Human Factors in Computing Systems*. 1–8.

[46] Gail A. Shafer-Crane. 2006. Repetitive Stress and Strain Injuries: Preventive Exercises for the Musician. *Physical Medicine and Rehabilitation Clinics of North America* 17, 4 (2006), 827–842. https://www.sciencedirect.com/science/article/pii/S1047965106000507 Performing Arts Medicine.

[47] Yejin Shin, Jemin Hwang, Jeonghyeok Park, and Soonuk Seol. 2018. Real-time Recognition of Guitar Performance Using Two Sensor Groups for Interactive Lesson. In *Proceedings of the Twelfth International Conference on Tangible, Embedded, and Embodied Interaction*. 435–442.

[48] Lucchas Ribeiro Skreinig, Ana Stanescu, Shohei Mori, Frank Heyen, Peter Mohr, Michael Sedlmair, Dieter Schmalstieg, and Denis Kalkofen. 2022. AR Hero: Generating interactive augmented reality guitar tutorials. In *2022 IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and Workshops (VRW)*. IEEE, 395–401.

[49] The Fretlight Guitar Store. 2023. Fretlight. https://fretlight.com/. (Accessed: July 25, 2023).

[50] Ting-Wei Su, Yuan-Ping Chen, Li Su, and Yi-Hsuan Yang. 2019. TENT: Technique-embedded note tracking for real-world guitar solo recordings. *Transactions of the International Society for Music Information Retrieval* 2, 1 (2019).

[51] Ubisoft. 2022. Rocksmith. https://www.ubisoft.com/en-us/game/rocksmith/plus. (Accessed: July 25, 2023).

[52] Roy Vanegas. 2007. The MIDI Pick: Trigger Serial Data, Samples, and MIDI from a Guitar Pick. In *Proceedings of the 7th International Conference on New Interfaces for Musical Expression* (New York, New York) *(NIME '07)*. Association for Computing Machinery, 330–332. https://doi.org/10.1145/1279740.1279812

[53] Tim Vets, Jonas Degrave, Luc Nijs, Federica Bressan, and Marc Leman. 2017. PLXTRM: Prediction-Led eXtended-guitar Tool for Real-time Music applications and live performance. *Journal of New Music Research* 46, 2 (2017), 187–200.

[54] Peter Visentin and Gongbing Shan. 2011. Applications of EMG pertaining to music performance-A review. *Arts BioMechanics* 1, 1 (2011), 15.

[55] Bryan Wang, Meng Yu Yang, and Tovi Grossman. 2021. Soloist: Generating Mixed-Initiative Tutorials from Existing Guitar Instructional Videos Through Audio Processing. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*. 1–14.

[56] Nozomu Yoshida and Katsutsugu Matsuyama. 2020. A picking interface seamlessly connecting passive and active performance on guitar. In *International Workshop on Advanced Imaging Technology (IWAIT) 2020*, Vol. 11515. SPIE, 364–368.