A Wearable Technology for Wind Musicians: Does It Matter How you Breathe?

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ABSTRACT

This paper presents an affordable and accessible wearable technology for wind musicians which provides real-time biofeedback on their breathing. We developed the abdominal thoracic expansion measurement prototype wearable technology (ATEM-P), to measure a wind musician's breathing-induced expansion and contraction while they are playing.

Our first study validates the ATEM-P with the gold standard of medical grade respiratory exertion measurement devices, the respiratory plethysmography inductance system (RIP). The results show that the ATEM-P has a strong correlation to the RIP system.

Our second study provides quantitative and qualitative data about the correlation between a musician's breathing technique and the quality of their performance. For the purpose of this research, we defined quality of performance (QOP), as sound quality, breath control, and use of vibrato. We expected the results to show a correlation between the ATEM-P peak amplitudes and QOP, however this was not the case. The results did show that there is a correlation between a musician's QOP and breath period.

Results from the studies show that the ATEM-P has potential as an affordable and accessible wearable technology for wind musicians: a performance enhancement tool and an educational tool.

CCS Concepts

•Human-centered computing → *Mobile devices;* **•Applied computing → Interactive learning environments; Performing arts;**

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1. INTRODUCTION

The use of wearable technology today is ubiquitous, and plays an important role in fields such as medicine and sports, helping individuals with the physicality of their movements. Wearable technology does not have the same presence in the field of music, and yet the physicality of playing a musical instrument would benefit from wearable technology solutions. Better physical movement broadens a musician's ability to be expressive and enhance their musical narrative. Can computer sensing and measurement tools be used to help musicians improve their physical movements while playing and thereby achieve a better quality of performance? For the purpose of this research, we defined quality of performance (QOP), as sound quality, breath control, and use of vibrato.

If we look at musicians and athletes, there are noteworthy areas of similarity: both musician and athlete require highly nuanced motor skills built by intense and enduring practice [9], skills that require agility, flexibility, neuromuscular coordination, and muscular endurance and strength [17]; both are performers, bringing expression and skill to their stage and are assessed by their technical proficiency and artistic presentation.

Evidence supports the benefits that athletes gain in performance and in injury prevention by using technology in their training routine [11] [6]. Wearable technologies measure and analyze the athlete's physical movements in order to guide them to improved technical proficiency, enabling a more expressive performance. The question is whether wearable technology customized for musicians can do the same: improve technical proficiency resulting in a higher QOP.

The scope of this research is breathing technique for wind instrumentalists. The need for efficient and effective breathing technique is undeniable; to perform long uninterrupted phrases, wind instrumentalists need supported airways [5, 3]. The importance of strong respiratory muscles as the power source for sound production is established [20]. It is accepted, though not empirically verified, that breath control and technique has a direct impact on sound quality and consequently performance [7, 8].

To address this issue, we have developed an affordable and accessible wearable device that provides meaningful information, the abdominal thoracic expansion measurement prototype (ATEM-P). The ATEM-P measures breathing-induced expansion and contraction, and provides real-time biofeedback while the musician is playing their instrument. The ATEM-P is portable and affordable, making it suitable for individual use and also as part of music school programs.

We have done two studies for this research, a validation study with the gold standard of respiratory exertion measurements, the respiratory inductance plethysmography system (RIP), and an observational study with 43 flutists to determine the correlation between breathing and QOP.

The validation study results show a strong correlation between the ATEM-P and the gold standard RIP.

The observational study revealed a correlation between breath period and QOP.

The results of the observational study were not what we expected. We expected that there would be a strong correlation between the breathing-induced expansion and contraction measurements and a musician's QOP. What the results showed instead is a correlation between the breath period and QOP, and to a lesser extent, between dynamic range and QOP.

2. BACKGROUND

2.1 Technology for musicians and athletes

Given the physicality of playing an instrument, it stands to reason that musicians, like athletes, can benefit from tools that precisely measure and analyze movements for performance improvement.

Studies show that technology has had a profound impact on how athletes train, and the results are evident in consistent improvements in performance [6], and reduction in injury [4, 18]. In professional athletics, technology is used to enhance performance through data-gathering wearables, data analytics, and virtual-reality-based practice [11].

For musicians, there is nothing resembling the sophisticated training technologies that are available for athletes. Where the athlete has access to 21st century technologies, the musician's training kit consists of tools carried over from the 20th century, such as a metronome and tuner. There are apps available to help students with tuning (e.g. Cleartune, TonalEnergy, iStroboSoft, Tunable , insTuner), tempo (e.g. Metronome Plus, Tempo/Tempo Advance, Time Guru, Dr. Betotte, Metronomic), and note learning (e.g. smartmusic, musictheory.net, Noteflight), but these are not designed to teach correct physical movement or posture while playing an instrument - they simply help with learning the music, notes, rhythms and intonation.

Musicians' physical demands can be compared to those experienced by professional athletes and can therefore benefit from the data measurement and analysis technologies like those available for athletes. The need for innovative and cutting-edge technology for the musician is on par with that for the athlete, and yet the same depth of research, implementation and usage does not exist for today's musician.

2.2 BREATHING PEDAGOGY

> "..everyone breathes, and today, few of us breathe well. Those with the worst anxieties consistently suffer from the worst breathing habits." [16]

Teaching proper breathing technique to music students is fundamental for wind players, brass players, and vocalists. Yet the issue of inconsistent and incorrect guidance given to music students continues to be a problem and underlines the need for clarification in the pedagogical documentation and techniques [5, 21, 13]. Could wearable technology offer consistency and accuracy in breathing training for musicians?

2.3 Respiratory Training Tools For Musicians

There are devices on the market used by musicians for improving breathing technique by strengthening respiratory muscles. These devices are founded on the principle that respiratory muscle training (RMT), is beneficial for healthy individuals as well as those suffering from respiratory, cardiac, and neuromuscular health issues [15, 19, 12]. Some of the respiratory training tools used by musicians include *The Breather*®, the *Breath Builder*®, and *Expand-A-Lung*®, ranging in price from \$25-\$60.

2.4 Respiratory Measurement Tools

There are two respiratory measurement tools on the market that were considered for this research.

2.4.1 Piezoelectric Respiration Sensor (PZT)

According to the PZT datasheet, using multiple PZT sensors simultaneously, provides biofeedback for diaphragmatic and thoracic breathing measurements. While PZT sensors seem like a good option for this research, the \$2000 pricetag does not satisfy the affordability goal of this research. Additionally, the PZT requires proprietary components and therefore does not meet the accessibility goal of this research.

2.4.2 Respiratory Inductance Plethysmography (RIP)

RIP is the gold standard of respiratory measurement and is of medical grade. According to the Sleep Centre's medical staff, a portable RIP system costs more than \$20,000, making the RIP unsuitable for this research.

2.5 Discussion

RMT devices are used by musicians and athletes with the goal of improving breathing through respiratory muscle training (RMT), both inspiratory (IMT) and expiratory (EMT). Research has validated that IMT produces statistically significant improvements in performance, but the data for EMT improvements is not as conclusive [15]. The RMT devices provide a means to strengthen respiratory muscles, but there is no measurement or analysis taking place during playing, i.e. no real-time biofeedback.

Respiratory measurement devices such as the PZT and RIP, take accurate respiratory exertion measurements, but are too costly and are not accessible.

This is where affordable and accessible wearable technology can make an impact with music training tools, by providing real-time biofeedback at an affordable price and without proprietary limitations.

3. ATEM-P DESIGN FOR MUSICIANS

3.1 Materials and Sensors

We performed preliminary tests to determine which material and sensor were best suited for the ATEM-P. The material needs to change properties with the breathing-induced change in body shape; it must have adequate elasticity to provide reliable repeatability; it must be affordable for broad deployment in schools with music programs.

Tests using conductive rubber cord showed good responsiveness and reliable repeatability. Therefore, conductive rubber cord was chosen as the sensing material for the ATEM-P. The rubber cord can be stretched 50-70% longer than the resting length, without losing the retraction. Additionally, the cost is reasonable with a 1-meter length priced at approximately $15, providing sufficient material for 5 belts.

The abdominal belt and the ribcage belt each use a Switchable Voltage Divider phidget [1], model #1134, $15 each. The sensors act as the variable resistors in these circuits. As the rubber cord stretches and contracts during inhalation and exhalation, resistance variation is tracked, providing the measurement data. The Phidget Interface Kit, a USB based controller that allows for analog, digital, and USB inputs/outputs, was used to connect the sensors to a Windows laptop for processing.

Max/MSP was used to program the ATEM-P application. The cost for an annual academic Max/MSP subscription is $59 USD. This programming could also be done using PureData, which is free software.

3.2 Construction

The ATEM-P wearable device consists of an abdominal belt worn at the waist and a ribcage belt worn across the chest, under the armpits. The belts are constructed from 2.5cm webbing, with parachute clips for sizing. The rubber cord is backed by a strip of 2.5cm wide elastic for support.

One end of the wires connects the phidget sensors to the phidget interface kit and the other end of the wires attaches to the conductive rubber cord ends. The rubber cord ends are attached to small rings that are sewn onto the belt webbing material, refer to Figures 1 and 2.

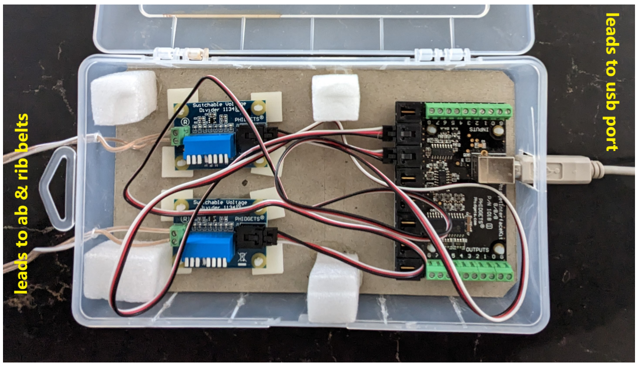

Figure 1: Phidgets: On the left, 2 switchable voltage divider phidgets, model #1134 lead to ATEM-P belts; on the right, phidget interface kit for A/D conversion.

The Max/MSP patch gathers analog data from the sensors in each of the belts, as the subject inhales and exhales. The program samples at a rate of 20 Hz.

4. STUDY 1: VALIDATION STUDY

The purpose of study 1 is to validate the ATEM-P wearable device with RIP, the gold standard of respiratory exertion measurement systems. We want to verify that the breathing-induced abdominal and thoracic expansion and contraction measurements generated by the ATEM-P have a strong correlation to the breathing-induced abdominal and thoracic expansion and contraction measurements generated by the RIP.

4.1 METHODOLOGY

For this research study, we followed the methodology of Løberg et.al[14]. The research goal of Løberg et al. was to allow people to perform a low-cost first step home diagnosis test for sleep apnea detection by utilizing smartphones, low-cost consumer-grade sensors, and data mining techniques.

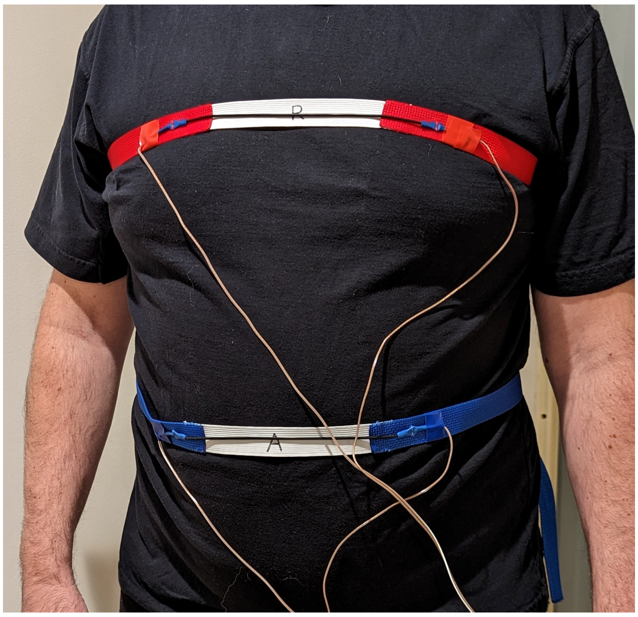

Figure 2: ATEM-P abdominal (blue) and ribcage (red) belts.

They evaluated the uncalibrated signal quality of four respiratory effort sensors, using a RIP sensor from NOX Medical as the gold standard.

4.1.1 Recruitment

We identified potential participants through their involvement in music groups. All recruitment materials provided an accurate description of the purpose of the research, study conditions, the foreseeable risks and/or potential benefits of participation.

Due to COVID-19 pandemic restrictions, this study was run as a pilot study with 10 participants rather than the originally planned 40 participants.

Participants were between the ages of 22–72, identified as male, female, and non-binary, and consisted of woodwind players, string players, and non-musicians. All participants were in general good health.

4.1.2 Study Steps

This study was run in March 2022 at the Foothills Medical Centre Sleep Centre, Calgary, Canada, using their RIP system.

Each participant was fitted with an ATEM-P abdominal belt and ribcage belt, over-top of their clothing. The RIP abdominal and ribcage belts were placed over-top of the ATEM-P belts. The participant remained standing for the duration of the study.

The Max/MSP patch displayed timed breathing cues for the participant, a real-time visual biofeedback on participant's breathing-induced expansion and contraction, and wrote the voltage data to files.

Participants performed the breathing exercises to the best of their ability, while the ATEM-P and RIP belts took measurements, refer to Table 1.

4.1.3 Data Treatment

We wrote Python programs to clean up and analyze the data.

- ATEM-P Max/MSP patch samples at 20 Hz: interpo-

Table 1: Study 1 Breathing Steps

Duration(s)	Breathing Instruction
60s	normal
30s	deep
30s	normal
30s	abdominal
30s	normal
30s	ribcage
30s	normal
30s	abdominal and ribcage
30s	normal
60s	inhale, hold breath; repeat

lated data to provide data at 50ms intervals.

- RIP samples at 100 Hz: Down-sampled RIP data by a factor of 5 to provide data at 50ms intervals.
- With the ATEM-P data, the valleys reflect expansion, and the peaks reflect contraction. As this is the reverse of the RIP system, the ATEM-P datasets were multiplied by -1. Now both RIP and ATEM-P peaks and valleys represent the same states of expansion and contraction.

4.1.4 RIP and ATEM-P Data Alignment

The RIP and ATEM-P systems were started manually by two individuals, and therefore required alignment and trimming.

Aligned and trimmed RIP and ATEM-P datasets as follows:

- Determine the time offset by visually matching a well-defined peak from the RIP data to the matching well-defined peak in the ATEM-P data.
- Isolate a small slice of data from both RIP and ATEM-P, and run though a program to determine, with more precision, the exact timestamps of the matching ATEM-P and RIP peaks.
- With the exact time offset established, trim and align both data sets.

4.1.5 Data Analysis

Measuring the similarity between the ATEM-P and RIP data files proved challenging as the belts were not calibrated and thus could not be compared directly. Furthermore, respiratory effort signals are by definition, not reproducible [14]. Both ATEM-P and RIP data had a considerable amount of noise, making it challenging to identify the peaks that were the actual inhalations. Therefore, we first identified actual breaths from the RIP system as the baseline. Next, we obtained breath detection accuracy metrics similar to Løberg et al. through the following steps:

1. **Peaks and Peak Amplitudes**
   (a) Processed data to extract peaks from both RIP belts.
   (b) Processed data to extract peaks from both ATEM-P belts.
   (c) From the peaks captured in step-a, calculate peak amplitudes from both RIP belts.
   (d) From the peaks captured in step-b, calculate peak amplitudes from both ATEM-P belts

2. **Sensitivity and Positive Predictive Value (PPV)**
   For the sensitivity and PPV equations, the following terminology was used:
   - TP: True peaks as a result of breath-induced inhalation.
   - FN: False negative peaks are those that were missing in the measurements.
   - FP: False positive peaks.

   Once the breath peaks were identified, the sensitivity and the positive predictive values of the RIP and the ATEM-P sensors were calculated for each participant.

   Sensitivity measures the proportion of real breaths detected by the sensors.

$$SENSITIVITY = \frac{TP}{(TP + FN)}$$

   Positive Predictive Value (PPV) measures the proportion of detected breaths that are real.

$$PPV = \frac{TP}{(TP + FP)}$$

   Note that Løberg et al. next calculated the breath amplitude accuracy metrics. For these metrics, they used the *weighted absolute percentage error (WAPE)* metric, also known as the *MAD/mean ratio.* At this point in our analysis, we deviated from Løberg et al., since we were not able to reproduce the *WAPE* metrics. We continued our analysis with the following metrics:

3. **Cosine Similarity** is the cosine of the angle between two vectors. Vectors that are the same (point in the same direction) have a cosine similarity of one. Unrelated, orthogonal signals have a cosine similarity of zero [2].

   Calculated the cosine similarity between the ATEM-P data and the RIP data for each participant, based on a sampling rate of 1 per second, refer to Table 5.

4. **Wavelet Coherence** analysis provides meaningful information on the coherence of the ATEM-P and the RIP signal data .

   To measure the wavelet coherence between the RIP and the ATEM-P signals, Dr. Jeffrey Boyd generated 3 plots for each participant:
   (a) Raw signal data from the ATEM-P and RIP abdominal and ribcage belts for reference, refer to Figure 3.
   (b) Wavelet coherence plot of 1) RIP versus ATEM-P abdominal belts 2) RIP versus ATEM-P ribcage belts, refer to Figure 4.
   (c) Wavelet coherence plot of RIP ribcage belt versus RIP abdominal belt, refer to Figure 5.

   There are similar plots for each participant but due to space limitations these are not included in this paper.

4.2 RESULTS

Tables 2, 3, and 4 shows a summary of the sensitivity values and PPV values for all of the 10 participants.

Tables 5 and 6 provide a summary of the cosine similarity values for each participant's ATEM-P and RIP belts, and the mean values.

Table 2: Sensitivity and PPV Values: Ribcage Belt

ID	Device	TP	FP	FN	Sens.%	PPV%
2G2FK	RIP	52	0	0	100	100
	ATEM-P	52	1	0	100	98.11
65NGJ	RIP	44	0	0	100	100
	ATEM-P	44	5	0	100	89.79
ASWP6	RIP	78	4	0	100	95.12
	ATEM-P	78	0	0	100	100
B8UNY	RIP	41	0	0	100	100
	ATEM-P	41	7	0	100	85.42
CLE7T	RIP	80	0	0	100	100
	ATEM-P	80	2	0	100	97.56
H6HXH	RIP	36	0	0	100	100
	ATEM-P	36	10	0	100	78.26
PY7YN	RIP	76	0	0	100	100
	ATEM-P	76	0	0	100	100
SQ44Y	RIP	75	1	0	100	98.68
	ATEM-P	75	4	0	100	94.93
TDX52	RIP	42	0	0	100	100
	ATEM-P	42	3	0	100	93.33
ZW4YZ	RIP	50	0	0	100	100
	ATEM-P	50	1	0	100	98.03

Table 3: Sensitivity and PPV Values: Abdominal Belt

ID	Device	TP	FP	FN	Sens.%	PPV%
2G2FK	RIP	54	0	0	100	100
	ATEM-P	54	0	0	100	100
65NGJ	RIP	45	0	0	100	100
	ATEM-P	45	3	0	100	93.75
ASWP6	RIP	73	0	0	100	100
	ATEM-P	73	5	0	100	93.58
B8UNY	RIP	41	0	0	100	100
	ATEM-P	41	5	0	100	89.13
CLE7T	RIP	78	0	0	100	100
	ATEM-P	78	0	0	100	100
H6HXH	RIP	38	0	0	100	100
	ATEM-P	38	3	0	100	92.68
PY7YN	RIP	75	0	0	100	100
	ATEM-P	75	1	0	100	98.68
SQ44Y	RIP	78	0	0	100	100
	ATEM-P	78	1	0	100	98.73
TDX52	RIP	43	2	0	100	95.55
	ATEM-P	43	7	0	100	86
ZW4YZ	RIP	49	0	0	100	100
	ATEM-P	49	5	0	100	90.74

See Figure 3 for participant 2G2FK's raw ATEM-P and RIP signal data plot, Figure 4 for wavelet coherence between ATEM-P and RIP, and Figure 5 for wavelet coherence between RIP abdominal belt and ribcage belt.

To interpret the wavelet coherence plots, note the following:

- Arrows in the plots represent the lead/lag phase relations between the two series. A zero-phase difference means that the two series move together on a particular scale.

Table 4: Sensitivity and PPV Means of All Participants

Device	Sensitivity Mean %	PPV Mean %
RIP	100	99.47
ATEM-P	100	93.94

Table 5: Cosine Similarity ATEM-P and RIP

Participant ID	Ribcage	Abdomen
2G2FK	0.90	0.90
65NGJ	0.93	0.97
ASWP6	0.93	0.97
B8UNY	0.94	0.95
CLE7T	0.95	0.96
H6HXH	0.92	0.91
PY7YN	0.95	0.94
SQ44Y	0.96	0.96
TDX52	0.89	0.93
Z4WYZ	0.99	0.99

Table 6: Cosine Similarity ATEM-P and RIP Mean

ATEM-P and RIP Belt	Mean Of All Participants
Ribcage	0.93
Abdomen	0.95

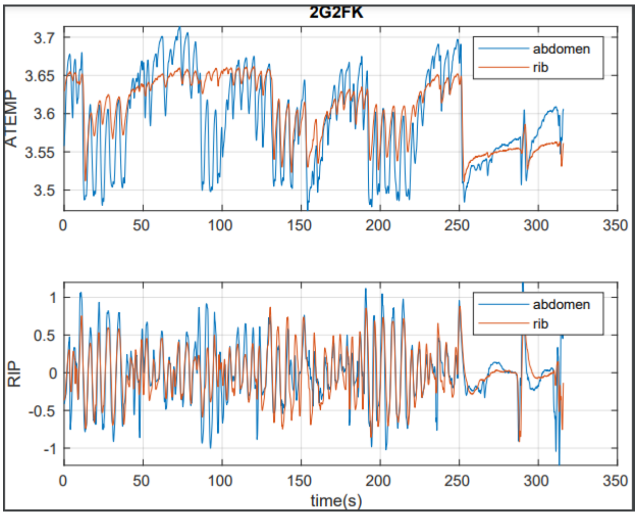

Figure 3: ATEM-P and RIP signal data for participant 2G2FK. y-axis = ATEM-P (top) and RIP (bottom) signal data measurements; x-axis = time(s).

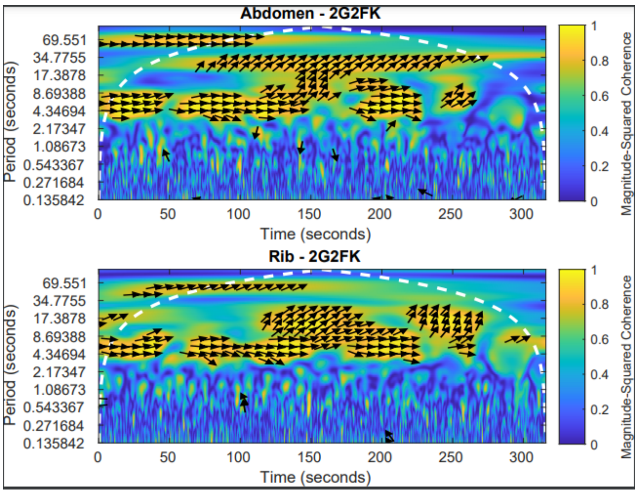

Figure 4: ATEM-P and RIP Wavelet coherence plots for participant 2G2FK.

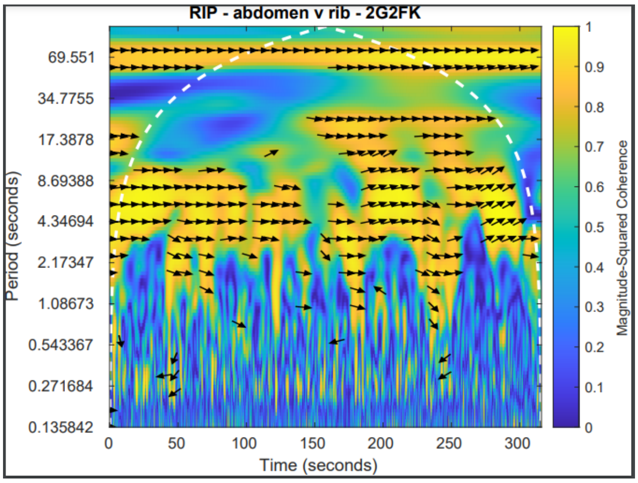

Figure 5: RIP ribcage belt versus RIP abdominal belt wavelet coherence plots for participant 2G2FK. This shows the wavelet coherence of the RIP system with itself, by comparing rib with abdomen.

- Arrows point right when the time series are in phase.
- Arrows point left when the time series are in opposite phase.

4.3 DISCUSSION

The sensitivity and PPV values from our study show strong similarity to the sensitivity and PPV values from Løberg et al.'s study. The mean sensitivity values from Løberg et al.'s study range from 97.3% to 99.61%. From our study, the mean sensitivity values are 100% for both the ATEM-P and the RIP. The mean PPV values from Løberg et al.'s study range from 86.64% to 99.16%. The mean PPV values from our study are 99.47% for the RIP and 93.94% for the ATEM-P.

The cosine similarity values for each participant's ATEM-P and RIP belts is high, with only one out of the 20 values being below 0.9. The mean cosine similarity for all participants is greater than 0.9 for both abdominal and ribcage belts, and therefore the ATEM-P signal data has a strong similarity to the RIP signal data.

A visual analysis of the wavelet coherence plots confirms that there is good coherence between the ATEM-P belts and the RIP belts. For example, from Figure 4, the period of 4-8 seconds, the participant's first breath, shows strong coherence. The period around 69 seconds also shows strong coherence and for a longer duration, approximately 100 seconds. This is the pacing of the sections of the test.

The ATEM-P is not intended as a medical grade device, but rather, as an educational device for musicians. Therefore, 100% correlation to the RIP measurements is not necessary, but a good correlation is enough to validate the ATEM-P for the purpose it is intended. The results show that there is a good correlation between the gold standard RIP signal data and the ATEM-P signal data.

5. STUDY 2: OBSERVATIONAL STUDY

The purpose of study 2 is to determine whether the ATEM-P's breathing-induced measurements of thoracic and abdominal expansion have a correlation to a wind instrumentalist's sound quality and breath control.

5.1 METHODOLOGY

5.1.1 Recruitment

We identified potential participants through their involvement in music groups. All recruitment materials provided an accurate description of the purpose of the research, study conditions, the foreseeable risks and/or potential benefits of participation.

The 43 participants were between the ages of 14–72, and were in general good health. The participants' playing experience ranged from 2-58 years, and skill level ranged from beginner to professional.

5.1.2 Study Setup

The study took place in the Telemedia Arts Lab at the University of Calgary, Alberta, Canada during April and May 2022. COVID-19 protocols were followed in accordance with Alberta Health Services and the University of Calgary.

RME Fireface UFX was used as the audio interface with two AKG C414 condenser microphones. Logic Pro X software was used to export the audio files as 24-bit wave files, providing mastering grade quality recordings for this study. No processing was done on the audio files.

We wrote a Max/MSP patch for the ATEM-P application. The Max/MSP patch uses the anticipatory score following component *antescofo*, a real-time module for Max/-MSP. The *antescofo* module accepts a symbolic music score and in real-time, listens to a musician (via a microphone) following their position in the score [10]. The Max/MSP patch does the following:

- Display the participant's breathing-induced expansion and contraction as captured by the ATEM-P belts.
- Display the participant's position in the score indicated by the cursor on the displayed *antescofo* score.
- Write the sensors' voltage readings to file.

5.1.3 Study Steps

Each participant ran through the study with only the researcher and the recording assistant present. The recording equipment was set up identically for each participant.

Each participant was fitted with an ATEM-P abdominal belt and ribcage belt. In a standing position, the participant played a set of predefined exercises that they had been given at least one week prior to doing the study. The ATEM-P belts generated breathing-induced measurement data, and an audio recording was made of each participant's session.

Each participant played the following exercises, to the best of their ability:

- Four F major scales: 2 octaves, recommended tempo ♩=80
    1. *piano*, no vibrato
    2. *forte*, no vibrato
    3. *piano*, vibrato
    4. *forte*, vibrato
- Six Long Tones: hold note as long as possible, no vibrato
    1. low register G, *piano*
    2. low register G, *forte*
    3. middle register G, *piano*

4. middle register G, *forte*
5. high register G, *piano*
6. high register G, *forte*

- **The Swan** by Camille Saint-Saëns: add dynamics and phrasing as desired, breath when necessary

1. Play from paper score.
2. Play from projected *antescofo* score.

5.1.4 Data Treatment
We wrote Python programs to cleanup and analyze data.

- When breathing-induced expansion occurs, the voltage readings decrease and when contraction occurs, the voltage readings increase. To reflect increased physical expansion and contraction with peaks and troughs respectively, the ATEM-P belt data were multiplied by -1.
- To align the ATEM-P data and the audio recording, we first identified well-presented audio recording breaths and the corresponding ATEM-P breaths. Then we lined up the audio recording with the ATEM-P data. The ATEM-P program was started before the recording, therefore excess data was removed from the beginning of the ATEM-P datasets where necessary.
- The ATEM-P belts are not calibrated, therefore we normalized the ATEM-P belts' data to fall in the range of 0 - 1.

5.1.5 Data Analysis
From the audio recording, the following quantitative measurements were derived:

1. **Breath period:** Counted breaths taken while the participant was playing and then calculated the breath periods.
2. **Dynamic range:** Extracted the dynamic range in dB, by subtracting the minimum dB from the maximum dB, a feature of *Audacity Audio Recording and Editing Software*.
3. **Pitch variability:** Using a KORG Orchestral Tuner OT-120, observed the minimum and maximum pitch Hz measurements. Calculated pitch variation; lower value indicates more stable pitch control.

We recruited a professional flutist and clarinetist to provide measures for the qualitative components of this study. The experts listened to the audio recordings and scored the following items:

1. **Sound Quality:** The experts assigned each participant a score from 1 - 5 with 1 being the lowest quality and 5 being the highest quality, refer to Table 7.
2. **Breath control and vibrato:** The experts assigned each participant a score from 1 - 5 with 1 being the lowest quality and 5 being the highest quality, refer to Table 7.

The following measurements were derived from the ATEM-P belts' signal data:

- Captured maximum peak amplitudes for scales, long-tones, and both versions of The Swan.

Table 7: Expert's Scoring Guidelines

Sc.	Sound	Breath & Vibrato
1	no support, breathy, thin	no vib., no taper
2	no support, breathy, full	some vib., no taper
3	supported, breathy, thin	some vib., no taper
4	supported, clear, thin	some vib., taper
5	supported, clear, full	full vib., taper

- Calculated the breath periods for scales, long-tones, and The Swan.

Limitations:
During the study, the antescofo score-following component proved to be unreliable and distracting for the participants and was therefore disabled by the 18th participant. The participants continued to play **The Swan** twice, but now they read the piece from the paper score both times.

5.2 RESULTS
The scatterplots look at ATEM-P and RIP breath periods, expert scores, dynamic range, and ATEM-P signal data peak amplitudes. Refer to Figures, 6, 7, 8, 9, 10, and 11.

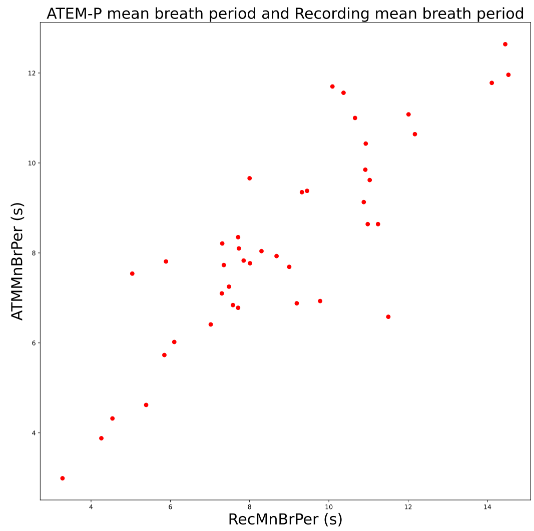

Figure 6: x-axis = recording mean breath period; y-axis = ATEM-P belts' mean breath period; Spearman rank coefficient: 0.790 ; Pearson correlation coefficient:0.848. Samples are correlated.

Tables 8, 9, 10, and 11 give a summary of the Spearman rank coefficient values and the Pearson correlation coefficient values.

5.3 DISCUSSION
The Spearman and Pearson coefficient values between the experts' scores are all above 0.8 and thus show a high correlation, see Table 8. From these values, we know that the experts listened for similar qualities in the participants' performance.

At the start of this study we expected to find a high correlation between the ATEM-P breathing-induced expansion measurements and the QOP: more expansion leads to better

Table 8: Spearman rank coefficient and/or Pearson: High correlation coefficient values, coefficient equal to or greater than 0.7. Legend: FltExp=flute expert, ClarExp=clarinet expert, sc=score, SND=sound, BRVIB=breath-vibrato.

		Spearman Rank		Pearson correlation	
x-axis	y-axis	coefficient	p-value	coefficient	p-value
ClarExp SND sc	FltExp SND sc	0.802	0.000	0.814	0.000
ClarExp BRVIB sc	FltExp BRVIB sc	0.897	0.000	0.895	0.000
ATEM-P mean breath period	Recording mean breath period	0.782	0.000	0.842	0.000

Table 9: Spearman rank coefficient and/or Pearson: Moderate correlation coefficient values, coefficient between 0.5 and 0.7. Legend: Exps=experts, FltExp=flute expert, ClarExp=clarinet expert, sc=score, SND=sound, BRVIB=breath-vibrato.

		Spearman Rank		Pearson correlation	
x-axis	y-axis	coefficient	p-value	coefficient	p-value
ATEM-P belts mean breath period	FltExp SND sc	0.526	0.000	0.526	0.000
	Exps mean BRVIB sc	0.512	0.000	0.540	0.000
	ClarExp BRVIB sc	0.510	0.000	0.559	0.000
	Exps mean SND sc	0.495	0.001	0.558	0.000
	ClarExp SND sc	0.477	0.001	0.538	0.000
Recording mean breath period	Exps mean SND sc	0.653	0.000	0.692	0.000
	ClarExp SND sc	0.602	0.000	0.634	0.000
	FltExp SND sc	0.691	0.000	0.681	0.000
	Exps mean BRVIB sc	0.655	0.000	0.661	0.000
	ClarExp BRVIB sc	0.618	0.000	0.650	0.000
	FltExp BRVIB sc	0.668	0.000	0.668	0.000
	Recording mean dynamic range	0.580	0.000	0.614	0.000

Table 10: Spearman rank and/or Pearson: Low correlation coefficient values, coefficient between 0.3 and 0.5. Legend: FltExp=flute expert, sc=score, BRVIB=breath-vibrato.

		Spearman Rank		Pearson correlation	
x-axis	y-axis	coefficient	p-value	coefficient	p-value
ATEM-P belts mean breath period	FltExp BRVIB sc	0.493	0.001	0.494	0.001
	Recording mean dynamic range	0.475	0.001	0.475	0.001
	Pitch variation mean	-0.326	0.035	-0.307	0.048
	Pitch variation median	-03.26	0.035	-0.321	0.038
Recording mean breath period	Pitch variation mean	-0.323	0.037	-0.301	0.053
	Pitch variation median	-0.294	0.059	-0.279	0.073

Table 11: Spearman rank coefficient and/or Pearson: No correlation. Legend: Exps=experts, sc=score, SND=sound, BRVIB=breath-vibrato.

		Spearman Rank		Pearson correlation	
x-axis	y-axis	coefficient	p-value	coefficient	p-value
Exps mean SND sc	ATEM-P AbBelt mean peak amplitude	-0.003	0.987	-0.062	0.696
Exps mean SND sc	ATEM-P RibBelt mean peak amplitude	0.070	0.658	0.098	0.538
Exps mean BRVIB sc	ATEM-P AbBelt mean peak amplitude	-0.101	0.524	-0.111	0.484
Exps mean BRVIB sc	ATEM-P RibBelt mean peak amplitude	0.027	0.867	0.048	0.764

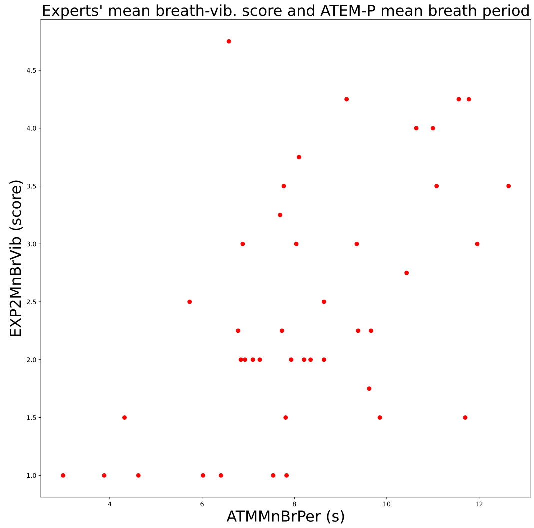

Figure 7: x-axis = ATEM-P belts' mean breath period; y-axis = Experts' mean breath-vibrato score; Spearman rank coefficient: 0.504; Pearson correlation coefficient:0.542. Samples are correlated.

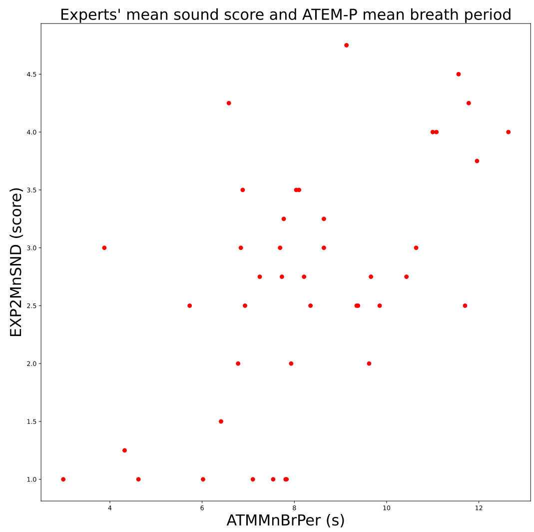

Figure 8: x-axis = ATEM-P belts' mean breath period; y-axis = Experts' mean sound score; Spearman rank coefficient: 0.494; Pearson correlation coefficient:0.566. Samples are correlated.

sound quality, breath control, and use of vibrato. This was not the case, those measurements were not correlated. The Spearman and Pearson coefficient values for the ATEM-P belts and the experts' scores range from -0.111 to 0.098, values that show there is no correlation, see Table 11.

The measurements that do show a correlation to the experts' QOP scores are the breath period of the ATEM-P and the breath period of the audio recording, both show a moderate correlation, see Table 9.

The ATEM-P breath period shows a low correlation to

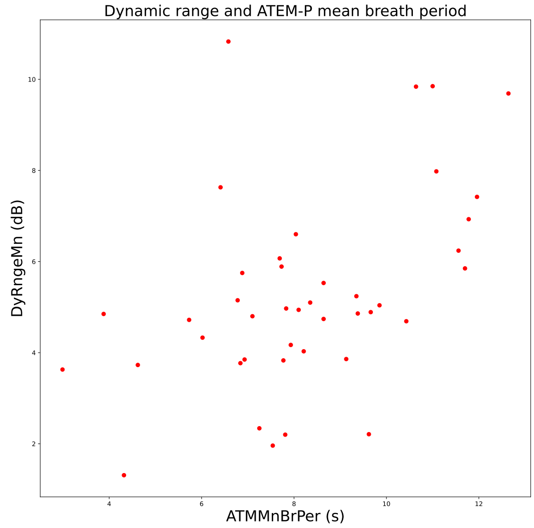

Figure 9: x-axis = ATEM-P belts' mean breath period; y-axis = Dynamic range; Spearman rank coefficient: 0.464; Pearson correlation coefficient: 0.470. Samples are correlated.

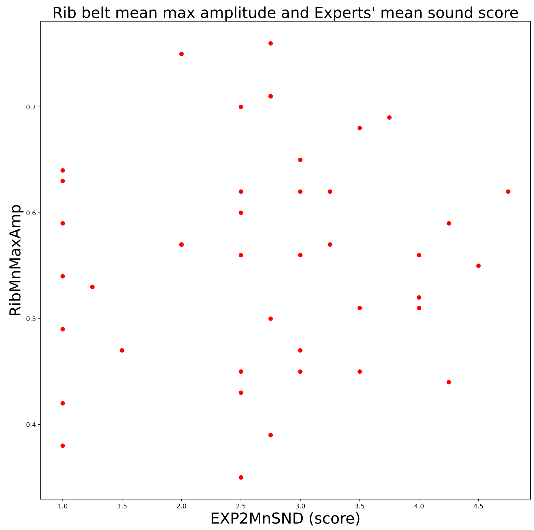

Figure 10: x-axis = Expert mean sound score; y-axis = ATEM-P ribcage belt mean maximum amplitude (normalized between 0-1); Spearman rank coefficient: 0.066; Pearson correlation coefficient: 0.094. Samples are uncorrelated.

the dynamic range measurements while the recording breath period shows a moderate correlation. The breath period of both ATEM-P and the recording show an inverse, low correlation to the pitch stability, e.g. a lower number means more pitch stability, see Tables 10 and 9.

From these results, we see that by means of the breath period, the ATEM-P does provide information about QOP.

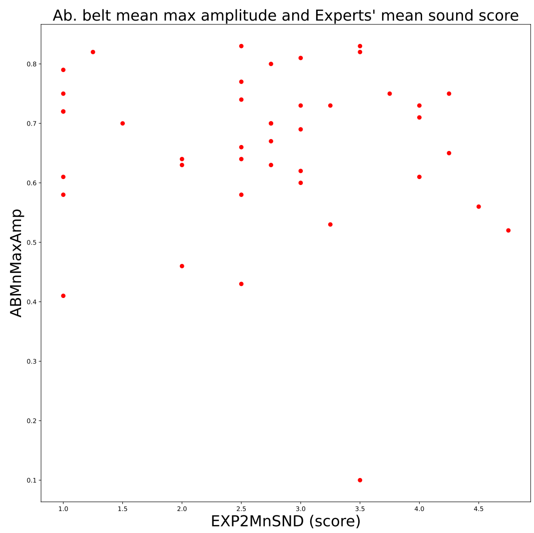

Figure 11: x-axis = Expert mean sound score; y-axis = ATEM-P abdominal belt mean maximum amplitude (normalized between 0-1); Spearman rank coefficient: -0.002; Pearson correlation coefficient: -0.060. Samples are uncorrelated.

6. CONCLUSION

Wearable technology for musicians is an area of research that has great potential. With wearable technology, musician's physical movements can be measured, and analyzed with the goal of improved technical proficiency. With better physical movement a musician's performance narrative becomes enhanced and the QOP improves.

This research developed an affordable, accessible, and meaningful wearable device for musicians, the ATEM-P. By measuring breathing-induced expansion and contraction and providing real-time biofeedback on the musician's breathing technique, the ATEM-P brings innovative wearable technology to the world of music, a training tool and performance enhancer for the 21st century musician.

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8. ETHICAL STANDARDS

Both studies discussed in this paper, have been approved by the University of Calgary's Conjoint Faculties Research Ethics Board (CFREB).

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