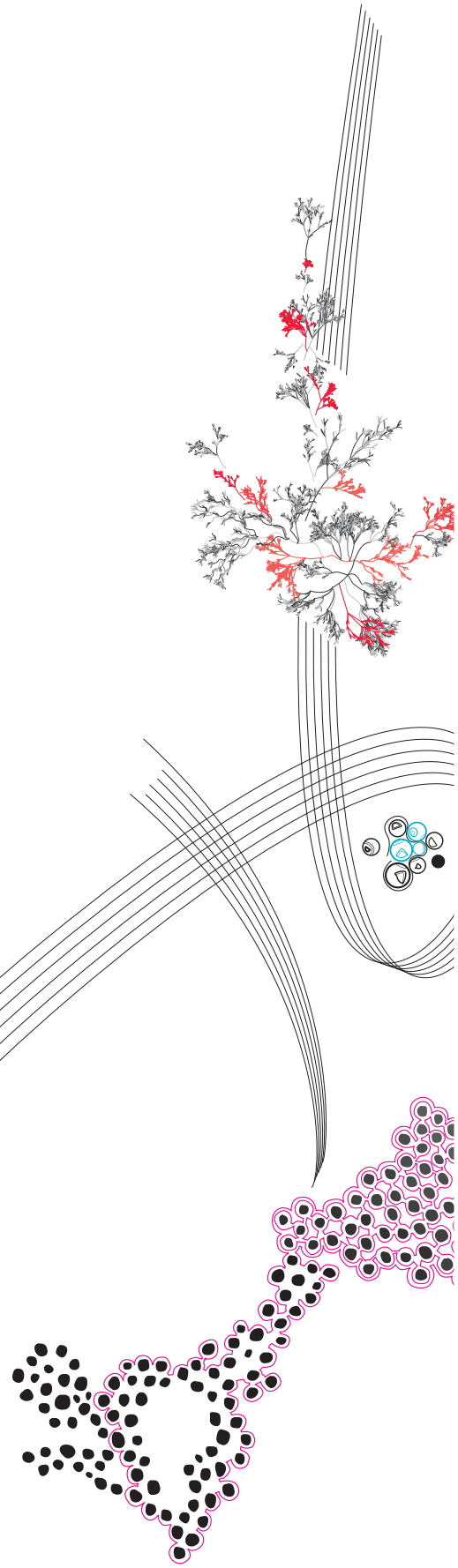

MSc Thesis Interaction Technology

B R E A T H E: Development and Design of a Wearable for Resonant Breathing Coaching with tactile feedback

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Abstract

Heart rate variability (HRV) describes the fluctuations of time between heart beats in milliseconds. It can be used as a marker of physiological and mental health as higher levels of HRV are indicative of a healthy heart and less stressed mental state. Resonance frequency breathing is a breathing technique that represents breathing between the ranges of 4.5 breaths per minute - 6.5 breaths per minute, and is hypothesised to be a pathway through which biofeedback improves heart rate variability.

Haptic feedback has been shown to be effective in many studies for breath guidance and is the most employed feedback modality in modern-day wearables. The purpose of this master thesis was to explore the possibilities to support breathing by haptic stimulation only, which led to the research question: **How to design a haptic feedback wearable for breathing guidance through heart rate variability training?**

The grove earclip sensor was used as the PPG sensor in this project and was employed to measure heart rate and heart rate variability as well as to estimate the breathing rate. This research conducted a within-subject experiment with 15 participants over the span of three weeks to evaluate the comfort, effectiveness and intuitiveness of an adjustable haptic belt with three patterns on three body positions. The results showed that whilst there were no significant results between the placements and patterns on heart rate variability, breathing with the haptic caused a significant difference in the HRV (RMSSD) of patients ($p = 0.03$), as opposed to breathing without it. The participants kept to the actuated breathing rate of the belt with an average deviation of 0.86 breaths per minute, which showed promising results of the participants understanding and interpreting the haptic cues from the belt.

Future research could focus more on different forms of wearables, other pre-processing methods and implementing fading feedback to help participants breathe slower without making them dependent. It could also research how to integrate additional sensors to gain supplementary information about the health and specifically breathing of the participant. A more controlled experiment design can also be considered.

Acknowledgements

"No one who achieves success does so without acknowledging the help of others."

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1 Introduction

"There are many ways to breathe as there are foods to eat.
And each way we breathe affects our bodies in different ways."

Life starts with the first breath and ends with the last. Breathing is a natural process that sustains life by the simple movement of air and for the most part happens unconsciously. Babies naturally practice the art of deep abdominal breathing also known as diaphragmatic breathing. The haptic form of interaction also has a considerable impact on the development of the motor learning process of newborns as it allows them to interact with the world and to perceive the interactions at the same time [1]. As humans get older factors like fear, bad posture and stressful lifestyles affect the way they breathe. The recent SARS-COVID-19 global epidemic has reminded many of the significance of breathing and the consequences of respiratory distress. With advances in medicine, psychophysiology and sports science we are learning more about this process more everyday [2]. Eastern religions and martial arts have used slow breathing techniques for centuries to produce psycho-physiological effects [3]. These breathing techniques have been gaining traction in the West since the 1900s. Studies have shown that slow breathing techniques promote autonomic changes that increase heart rate variability and respiratory sinus arrhythmia, that result in increased comfort, relaxation and pleasantness but also reduced symptoms of anxiety, anger and depression [4]–[6]. Since the 1970's there has been rising interest in heart rate variability (HRV) and breathing, and today HRV is recognised as an important biomarker for physical and mental health [7]. Low HRV is associated with mood and anxiety disorders and high HRV is associated with health and well-being [8]. Breathing at certain frequencies can help alter the heart rate variability and thus influence the mood of the participant. This is known as heart rate variability biofeedback training, where the participant receives live feedback data of their heart rate that they try to synchronise with their breathing for optimal gas exchange within the body [9]. More information the inter-dependence between the cardiovascular and cardio-respiratory system can be found in section 2.1.

Haptic feedback has been employed in many studies to help with breath guidance and has even been stated by multiple participants over multiple studies as the preferred modality because it is more natural to follow, less distracting, easier to engage and gives a greater sense of presence over audio or visual stimuli [10], [11]. However, this feedback should be given at a comfortable body location but also at a pleasant intensity and engaging pattern to ensure prolonged usage of the device. Careful and thorough design considerations need to be made for this application.

Thus, the main objective of this thesis is to design a comfortable, effective and intuitive haptic wearable for breathing practice through heart rate variability biofeedback training. For this, several research questions have been formulated with the main one being:

How to design a haptic feedback wearable for breathing guidance through heart rate variability training?

This research question is complemented by sub-research questions that serve the purpose to deepen insight into the topics that make up the main research question. Knowledge questions are habitually approached through literature research and design questions through experimentation. These questions are listed below.

Knowledge Questions:

1. How do humans breathe?
2. What breathing techniques exist? What parameters can be tuned to alter breathing?
3. What is heart rate variability biofeedback training and what are its advantages over other breathing techniques?
4. What parameters influence the design of effective haptic feedback for breath guidance?
5. What is the state of the art for wearables and haptic feedback for breath guidance?
6. How can heart rate variability be measured and what sensors should be employed?

Design Questions:

1. Where is the most suitable placement for the wearable to stimulate resonant breathing?
2. Which type and patterning of feedback is most effective to stimulate resonant breathing?

2 Context Analysis

"The healthy heart is not a metronome".

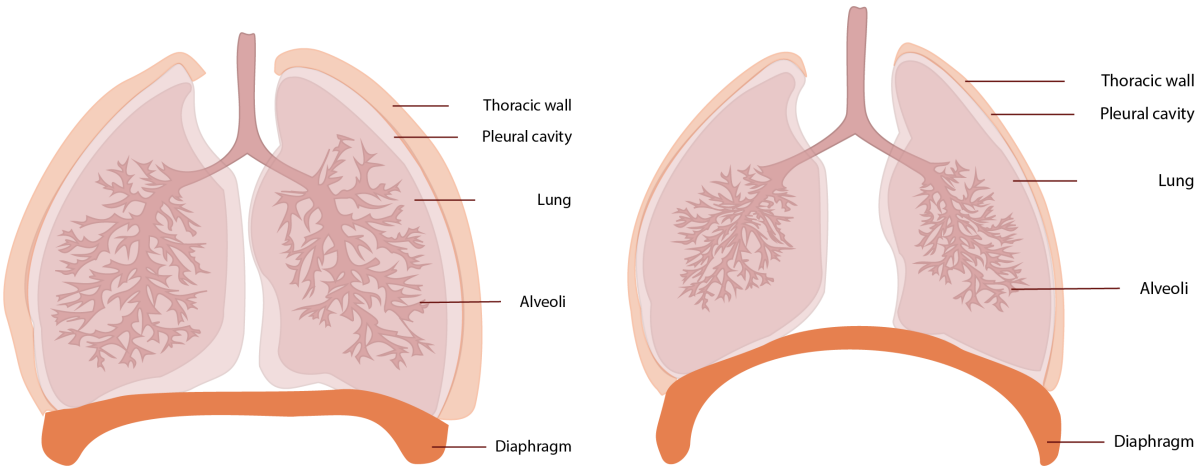
This chapter is split into four sections. The first section provides an introduction on the physiology of breathing. The second section conducts a literature study on different breathing techniques and physiological differences of altering different parameters. The third and fourth section also present findings of literature studies conducted firstly on haptic feedback for breathing in previous research and later on commercial products that integrate haptics for breathing. This chapter will answer the first five knowledge research questions.

2.1 Physiology

This section describes the mechanics of breathing, starting at the lungs (respiratory system), then the heart (cardiovascular system) and finally the brain (cardio-respiratory unit). It briefly touches upon the baroreflex, which is the system that the heart rate variability training tries to strengthen. The purpose of this section is to answer the first knowledge question of *"How do humans breathe?".*

2.1.1 Respiratory system

This subsection will explain the pressure differences during breathing that causes movement of the lungs and will expand on the relationship of tidal volume (amount of air [L] that moves through the lungs in a respiratory cycle), dead space (volume of inhaled air [L] that does not partake in gas exchange) and breathing rate (amount of breaths a person takes per minute [bpm]). Breathing describes the action of moving air across a surface of a respiratory structure to facilitate the exchange of oxygen and carbon dioxide with the environment. This process is also called pulmonary gas exchange [12].



(A) Inspiration: Lung (B) Expiration: Lung

FIGURE 1: Respiratory system

The resting respiration rate for humans can range between 9 - 24 breaths per minute [4], [13]. The diaphragm, is the main breathing muscle which divides the chest from the abdomen. Inspiration tightens the diaphragm, pushing it down on the abdominal contents, which forces

the abdominal wall out, increasing the abdominal pressure. At the same time, the muscles between the ribs contract and pull upwards, which increases the size of the thoracic cavity (at the thoracic wall) by decreasing the pressure inside. This allows air to flow into the lungs allowing pulmonary gas exchange through diffusion via the alveoli [4]. This phenomenon is illustrated in Figure 1 A.

Expiration is passive with the diaphragm returning to its resting position, which decreases the abdominal pressure but increases the thoracic pressure, causing the cavity to contract. As a result, the lungs deflate and expel air [4], as illustrated in Figure 1 B. The first two graphs in Figure 4 depict the relationship between the pressure in the thoracic cavity (intra-thoracic pressure) and the lung expansion. It can be seen that they are inversely proportional to each other. The pressure in the thoracic cavity needs to drop for the lungs to expand and vice versa. Kolář et al conducted an analysis of diaphragm movement during breathing using MRI and found that the greater the difference in diaphragm movement between inspiration and expiration, the greater the tidal volume [14]. This aligns with the studies of Harbour et al [2] and Russo, Santarelli and O'Rourke [4], as they defined minute ventilation (V_E $[L$ / $min]$) as the breathing rate (BR $[bpm(breaths\ per\ minute)]$) multiplied by the tidal volume (V_T $[L]$) as is written in Equation 1.

$$V_E = BR * V_T \tag{1}$$

As BR is inversely proportional to the V_T at a given V_E, slower breathing implicitly induces greater depth of breathing [2]. This can also be seen in the three scenarios depicted in Table 1. The physiological dead space V_D is the sum of air [ml] that does not partake in the gas exchange because it remains in the airways or reaches poorly perfused alveoli. There is a fixed amount of V_D, which results to an average of 150ml [2]. The alveolar ventilation rate represents the volume of air that reaches the alveoli per minute. This is lesser than the minute ventilation V_E because of the physiological dead space V_D. The relative V_D, seen in Table 1, describes the ratio of physiological dead space to the tidal volume (V_D : V_T) in percentage. Because of this, in the (V_D : V_T) ratio, increasing V_T is the only way to decrease the relative dead space.

To foster optimal gas exchange, the tidal volume $[V_T]$ and the alveolar ventilation rate should both be maximised and the relative dead space $[V_D/V_T]$ should be minimised. This would allow for most efficient space usage in the lungs and can only be done by slowing the breathing rate and consciously breathing deeper for oxygen-richer breaths.

Breathing pattern	**Minute ventilation** ($V_E, L/min$)	**Breathing rate (BR, bpm)**	**Tidal volume** (V_T, L)	**Dead space volume** ($V_{D,ml}$)	**Alveolar ventilation rate** (L_{min})	**Relative** V_D ($V_D/V_T, \%$)
Normal	10	20	0.5	150	7.0	30%
Slow, deep	10	10	1.0	150	8.5	15%
Fast, shallow	10	40	0.25	150	4.0	60%

TABLE 1: Effect of breathing pattern on alveolar ventilation and dead space [2]

2.1.2 Cardiovascular System

This subsection will explain the pressure differences that cause movement of the heart chambers and changes in blood flow and heart rate that are connected to respiration.

Blood circulation is influenced by oxygen demand, physical activity, stress, temperature and respiration [15]. The right side of the heart has de-oxygenated and carbon dioxide rich blood where as the left side of the heart has oxygen rich blood. This is illustrated in Figures 2 and 3 where the de-oxygenated blood is blue and the oxygen-rich blood is red. During inspiration, the thoracic pressure decreases, leading to an increase in abdominal pressure as stated in section 2.1.1. As the inferior vena cava passes through both the abdominal and thoracic cavities, an increase in abdominal pressure together with a decrease in thoracic pressure squeezes the blood upwards towards the heart, illustrated in the first heart of Figure 2. As a result, the pressure gradient between the right heart and systemic circulation (circulation between body and right side of the heart) is increased and follows in the filling of the right atrium and right ventricle [4], [16], illustrated as the full blue ventricle in the second heart of Figure 2. The filling of the ventricles is called the diastole and is illustrated in the second heart of the Figures 2 and 3, whereas, the pumping of the blood out of the heart is called the systole and is illustrated as the third heart in Figures 2 and 3. The stroke volume describes the amount of blood ejected out of the left ventricle of the heart during each systolic cardiac contraction and is decreased during inspiration, illustrated as the half full oxygen-rich left ventricle in the second heart of Figure 2. This is due to the expansion of the lungs causing the pulmonary blood volume (the pulmonary circuit is between the lungs and the left side of the heart) to increase and the blood flow from the lungs to the left atrium to decrease. Inspiration is associated with a lower systolic blood pressure (pressure in arteries when the heart beats) which is paired with a higher heart rate to ensure that enough oxygen-rich blood is pumped throughout the systemic circuit, as the left ventricle does not at fill at full capacity during this phase.

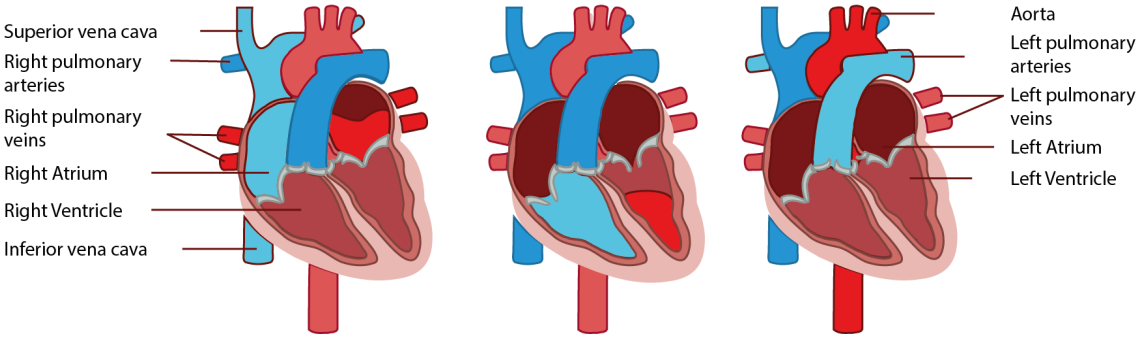


FIGURE 2: Inspiration: Heart

During expiration, the diaphragm moves up and the pressure in the thoracic cavity reverses as described in section 2.1.1. This causes the venous return to decrease, illustrated as the half full right atrium in the first heart of Figure 3. The pulmonary blood vessels that were previously expanded during inhalation, shrink from altered the pressure difference, leading them to pump more blood through the pulmonary veins into the left atrium. Stroke volume increases as a result [4], [16], [17]. These steps are illustrated in the second heart of Figure 3. Opposite to inspiration, now that the stroke volume is full, the heart rate decreases, as it can pump more blood with every contraction. Expiration is also usually paired with a higher systolic blood pressure, which also contributes to the heart beating slower. The pressure differences of the respiratory system and cardiovascular system are visualised in Figure 4.

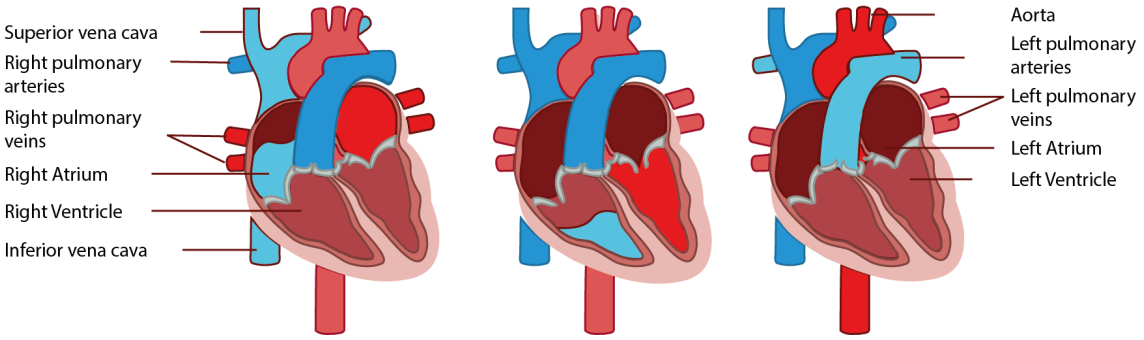


FIGURE 3: Expiration: Heart

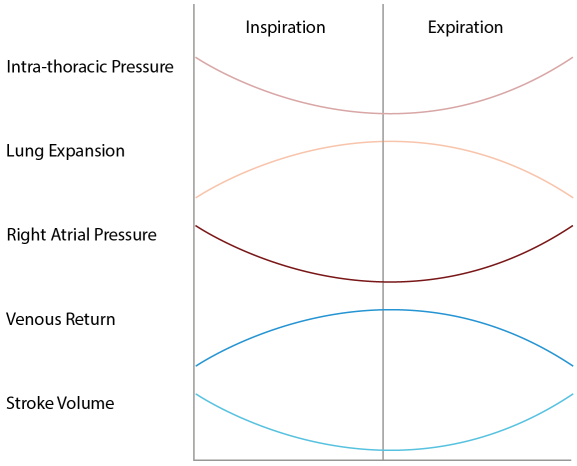


FIGURE 4: Cardiorespiratory system pressure changes

2.1.3 Cardiorespiratory System

This section provides an overview of other systems that play a part in breathing but are not main organs such as the lungs and the heart. It will cover respiratory sinus arrhythmia, a breathing induced natural variability in the heart, the autonomic nervous system, the system responsible for all involuntary processes and the baroreflex, the mechanism behind heart rate variability training.

Respiratory Sinus Arrhythmia (RSA)
As mentioned in section 2.1.2, the heart beats faster with inspiration and slower with expiration and is illustrated in Figure 5. The variability of the heart is smaller when the heartbeats are close together and larger when they are further apart. The grey dashed line represents the respiration wave in terms of heart rate variability and the red signal represents heartbeats by an ECG signal. Breathing thus, controls the rate of gas exchange at the alveoli [13]. Respiratory sinus arrhythmia describes this variation of heart rate and is a normal finding in heart monitoring measurements [9], [18]–[21]. It is usually more pronounced in children and in young adults than in older subjects, but data on the exact age of its disappearance is inconsistent [22].

RSA is a measure of heart rate variability. It can be assessed in several manners, as will be described in more detail in section 3. One way is to take the root mean square of the

successive differences inter-beat differences (RMSSD). This describes the differences in heart beats and is visualised as the grey dashed line in Figure 5. Over time and with more breaths, this grey dashed line would show periodic behaviour and therefore, the average RMSSD can be taken as a measure of heart rate variability. This is usually done in clinical settings by an electrocardiogram (ECG) and a computer. RSA can be quite marked (up to 10 to 20 beats/min or more), typically has a frequency of 0.25Hz and is an indicator of vagal tone [4], [23]. Vagal tone refers to the activity of the vagus nerve, an important component of the parasympathetic nervous system. It is often used to assess heart function and will be elaborated more on in section 2.1.3.

Studies have shown that heart rate variability can be tuned such that the variation in cardiovascular oscillations match the respiration phases, which can reduce the physiological dead space, enhances pulmonary gas exchange and minimizes the energy expenditure [4], [9], [13], [18], [19], [21]. RSA can usually be seen with clarity in slow paced breathing in the low frequency band in spectral analyses. It decreases with a higher respiration frequency as the vagal effectors (parasympathetic nerve fibres that carry signals from the brain to the peripheral nervous system) are less able to follow higher frequency variations [24].

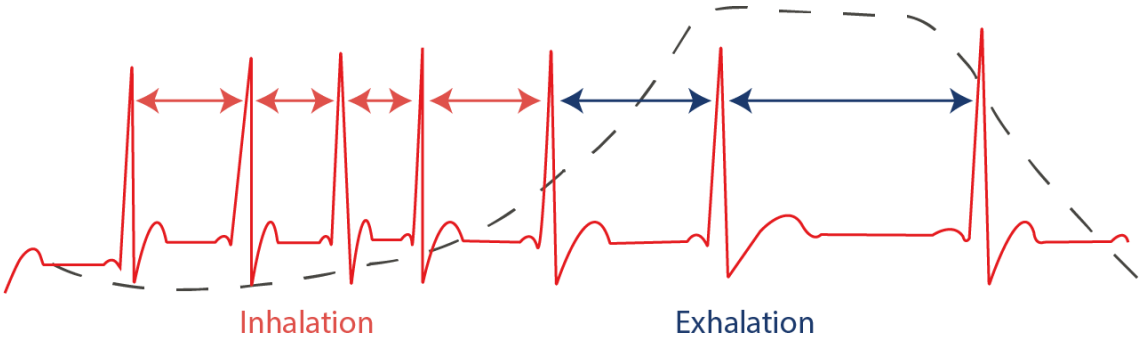


FIGURE 5: Respiratory sinus arrhythmia (RSA). The heart rate increases during inhalation and decreases during exhalation (Adapted from [25])

The Autonomic Nervous System (ANS)

The autonomic nervous system belongs to the peripheral nervous system and is responsible for the control of essential functions such as heart beat, breathing and digestion. This system is under involuntary control, as it operates automatically [26]. From an anatomical point of view, the autonomic nervous system can be divided into the parasympathetic nervous system (PNS) and the sympathetic nervous system (SNS) [24]. The PNS, also known as the "rest and digest system [24]", is typically associated with energy conservation, characteristics of relaxation and lower levels of stress. Some of its functions are decreasing the heart rate, constricting the bronchi resulting in a slower breathing rate and contracting the bladder, allowing urination [27]. The SNS, also known as the "fight or flight system [24]", directs the body's involuntary response to dangerous or stressful situations. In contrast to the PNS it accelerates the heart rate, dilates the bronchi and inhibits bladder contraction, amongst other functions [27]. Inspiration emphasizes sympathetic activity, as it manifests a faster heart rate and expiration emphasizes parasympathetic activity due to the slower heart rate [28], RSA and the heart rate component of the baroreflex are under parasympathetic control, in particular by the vagus nerve [9]. Activity in the vagus nerve affects the brain and vice versa due to many of the vagus nerve fibers being afferent, meaning they bring

sensory information to the brain [9]. RSA is affected by vagal pathways and can thus be considered a measure of cardiac vagal tone, which is an indicator of how the vagus nerve is functioning.

The Baroreflex

The baroreflex is a negative feedback mechanism that is responsible for promoting blood pressure homeostasis through stretch receptors called baroreceptors in the carotid artery [4]. The baroreceptors relay the signals they receive to the medulla oblongata, the control center of the heart, which activates the sympathetic cardiac or vagus nerve leading to the SA node. This is illustrated in Figure 6.

The sinoatrial node (SA node) is the pacemaker of the heart [18]. It is located in the right atrium of the heart, as seen in Figure 6. In absence of any external stimuli, it acts as a self-sustaining oscillator at its own intrinsic rate (around 100 beats per minute [19]) [29]. The resting heart rate in humans ranges between 60 and 100 beats per minute, with women having a slightly higher resting heart rate than men [30]. The external stimuli are signals from the vagus and sympathetic nerves, which both are linked to respiration activity. Thus, the sinus node is secondarily modulated by the respiratory rhythm [2], [4], [18], [28], [31].

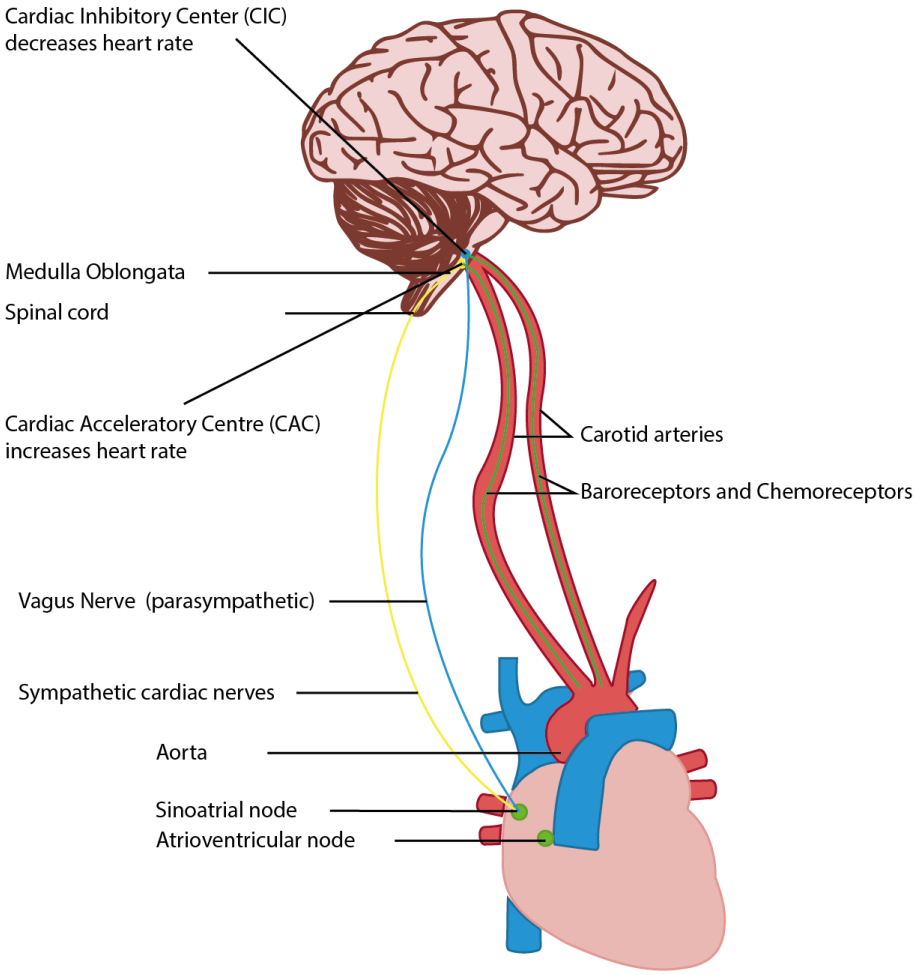


FIGURE 6: Baroreflex

As mentioned in section 2.1.2, increases in blood pressure generate heart rate decreases, while decreases in blood pressure generate heart rate increases. The mechanism responsible for this phenomena is the baroreflex [21]. Arterial baroreceptors detect stretching of the walls as the blood pressure increases [9]. They signal the cardiac inhibitory centre (CIC), located in the medulla oblongata, which creates an immediate decrease in heart rate by stimulating the parasympathetic nervous system through the vagus nerve to slow the firing of the SA node. This leads to a mechanical decrease in blood pressure due to less blood flowing through the vasculature with a constant delay of around 5 seconds [9], [21], [28].

When the blood pressure falls, the baroreflex activates the cardiac acceleratory centre (CAC), to activate the SA node through the sympathetic cardiac nerve to increase the heart rate, leading to an increase in blood pressure. This again has a delay of around 5 seconds [9], [21], [28]. The delay may be longer among taller and muscular people and consequently in men, as the length of delay is caused by the amount of blood in the system [9], [21].

The time delay in the baroreflex system tends to produce a rhythm in everyone's heart rate with a period of about 10 seconds (0.1Hz) and is known as the Mayer wave. Spectral analysis of both blood pressure and HRV fluctuations show two significantly correlated rhythmic oscillations at 0.25 Hz (high frequency (HF)) and 0.1 Hz (low frequency (LF)). The HF oscillations relate to the resting respiration rate of 15 breaths per minute (0.25 Hz) [4], [9]. The LF oscillations relate to the cardiac feedback mechanisms regulated through the baroreflex. Studies have found that slow breathing increases the amplitude of the LF HRV oscillations, especially at 0.1 Hz [4]. This will be further described in section 2.2.2.

To summarise, this section has illustrated that breathing is a complex partnership between the respiratory and cardiovascular system. Slow breathing can reduce alveolar dead space and ensure optimal gas exchange for oxygen richer breaths. This in turn can trigger the parasympathetic nervous system to reduce feelings of stress and increase physical and mental well-being.

2.2 Breathwork Strategies

This section provides an overview of some known breathing techniques and goes further to explain which parameters of breathing can be altered. It briefly touches upon the advantages and disadvantages of every parameter before selecting the breathing method of choice for this thesis, namely resonant frequency breathing or heart rate variability training. The purpose of this section is to answer the second knowledge question of *"What breathing techniques exist and how can breathing be altered?"*.

Breathing is both natural and automatic, sustaining life by the simple movement of air [2]. Zaccaro et al. conducted a systematic review on 15 articles on the psycho-physiological correlates of slow breathing ($<$10 breaths/minute) and found that slow breathing techniques promote autonomic changes increasing Heart Rate Variability and Respiratory Sinus Arrhythmia paralleled by Central Nervous System activity modifications [5]. The psychological outputs of the slow breathing practices were increased comfort, relaxation, pleasantness and reduced symptoms of anxiety, depression, arousal and anger. These findings are aligned with Brown and Gerbarg [3], Russo et al [4], Prpa et al [32] and Bachler et al [33]. The above mentioned studies also all confirm that slow breathing increases arterial baroreflex sensitivity, vagal tone and decreases blood pressure.

This section covers some established breathing techniques and parameters of breath that can be changed depending on the training method.

Pranayama

Pranayama is the practice of breath regulation. In Sanskrit, "prana" means life energy and "yama" means control [3]. The practice originates from Ancient India and consists of 8 main forms that all have the same three stages, namely, inhalation through nostrils, retention and exhalation performed at varying rates and depths [34], [35]. Pranayama was introduced to the West in the late 1800s and popularity rose in the mid 1900s [4]. It has been shown to improve pulmonary function and cardiovascular profile as well as stress, anxiety and depression [3], [35], [36].

Buteyko Method

The Buteyko method developed within the Russian medical community in the 1950's and spread across several continents and reported positive results in the treatment of asthma [4]. Buteyko breathing is a series of techniques that include varying the depth, frequency, velocity, timing and rhythm of breathing with the primary aim of reducing chronic hyperventilation (over-breathing). Similar to pranayama, all breathing variations are practiced with nasal breathing [37]. It has been shown to benefit children and adults with mild asthma to give them a better quality of life [38]–[40].

Wim Hof Method

The Wim Hof method stands on three pillars, namely, breathing exercises, cold exposure and meditation [41]. Its aim is to help practitioners connect more deeply to their body with powerful inhalations, relaxed exhalations and prolonged breath holds [42]. Studies have found that this method may indeed reduce stress symptoms in participants on an Antartic expedition and increase autonomic reaction [43], but has not always altered parameters of breathing economy

during interventions [41], [44].

The above mentioned techniques still do not describe "one way of breathing", as they can all still be expanded into various exercises by varying different parameters. Even though they all have different names and come from different locations, the parameters they all share the aspect of nasal and slow breathing.

2.2.1 Breathing Parameters

Harbour et al summarised a description of breathing parameters that can be tuned in the context of breathing training for exercise [2]. They will be summarised here and applied to the context of breathing training at rest. These have been summarised in Table 2 and are organised in ascending order of benefit, complexity and risk. Section 2.1 already covered the breathing rate and depth that can be adjusted for maximum gas exchange and will therefore not be elaborated on here again.

Nose
Ritz and Roth [45] and Dallam and Kies [46] found that breathing through the nose rather than the mouth can result in greater efficiency of breathing and gas exchange. Furthermore, nasal breathing is known to improve inspired air by humidification, warming, and filtration for pollutants and allergens [2], [45]. It also increases nitric oxide production in the airway and has positive effects upon pulmonary perfusion, head posture and cognitive function [2], [47]. The results of the meta analysis run by Zhao et al showed that mouth breathing as opposed to nasal breathing can lead to underdevelopment of the jaw in children [48]. Despite nasal breathing utilising a smaller airway than mouth breathing, it appears to also increase diaphragmatic function and has been used a lot in yoga practices and other eastern meditation practices.

Active Exhale
Inspiration enhances sympathetic and suppresses parasympathetic activation, whilst expiration does the opposite. Longer exhales may therefore exploit RSA to improve HRV and subjective well-being at rest [2], [5]. Schwerdtfeger et al [19] and van Dienst et al [49] have both shown psychological benefits from low inspiration/ expiration ratio (longer expiration than inspiration). The difference in tidal volume was more pronounced when breathing at a low i/e ratio compared to breathing at a high one as well as higher pleasure, less arousal and higher RSA and HRV [49], [50]. Stronger / forced exhales in combination with a lower duty cycle make the "active exhale". This causes a fuller contraction of the diaphragm, lowers diaphragmatic work and assists in postural stabilisation [2].

Sync
Locomotor-respiratory coupling (LRC), describes phase-locking between breathing and stepping rhythms [51]. This method is usually employed by runners who want to optimise their breathing during sport. LRC has been said to reduce the work of the ventilatory muscles to prevent respiratory muscle fatigue and to enhance gas exchange [2], [51]. It even fulfils the conditions for inducing a hypnotic state as it requires physical exertion, rhythm and concentration and therefore can lower stress on the nervous system by reducing cognitive fatigue through comfort [2]. An odd ratio (such as 5:1 or 7:1 steps per breath) should be used capture the benefits of longer exhales and to prevent the side stitch [2].

Strength

Respiratory muscle training (RMT) employs resistive breathing devices to stress the respiratory system to result in higher ventilatory efficiency and reduced work of breathing (WOB), which describes the energy expended to breathe [2]. Hellyer et al studied the effects of inspiratory muscle training (IMT) during stationary cycling and found greater diaphragmatic activity of performing IMT cycling in an upright posture rather than at rest, suggesting that the combination of the two could provide an additive effect [52]. However, RMT is an underexplored field and further research could help strengthen these claims.

Hold

Breath holding techniques have gained popularity due to performance benefits reported in swimming and free-diving [2]. Similar to RMT, breath holding is a forceful metabolic stressor that causes accelerated muscle deoxygenation (hypercapnia). TBreath holding training lasting 3-5 weeks can already increase stroke volume (up to 30%) and haemoglobin concentration (up to 10%) due to increased left ventricular stroke volume and spleen contraction [2], [53].

Breath tool	Description	Primary mechanisms	Advantages	Disadvantages	Applications
Rate	↓ and/or paced BR	↓ relative V_D; ANS regulation	↑ perfusion; ↓ dyspnoea; and pacing assistance	↑ V_T at less compliant lung volumes, initial air hunger	Novice runners; low intensity exercise
Deep	↑ V_T via diaphragmatic engagement	↓ BR; ↑ abdominal ribcage contribution to V_E	↓ work of breathing, lung operating volume; ↑ postural control	Difficult to cue	Biofeedback; thoracic-dominant breathers
Nose	Constant or intermittent nasal breathing	↑ air humidification, warming, and filtration	↓ airway constriction; ↑ diaphragmatic activation	Difficult at high intensities; time required for habituation	Low intensity exercise; extreme climates
Active exhale	Longer, forceful exhale phase with / without phonation	↓ expiratory flow velocity: ↑ abdominal engagement, expiratory pressure	↓ flow limitation, lung operating volume; ↑ perfusion; and ANS regulation	↓ relative TI; difficult to cue	Constant for calming effects; intermittent during high intensity or at altitude
Sync	Step & breath synchronization at wholeinteger ratios	Stepdriven flows; rhythmic entrainment	↓ work of breathing; pacing assistance; hypnotic	Difficult to learn; even ratios ↑ side stitch	Odd ratios for ↓ side stitch; ↑ breath awareness
Strength	Respiratory muscle resistance training	↑ ventilatory muscle activation, metabolic stress	↓ work of breathing, dyspnoea; ↑ diaphragmatic activation	Special equipment needed; unclear protocols	Low intensity exercise; training for competition
Hold	Intermittent brief end-expiratory breath holds	↑ biochemical stress, spleen contraction	↓ chemosensitivity; cardiovascular performance	Risk of syncope, intense air hunger unpleasant	Pre-competition; elite sport

TABLE 2: Overview Breath Tools [2]

As seen from the section above, the parameters mentioned are already varied in the multiple exercises of the stated techniques and studies have found multiple benefits of slow breathing [5]. The sheer possibilities of tweaking every parameter for every technique in order to find the anatomically most efficient one was not a feasible task for the time-period of this thesis. Especially since most breathing techniques have overlapping exercises. Therefore a new breathing technique was found that had physiological explanations and evidence of its benefits and uses the parameters rate, deep and nose to encourage the participant to breathe at around 4.5 - 6.5 breaths a minute. This was first reported by Angelone and Coulter in 1964 and has been developed by multiple studies since and is now called resonant frequency breathing [4].

2.2.2 Resonant Frequency Breathing

This section will answer the third research question of *"What is heart rate variability biofeedback training and what are its advantages over other breathing techniques?"*

Heart rate variability (HRV) describes the variation in time intervals between consecutive heartbeats. It can be measured with both time-dependent measures and frequency dependent measures, as explained in section 3. HRV is controlled by the parasympathetic nervous system (PNS) ($<$ 1s), as the sympathetic nervous system (SNS) exerts its effects too slowly to elicit beat-to-beat changes ($>$ 5s) [24], [54]. As mentioned in section 2.1.3, the heart beats faster with inhalation and slower during exhalation [54]. Higher levels of HRV are indicative of a healthy heart and a marker of overall healthy physiological functioning [9], [20] and can lead to a higher life expectancy and greater cognitive flexibility [24]. Low HRV has come to the foreground as an important marker of mortality in recent years [55], but has also been shown to occur in depression, anxiety and chronic stress. High heart rates are inversely correlated with the levels of HRV, as there is less opportunity for variability between heart beats when they are closer [20]. The biofeedback in the HRV biofeedback training implies that the participants are given feedback on their performance whilst breathing at their resonance frequency.

In everyday activity, respiration and heart rate habitually oscillate with a $90°$ phase angle so that the peak heart rate occurs in the middle of a breath, resulting in an average gas exchange efficiency [9]. This is visualised in the middle picture of Figure 7. Gas exchange efficiency is at its lowest when respiration and heart rate are at a $180°$ phase angle from each other [9], visualised on the right in Figure 7. Through resonant frequency breathing or heart rate variability biofeedback (HRVBF), the participant tries to maximise their HRV by getting feedback on their heart rate patterns to create a sine-wave like curve that aligns with a slower breathing rate [9], as depicted on the left in Figure 7. This type of method has shown benefits for asthma, chronic obstructive pulmonary disease (COPD), irritable bowel syndrome (IBS), depression, pain, post-traumatic stress disorder (PTSD) and anxiety [5], [9], [13], [19], [20], [28]. The red dashed line in Figure 7 depicts the heart rate and the blue line depicts the breathing rate. In the $0°$ phase shift, the fastest heart rate can be seen in the peak of the inhale and the slowest heart rate in the minima. This correlates with Figure 5. The other scenarios follow the same logic.

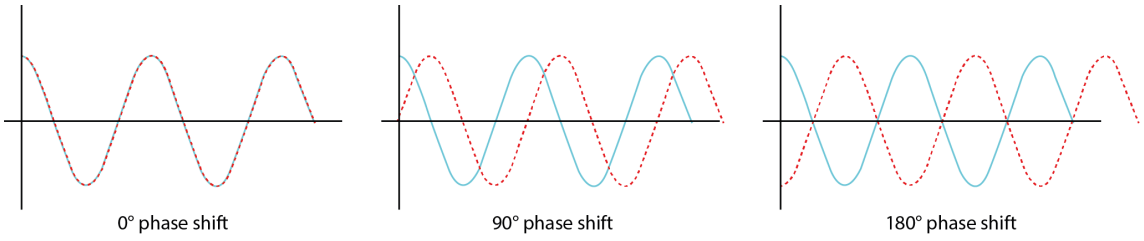


FIGURE 7: Respiration and heart rate oscillations (Adapted from [13])

At any given moment, approximately 10% of the blood in the whole vasculature is distributed in the pulmonary circulation (lungs and right heart circuit) and 10% of this blood lies in the pulmonary capillary bed [18]. The stroke volume is therefore almost equivalent of the blood circulating in the pulmonary capillary bed. This blood participates in alveolar gas exchange and is replaced / pumped out with every heartbeat. Therefore, if the respiration and heart rate oscillations are in phase with each other, gas exchange efficiency can be maximised [9], [18].

Due to the principal of resonance, synchrony of heart rate and breathing can increase heart rate oscillations up to 4 - 10 times from resting baselines ($HR_{max} - HR_{min}$) leading to high levels of HRV [20], [28].

All oscillating feedback systems with a constant delay can be described as resonant systems. When these systems are stimulated, they provide high-amplitude oscillations at a single frequency that recruit or overshadow other frequencies to produce a sine wave oscillation with a high amplitude [9].

As mentioned in section 2.1.3, the baroreflex oscillates at 0.1Hz. This value can differ across individuals between 0.075 - 0.12 Hz, depending on their height [24]. These frequencies correspond to a breathing rate of 4.5 - 6.5 breaths per minute [9], [24], [28]. Furthermore, it has also been found that rhythmical muscle tension and rhythmical presentation of emotion-inducing pictures can produce the same effect on the cardiovascular system if presented at 0.1Hz [9].

This section has addressed four breathing techniques and seven breathing parameters that can alter respiration practices. It has shown that breathing at around 0.1 Hz can stimulate the baroreflex, maximise gas exhange and boost HRV, which in turn increases the activity of the parasympathetic nervous system and results in feelings of calm and relaxation. Because of the physiological reasoning presented in this section, the breathing technique that will be implemented for this thesis is resonant frequency breathing. The next section will present an overview of measurement techniques to assess resonant frequency breathing.

2.3 Haptic technology

This section presents a literature review conducted on the benefits of guided breathing and the employment of haptic feedback to stimulate and guide breathing. The studies that were analysed for the latter topic dated back to 2016 earliest. This research choice was made to only consider the newest state of the art, as technology evolves rapidly and sensors are developing at a fast pace. The purpose of this section is to answer the third and fourth knowledge research questions.

2.3.1 Haptic Feedback

This section will answer the fourth research question of *"What parameters influence the design of effective haptic feedback for breath guidance?"*. It will thereafter present an overview of the current state of the art in both research and commercial products to provide some background for the fifth research question of *"What is the state of the art for wearables and haptic feedback for breath guidance?"*

Feedback to the user communicates the result of any interaction, making it understandable to the user about the success / failure of performing a task. When talking about interaction design, there are four modalities of feedback, namely visual, auditory, haptic and multimodal, where the latter consists of a combination of the first three [56]. In this thesis, the haptic modality will be considered.

Haptic feedback consists of tactile and kinesthetic feedback. Tactile feedback addresses perception from the skin, such as vibrations, also called vibrotactile feedback. Kinesthetic feedback addresses the perception of our own muscular effort and bodily movement [57]. The haptic modality can be chosen over visual or auditory as its nudges do not disturb people nearby and is more subtle [58], [59]. Figure 8 visualises the dimensions of haptic feedback and shows how the tactile branch can be differentiated in five ways.

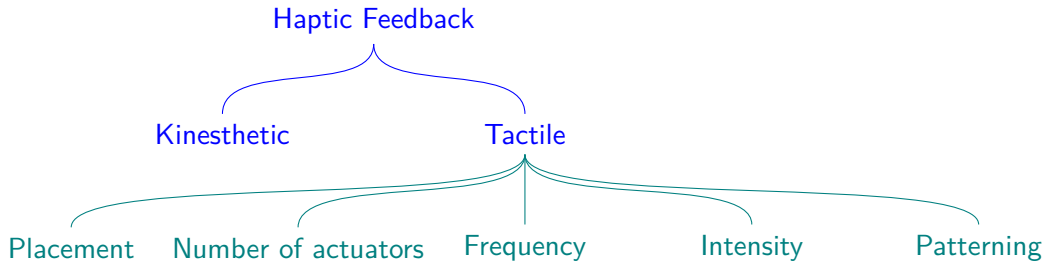


FIGURE 8: Modalities of Haptic Feedback (Adapted from [56])

Having tactile feedback in a device is a new sensory experience, especially when most media and interactive applications nowadays focus on the visual and auditory feedback modality. Miri et al mention 15 studies that have developed vibrotactile-based devices to increase affect regulations in stressful situations where our auditory and visual channels are overtaxed [60]. Shabani et al researched the effectiveness of haptic vs. visual feedback for neurofeedback training and found that the users performed significantly better with the haptic-only feedback as compared to the visual-only or haptic and visual combined [61]. Parades et al conducted a study for a guided slow breathing intervention for drivers with haptic and auditory feedback [10]. They found that even though both modalities helped reduce the drivers breathing rate, most users preferred the haptic feedback better as they found it more natural to follow, less

distracting and easier to engage with as compared to the audio stimuli. Gibbs et al. compared effects of haptic and visual feedback on presence of a ball in virtual reality and found that the haptic-only modality gave rise to a greater sense of presence than visual-only. They also argued that the haptic feedback discerned the balls location more than the visual or bimodal aspect [11]. Previous studies have shown that haptic feedback can also assist in comforting newborns by mimicking their parents heartbeat in forms of teddy bears [62] or cushions [63]. However, it should be noted that just because the results in these studies [10], [11], [61] have shown that haptic feedback is more effective or preferred when comparing it against another modality, does not mean that this is the case for all contexts. Before choosing a feedback modality, the context of use, the users and the application should be thoroughly considered.

Prpa et al. analysed 31 breath based interactions into visual, auditory and kinesthetic with the justification that all strategies that translate breathing data into perceptible sensations on the body support the kinesthetic experience [32]. This definition is the one that will be used from this point forward, as the purpose of this project is to increase mindfulness through resonant breathing.

2.3.2 Haptics for motor learning

The definition of motor learning is a lasting change of motor performance caused by training. At a behavioural level, it can be classified by three phases [1].

1. **Attention-demanding phase:** The motor program of the to-be learned task is formed. The learning progresses rapidly.
2. **Refinement phase:** The motor presentations are refined. Error and movement variability are improved.
3. **Automatization phase:** Movements are performed in a highly automized and consistent manner.

Breathing is an unusual motor act as it can be controlled both consciously and unconsciously [64]. It must be controlled for acts such as coughing and sneezing but also for more complex acts such as exercise and and vocalisation. For the purpose of this thesis, the users should learn to slow their breathing and to breathe diaphragmatically through their nose. The first two phases of motor learning will be the focus, as the haptic actuation will have to be designed to allow for learning to progress rapidly and errors to decrease over time.

There are three modalities to the timing of feedback, as is illustrated in Figure 9. It can be provided before the movement in form of a demonstration or instruction, during the movement, or after execution of the movement.

All the studies in section 2.3.3 used haptic feedback during the movement. However, studies state that despite concurrent feedback having the advantage that it enhances performance in the attention-demanding phase, these gains are lost in retention tests [1], [56]. For complex tasks, concurrent feedback can prevent cognitive overload and enhance learning [1]. For simple tasks, concurrent feedback creates a dependency and has been shown to hamper motor learning, however this is most profound for visual augmented feedback [56]. Breathing combines many different physiological systems and is a constantly occuring movement. According to Gentile's taxonomy of motor skills, the task is relatively simple as the participant is in a stationary condition and the haptic actuation causes the inter-trial variability [65]. Terminal feedback has

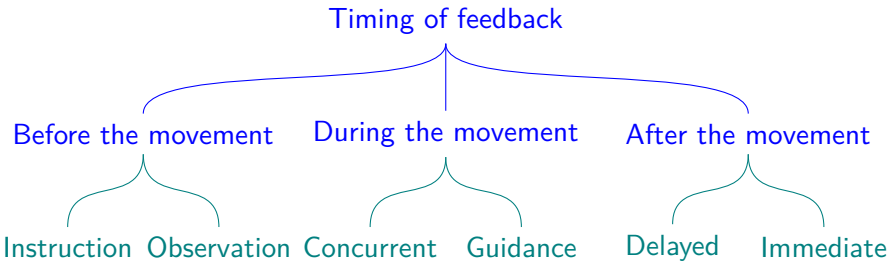


FIGURE 9: Modalities of Feedback Timing (Adapted from [56])

been shown to be effective for both low and high task complexity, as the gains in performance remain in retention tests [56]. Terminal feedback can be given directly after the movement or after a certain delay. This does not mean that feedback after the movement is the gold standard for every use-case scenario. User tests can validate the choice of feedback for the application and this should be experimented with during the prototype phase. More information on the design of the haptic feedback can be found in chapter 4.

This section has shown that there are are five dimensions of tactile feedback, namely placement, number of actuators, frequency, intensity and patterning. All these dimensions can be altered to provide a different sensation of tactile feedback. Furthermore, there are three main timing modalities of haptic feedback, namely before the movement, during the movement and after the movement. Choosing the correct timing feedback modality is essential to properly support to motor learning. For breathing wearables, the during the feedback modality is usually chosen to support the attention-demanding phase and the refinement phase of motor learning. This section has presented various parameters that can influence the design of haptic feedback for breathing guidance and thusly answered the fourth knowledge question.

2.3.3 Haptics and breath control

This subsection will provide an overview over studies that have used haptic actuators for breathing guidance and will conclude with a list of recommendations the authors suggest for future implementations of their works.

The studies of Parades and Chan [66], Costa et al [67] and Choi and Ishii [68] all research how to reduce anxiety and induce feelings of calm through haptic feedback in the form of a wrist watch. Through the haptic feedback given based on the users heart rate [67] or heart rate variability [68] or both [66], all three studies showed that they were able to lower users heart rate significantly and thereby activate their parasympathetic nervous system to get them to feel more relaxed.

Previous studies have made variations of cushions to handle different forms of stress and anxiety [69]–[71]. The users of these studies mentioned that the respective interventions made them mindfully deliberate on their breathing patters and that they felt calmer after having "breathed" with the respective intervention. Similar to the previous studies mentioned [67], [68], the methodology of Yu et al [69] was also to guide the breathing rate of the user by only using a PPG sensor to detect heart rate variability. In the studies of Haynes et al [70] and Ban et al [71] the pillow was set to inflate and deflate at a predefined rate. In the study of Haynes et al. 5 different prototypes were tested to help undergraduate students to breathe at 10 breaths a minute to reduce test anxiety and they found the haptic modality to be most

effective [70].

In 2018, Balters et al developed a car seat that provided haptic feedback to the driver to increase their alertness through fast-paced breathing, up to 500% of the users initial breathing rate [72]. Two years later Balters et al used that same tactile car seat set-up to reduce stress of drivers through slow-paced breathing with a reduction of 30% to their baseline breathing rate [59]. Parades et al also worked with the same car-seat to research whether voice, haptic or both stimuli together could help calm drivers more through slow breathing cues and found that even though both forms of feedback helped decrease breathing rate, the haptic feedback was perceived as less obtrusive and more relaxing than the voice commands [10]. Furthermore, the continuous haptic feedback helped maintain the breathing pace and participants said that it was more natural to follow, less distracting and easier to engage with than the voice stimuli [10].

Miri et al explored both where haptic feedback devices should be placed on the body and which vibrotactile pattern should be used to make paced-breathing guidance most effective to reduce anxiety [73]. As the research team of Miri et al consisted of biofeedback breathing practitioners who guide patients by touching them with both hands at symmetrical places on the abdomen, they decided to use symmetrically placed tactors on the abdomen to simulate this. Furthermore, this design choice was justified by stating that breathing is a symmetrical experience as the respiratory system consists of two lungs and two nostrils, therefore the feedback should also be symmetrical [73]. 2 years later, Miri et al developed a vibrotactile system to facilitate affect regulation through slow breathing in children diagnosed with autism spectrum disorder where they used two devices to be held in each hands following the justification given above [60]. They only used a PPG (photoplethysmogram) sensor compared to the 4 sensors they used in [73] to slow the breathing rate. In both studies, Miri et al give recommendations for a thorough personalisation procedure that should include a stressor [73] and perhaps be gamified [60]. They also underline that it is important that the participants are briefed on how to breathe slowly before the experiment starts [60].

Other forms of haptic feedback devices for breath rate regulation have been sleeves [74], a mechanical lotus flower [75], a fanny-pack [76], a belt [77], [78] and even an exoskeleton, developed specifically for voice-training [79]. Most of the aforementioned studies wanted to improve stress levels in their participants or wanted to induce feelings of calm. Many of their recommendations for future studies align with an emphasis being put on the following five points.

Preliminary requirements

- **Personalised feedback**
  Let the user personalise the tactile pattern, the intensity and their own breathing rate [10], [59], [60], [67], [72], [76].

- **Stimuli for progress**
  Reward good performance instead of indicate bad performance [72]. Challenge the user to lower their breath rate even more [69].

- **Adaptable**
  The system should be able to sense the physiology of different users and adapt to their heart rate, rather than just have a set number of pulses per minute [67]. The users should also be able to clip the device where ever they want to (fanny pack) [76].

- **Better understanding of the task at hand**
  Let the users play and explore the device first to discover how it works themselves before operating it [59]. Provide tutorials on how to breathe slowly before using the device [60].

- **More research into materials**
  Play with the size, shape parameters of the device to make it more ergonomic [70]. Explore the field of inflatable material and heating wires together rather than apart [74].

All papers mentioned in this section have been summarised in Table 3.

TABLE 3: State of the Art: Haptics for Breath Guidance

Name	Problem Statement	Sensor and location	Actuation	Guidance	Form	Participants	Results	Recommendations
ambienBeat (2020) [68]	Mental Stress	Heart rate (PPG) on wrist, pressure sensing	Voice-coil actuator	HRV pattern guidance	Watch	12 (4m, 8f)	Tactile stimulus had most significant effect on lowering users heart rate compared to visual and auditory.	Further studies into EDA (electrodermal activity)
Breath Booster (2018) [72]	Emotion Regulation	Polar H7 (Heart rate monitor around chest), EmotionCheck device (wrist)	3 vibration motors	Heart rate (bpm)	Watch	67 (43f, 14m)	Slower heart rate group showed statistically significant lower anxiety	Personalise the feedback according to the situation and the user to increase effectiveness of intervention. Truthful feedback about the user's performance could induce more anxiety if it is not positive. Try to expose to stimuli for progress instead.
EmotionCheck (2016) [67]	Increase autonomic activity for more alertness when driving through fast paced breathing	Zephyr BioModule Device 3.0 around chest, ECG	41 LRA motors over car seat which pattern that swipes over the users whole back at predetermined breathing rate	Boosting breath rate for drivers	Car Seat	8 (2f, 6m)	Haptic feedback can increase the rate and intensity of breathing as well as heart rate. 80% of participants said they also felt more energised through the intervention.	Personalised system that can sense the drivers behaviour and physiology but is also adaptable for the individual differences of breathing paces.
Just Breathe (2018) [10]	Stress whilst driving	ECG, Zephyr BioModule Device 3.0 around chest, Empatica E4 bracelet around non-dominant wrist	41 vibrotactile motors over car seat and voice speaker	Breath rate regulation for destressing	Car Seat	24 (12f, 12m)	Haptic feedback was perceived less obtrusive and more relaxing than voice commands. Continuous haptic feedback helped maintain rhythmic breathing pace. Both voice and haptic feedback helped decrease breathing rate and increase HRV with most participants preferring haptics for being more natural to follow, less distracting, easier to engage than voice stimuli.	Investigate multimodal interventions that combine light, heat, pressure, airflow and sound. Try to personalise parameters to deliver optimal guidance with minimal cognitive distraction.
Calm Commute (2020) [59]	Stress whilst driving	Zephyr Biomodule Device 3.0 around chest, ECG	41 LRA motors over car seat which pattern that swipes over the users whole back at predetermined breathing rate	Breath rate regulation for destressing	Car Seat	24 (12m, 12f)	Intervention adoption rate was 82%. Breath rate and physical arousal was reduced significantly.	Investigate different vibration patterns for personalisation. Include exploration mode that allows users to interact with system to get to know it, before using it.
ViBreathe (2021) [69]	Workaday Stress	PPG sensor in handheld cushion, Belt stretch sensor around abdomen	LRA vibration motor	Breath rate regulation	Handheld cushion	24 (13m,11f)	Responsive guidance made users mindfully deliberate on their breathing but adaptiveness of guidance has potential for more	Incentivise users to get out of their comfort zone and try to lower their breath even more. Feedback mechanism should "reward" users good performance instead of "indicate" bad performance.
FAR (2022) [60]	Difficulties in affect dysregulation in youth with autisum spectrum disorder	PPG sensor in device A	1 vibration motor in Device A and Device B, with companion app	Breath rate regulation	2 handheld pacers in both hands for symmetry	1 (1m)	User enjoyed the haptic sensation and was able to concentrate on his homework better.	Gameify the personalisation procedure (e.g the intensity of the vibrations through a game questionnaire). Make a tutorial video on how to breathe slowly.

Name	Problem Statement	Sensor and location	Actuation	Guidance	Form	Participants	Results	Recommendations
A Calming Hug (2021) [70]	Test Anxiety in undergraduate students	none	5 prototypes were tested to help breathe at 10 breaths a minute. 1) Breathing simulator through syringe pump 2) Heartbeat simulator by DC motor pulses 3) Purring by coin cell vibration motor 4) Purring and breathing 5) Rotating rainbow ring of light	Fixed rate at 10 - 12 breaths per minute. Stimulus differed per prototype	Cushion	129 (96f, 33m)	Breathing prototype was the most pleasant to interact with as it was "calming" and "soothing". It was also the most effective in reducing pre-test anxiety compared to a control condition.	Should experiment more on cushion size, shape, stiffness, lung design and breathing characteristics as the cushion was not a typical replica of a human torso.
Affective Sleeve (2019) [74]	Emotion Regulation	Zephyr BioPatch chest sensor, Empatica E4 wristband sensor	6 vibration motors along sleeve of lower arm of dominant hand	Breath rate regulation	Sleeve	18 (9f, 9m)	Positive correlation with haptic action and respiration rate.	Further research into inflatable material and heating wires independently rather than together.
aSpire (2021) [77]	Exploration of biofeedback advisory system	Zephyr BioHarness chest belt sensor, Affectiva Q-sensor around non-dominant hand	3 soft modeules with stretachable pressure sensors and pneumatic control system module	Breath rate regulation	Belt	15 (8f, 7m)	80% of participants were able to lower their breathing rates by 24.8% of their baseline. Preferred stimulation pattern was sequential over synchronised.	Further research into pneumatic-vibrotactile stimulation for EDA levels is needed.
PIV (2020) [73]	Affect regulation	Breathing gauges around the chest and abdomen, EDA, pulse and temperature sensor on non-dominant hand	2 tactors on abdomen	Breath rate regulation	2 taped motors on abdomen	97 (61f, 36m)	Results indicate that intervention from PIV helped reduce anxiety in the treatment group.	This research was conducted without a presence of a stressor. In the next iteration the personalisation with the presence of a stressor should be studied.
Lotus (2020) [75]	Increase Mindfulness, decrease stress	HR monitor (pulse oximeter) on lotus	Stepper motor opening and closing lotus	Breath rate regulation	Lotus	10	Users claimed to be highly satisfied with look of the device and said they felt calmer after interacting with it	HR is not an accurate measurement of stress, HRV should be used instead. A smart watch can be used to measure HR and makes interaction hands-free
Li, Piao and Xia (2021) [79]	Breath Guidance in Vocal Training	Exoskeleton behind the upper back and belt around waist	Mechanical transformation of spine exoskeleton and loosening / tightening of belt	Posture and diaphragmatic movement	Exoskeleton	9 (4f, 5m)	Participants showed high acceptance of device for vocal training and device had positive effects on diaphragmatic breathing guidance.	Modify structure to make deice more wearable and signals stronger. Make adaptable to every user.
Choi et al. (2022) [76]	Assist in mindful breathing and regulate perceived workload without disturbing task during daily routine. Decrease BR to 70% of what it was	Zephyr BioHarness chest strap, Empatica E4 wristband on non-dominant hand	DC Motor Air Pump	Breath rate regulation	Fanny Pack	Mixed	Significantly incrased participants breathing awareness without inducing extra perceived stress, anxiety or arousal.	Include higher levels of intensity in the settings to make haptic feedback more noticeable, especially synchronised pattern. let participant choose tactile pattern. Let participants choose their own breathing rate. Let them clip it where they want to.

2.4 State of the Art: Products

This section provides both an overview of the state of the art of commercially available breath guidance wearable devices and wearable devices that allow for PPG measurements. These will be analysed on placement on the body, sensor, actuation and price. The results will be summarised and presented in a table. The findings of this section together with the findings of section 2.3 answer the fifth knowledge question of *What is the state of the art for wearables and haptic feedback for breath guidance?*

Commercially available breathing products

There are a variety of products that exist on the market for breath training with haptic feedback. Not all devices mentioned here are wearables, but are meant to reduce anxiety and increase mindfulness through different methods. Breathe with b, depicted in Figure 10a, is a mouth pen that gives both vibrotactile and visual feedback depending on the inhale / exhale pressure measured by the pressure sensor in the tube. The Shift, seen in 10b, is a necklace that is meant to remind users to breathe deeply and to "shift" their stress for calm. There are no sensors or feedback mechanisms in this necklace, it simply serves as a reminder to breathe deeply. Melo, shown in Figure 10c, is a handheld device with three different breathing patterns given through visual and / or tactile feedback. Moonbird, as seen in Figure 10l, is also a handheld device but unlike Melo, includes a PPG sensor to gather pulse data and respond by expanding and contracting when the user should breathe [80]. This form of feedback is given through pneumatic actuators rather than vibration motors. The VITALI smart bra in Figure 10d and Lief device in Figure 10e are wearables that are meant to be worn underneath clothing. Both of them give vibration cues when they detect that the user is stressed, either through ECG measurements [81] or their heart rate [82]. The goal of both these devices is to synchronise the wearer's breathing rate with their heart rate through haptic feedback, but still showcase the user's daily data on the accompanying smartphone application. The Airofit device depicted in Figure 10f is aimed at improving sports performance. It has an airflow sensor integrated into the mouthpiece and users need can see real-time visual feedback with the paired smartphone app. Apple also has a breathing watch face [83] that is paired with an audio guided meditation and wants the user to inhale slowly as the animation grows, then exhale as it shrinks. It can also monitor the heart rate of the wearer as it has an integrated electrical heart rate sensor.

PPG wearables

Wearables that have an integrated PPG sensor are commercially available as fitness trackers for health monitoring purposes. This subsection will provide a brief overview of current devices on the market that are able to non-invasively measure heart rate. The Oura ring uses an integrated PPG sensor to monitor blood oxygen levels and heart rate of the user 24/7 that it shows on an integrated app and is depicted in Figure 10h [84]. Its primary purpose is sleep monitoring and not breath guidance, but still can be used for it. The fitbit charge 3 also works with the same PPG technology but is in a form of a wristwatch and can be seen in Figure 10i [85]. The Fitbit sense 2, seen in Figure 10j has an electrical heart sensor to detect atrial fibrillation and to also monitor heart rate. It provides an overview of the users statistics in a paired app [86]. The Joule earring, depicted in Figure 10k, is a product that is still in its pre-launch phase and has a PPG sensor integrated in the push back [87]. It is a fitness tracker geared towards women with its unobtrusive and delicate design and can be paired with any stud earring with a 18mm diameter wire. The pulse oximeter is used by clinicians to monitor their patients but can also be employed for at-home usage. It is a small device that shows the users heart rate and blood

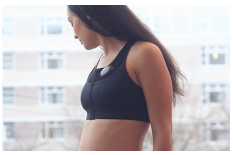
oxygen saturation on the small LED screen.

All the devices that are listed in this section have been designed in a compact and portable manner and are wireless. Breathe with b [88], Melo [89], VITALI smart bra [81] and Get Lief [82] are the only devices that provide haptic feedback. All other devices with the exception of Shift [90] provide feedback through a paired app. More information on the individual devices can be seen in Table 4.

(A) Breathe with b [88]

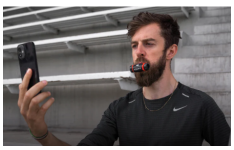
(B) Shift [90]

(C) Melo [89]



(D) VITALI Smart Bra [81]

(E) Get Lief [82]



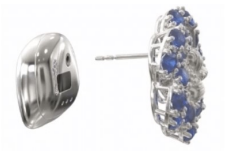
(F) Airofit [91]

(G) Apple Mindfulness App [83]

(H) Oura Ring [84]

(I) Fitbit Charge 3 [85]

(J) Fitbit Sense 2 [86]



(K) Joule Earring [87]

(L) Moonbird [80]

FIGURE 10: Commercial products for breath guidance (A-G) and fitness monitoring (G-L)

This section has shown a wide array of previous research projects on haptics and breath guidance as well as given an overview of some commercial products for the same cause. These findings contribute towards the answer of the fifth knowledge question. Many research projects are still in their early stages, as studies still urge for improvement in the personalisation and

adaptability of the wearable as well as with a better understanding of the user of the task at hand. They also suggest the feedback to be rewarding instead of reprimanding and propose further research into more comfortable materials and ergonomic shapes. These suggestions still hold true for the commercial products that already exist on the market, as all of the devices listed have none of the five recommendation points described in section 2.3.3. This indicates that there may be a potential gap in the market for a novel wearable for breath guidance.

Name	Problem Statement	Sensor	Actuation	Guidance	Form
Breathe with b [88]	Less stress, more focus, better wellbeing	Pressure sensor in mouth	Vibrotactile and visual. Vibration cues with LED lights on inhale / exhale and touch sounds	Breath rate regulation	Mouth pen
Shift [90]	Quit smoking / vaping. Increase mindfulness	Touch shift when you feel a craving and remember to breathe slowly	None	None	Mouth pen / Necklace
Melo [89]	Control stress and anxiety	None	Vibrotactile and visual. Expanding and contracting light rings with vibrations to indicate inhale / exhale	3 different breathing patterns	Stone / Handheld device
Moonbird [80]	Less stress	PPG sensor	Vibrotactile and visual. Expanding and contracting actuation of the device to indicate inhale / exhale with different breathing patterns	Either choose method on smartphone or just use the predefined rhythm on the device	Handheld device
VITALI Smart Bra [81]	Less stress	Electrical heart sensor sewn into bra and IMU in the device	Vibrotactile. When HR measure is fast or the posture is not straight, device sends vibrotactile cues to breathe slower or to rectify posture. Data is streamed to a connected app	Breathing guidance to synchronise BR with HR	Clip on device, bra and app
Lief [82]	Less stress	Electrical heart sensor on heart	Vibrotactile. When HR measure is fast, device sends vibrotactile cues to breathe slower Data is streamed to a connected app	Breathing guidance to synchronise BR with HR	Heart sticker and app
Airofit Pro [91]	Improve health, wellbeing and sports performance	Airflow sensor	Visual. All data is streamed live to the connected app	Smartphone guidance to inhale and exhale with 17 breathing patterns	Mouth device and app
Apple Watch 5 [83], Oura Ring [84], Fitbit Charge 3 [85], Fitbit Sense 2 [86], Joule Earring [87]	Health monitoring	PPG or electrical heart sensor	Non-intrusive monitoring of biosignals. All data is streamed live to the connected app	Apple Watch has visual cues to breathe slower [83] but nothing for the others	Watch [83] [85] [86], Ring [84], Earring [87]
Pulse Oximeter	Health monitoring	PPG on finger clip	Visual. Data can be seen on LED screen	None	Finger clip

TABLE 4: Overview Commercial products for breath guidance

3 Methods and Techniques

"To measure the man, measure his heart".

This section describes which variables are used to capture heart rate data and which measurement methods can be used by comparing the electrocardiography with an ECG to the photoplethysmography with a PPG. It also presents results of an experiment conducted to compare the output of 3 PPG sensors in comparison to the ECG baseline to assess their feasibility for this project. This chapter provides the theoretical background for the sixth knowledge question of *"How can heart rate variability be measured and which sensors should be employed?"* This question will be worked out more in chapter 5.
Habitually, breathing is measured using respiratory inductance plethysmography (RIP) or spirometry. RIP utilises 2 belts, one strapped around the thorax, at the level of the nipples and the other at the navel and measures respiration through expansion and contraction of the chest and abdomen. Spirometry uses a mouthpiece that patients breathe into and measures the amount of air and its speed. However, both these methods would not be suitable for integration into a haptic wearable, as the haptic actuation would interfere with the RIP measurements and spirometry would be too obtrusive to use in an everyday setting. This will be explained more in section 4.1.1. Measuring the heart rate to link back to breathing is a more suitable choice.

To determine the participants' individual resonant frequency, most studies use a simple heart rate monitor, as they are either free or low cost [13], [20]. The participants are either asked to practice paced breathing at different rates where the researcher can determine which rates produce the largest HRV swings, or asked to follow a HR tracing on a computer screen or asked to play a game where some movement will be proportional to their HRV with each breath [13].

In general, HRV can be calculated using linear and non-linear methods. Linear methods consist of time-based and frequency based methods [55]. Non-linear methods allow for quantification of the unpredictability of time-series measurements and act differently compared to linear systems [55]. The non-linear methods will not be looked into in this project as they fall outside the scope.

3.1 Time-domain

This method quantifies the amount of variability in measurements of the interbeat interval (IBI) of HRV. Here, HRV is measured in the range from shorter than 1min to longer than 24h. The gold standard for clinical HRV assessment is 24h [92], however short term recordings of 5 minutes can also be used [8], [55], [93]. Table 5 has been put together by combining measures used from multiple HRV studies ([13], [20], [28], [55], [92]) and selecting common denominators in all of them. As this project will have recordings shorter than 1h, all measurement methods that need 24h or have been removed from Table 5.

3.2 Frequency-domain

This method differentiates heart rate signals in compliance with their frequency and intensity [55]. Power spectral density and Fast Fourier Transformation are two common methods that have been used since the 1960s to seperate HRV components into four frequency bands [55], [92]. These components are listed in Table 6 below. The ultra-low frequency band requires a

recording of at least 24h, which as mentioned above, is not in the scope of this project but is listed in Table 6 for completeness.

Variable [Unit]	Explanation
NN $[ms]$	The cycle length between two discretized RR intervals.
SDNN $[ms]$	Standard deviation of the normal RR intervals. Reflects the parasympathetic component of the autonomic function.
RMSSD $[ms]$	Root mean square of the successive differences between the RR intervals. Considered an important indicator of parasympathetic activity.
HR_{max} - HR_{min} $[bpm]$	Also called peak-to-trough amplitude and can be used to quantify RSA

TABLE 5: Time-domain measures (Adapted from [13], [20], [28], [55], [92])

Frequency bands	Explanation
Ultra Low Frequency (ULF), $<$ 0.0033 Hz	Characteristics not fully understood but could hold information abour circadian rhythm, metabolism and core body temperature.
Very Low Frequency (VLF), 0.0033 - 0.04 Hz	Thought to originate from thermal and hormonal control and SNS appears to influence its amplitude and frequency.
Low Frequency (LF), 0.04 - 0.15 Hz	Combination of parasympathetic and sympathetic effects. Range includes the baroreceptor activity. Oscillations related to blood pressure and vasomotor tone.
High Frequency (HF), 0.15 - 0.4 Hz	Reflects parasympathetic activity and is a major determinant of RSA. This band is highly correlated with the RMSSD time-domain measure.

TABLE 6: Frequency-domain measures (Adapted from [55], [92])

3.3 Sensor Comparison

As resonance frequency measurement assessment can be tuned by adjusting the respiration rate to match the a multiple of the heart rate frequency, the latter needs to be measured. In this section, the electrocardiogram (ECG) and photoplethysmograph (PPG) will be compared to each other. Clinicians monitor heart rate using an electrocardiogram (ECG) as it considered the gold standard in HRV research, but photoplethysmography is being used more and more in research as it is more accessible, cheaper and non-invasive [94].

3.3.1 Electrocardiogram (ECG)

The electrocardiogram is a fundamental tool of clinical practice and is also the most commonly used cardiovascular diagnostic procedure today [95]. It detects and records the strength and timing of the electrical activity in the heart using at least 3 Ag/AgCl electrodes that are attached to the subjects body, which limits the flexibility and mobility of the users and can lead to skin irritation [95]–[97]. The sequence of events that happen between the beginning and the end of a heartbeat is called a cardiac cycle and consists of a diastole and systole [97], which are visualised in Figures 2 and 3. In an ECG wave, these can be identified by five major points (P,Q,R,S,T) as are illustrated in Figure 11. The time between consecutive cardiac cycles can be measured by obtaining the time between the R-R intervals which is a measure for HRV. R peaks are easily identified in most ECG traces and due to its magnitude, physical origin and frequency content, they are ideal markers for segmenting cardiac cycles [98]. The different waves of the ECG signal will be described in the list below. The end of the T-wave to the peak of the R wave describes a ventricular diastole and the peak of the R-wave to the end of the T describes a ventricular systole [99], [100]. This is also illustrated in Figure 14.

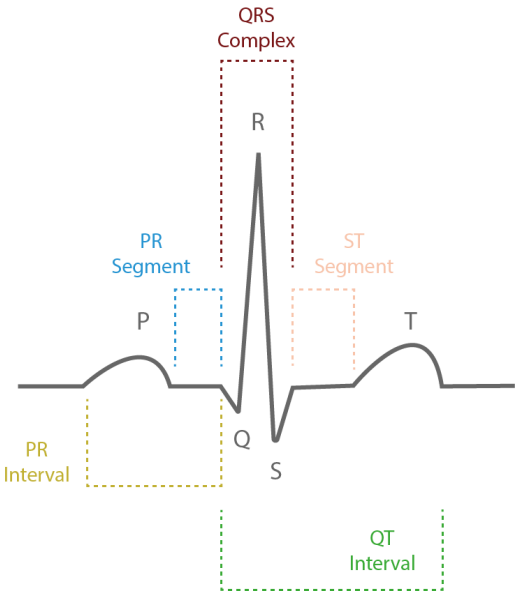


FIGURE 11: ECG signal (Adapted from [99])

- **P wave:** SA node (as illustrated in Figure 6) causes both atria to contract and pump blood into the ventricles.
- **Q wave:** The electrical signal from the SA node passes down to the AV node (as illustrated in Figure 6), slowly, allowing the ventricles to fill with blood.

- **QRS Complex:** The signal travels across the His bundle, causing the ventricles to contract, pumping blood to the lungs and body. The Q,R,S waves usually happen in quick succession, which is why they are grouped together. The R wave is the most prominent wave of the ECG signal and relates directly with the ventricular contraction of the cardiac cycle.
- **T wave:** Recovery stage of the ventricles, allowing the muscles to relax and the atria to fill with blood again for the process to repeat.
- **PR Interval:** Time from the beginning of the P wave to the QRS complex.
- **PR Segment:** Represents the delay of the electrical impulse in the AV node.
- **ST Segment:** Connects the QRS complex and the T wave and represents the beginning of the electrical recovery of the ventricles.
- **QT Interval:** Represents the time during ventricular stimulation and recovery. This interval is shorter at a faster heart rate and longer at a slower heart rate.

There have been growing developments for wearable ECG systems in simplicity and weight but the excellent signal quality is paired with electrodes (gel, adhesive, metal stud), that are prone to skin irritation and discomfort during prolonged use, which hinders them from being long-term solutions [95]. The sampling rate of ECG measurements is around 125 - 250 Hz [101]. Studies have shown that when frequency domain information is not needed the signal can be down-sampled to 100 Hz [102] and sometimes even 50 Hz [103]. Interpolation can improve HRV accuracy from lower temporal resolution signals [104].

3.3.2 Photoplethysmography (PPG)

Photoplethysmography sensors use an optical measurement technique that emits infrared light into the tissue and captures the back-scattered light with a photodetector, which can relay information about the blood volume in tissue and thereby also the cardiovascular system, as described in section 2.1.2. These sensors have been gaining in popularity over ECGs for health monitoring as they are non-invasive, effortless to wear and more cost-effective [95], [97].

Similar to ECG signals, PPG signals are also related to the cardiac cycle and are formed out of two components [97]. 1) the DC offset represents the constant absorption of the light passing through the tissue and 2) the AC component which is generated by the heartbeats affecting the blood volume when the light traverses through the artery [97], [98]. An increase in blood volume at the measurement point indicates decrease in light intensity (systole) and a decrease of blood volume at the measurement point increases the light intensity (diastole) [105], [106]. As these characteristics align with the cardiovascular system, several physiological parameters such as heart rate, respiratory rate, pulse volume and oxygen saturation can be extracted from the PPG signal [106]. The time between consecutive pulses can be measured known as the pulse-to-pulse interval (PPI) [98], illustrated in Figure 14.

There are two types of operating principles of PPG sensors, either by transmission or reflection of light through or by a certain body part, as seen in Figure 12 [97]. In transmission mode, the LED passes through absorbent substances (skin pigmentation, bone, blood) and is received by the detector on the other side. This mode is usually implemented in medical applications such as pulse oximeters on the finger or vitality monitoring as an earclip [107]. In reflection mode, the LED is reflected on the skin and received by the detector on the same

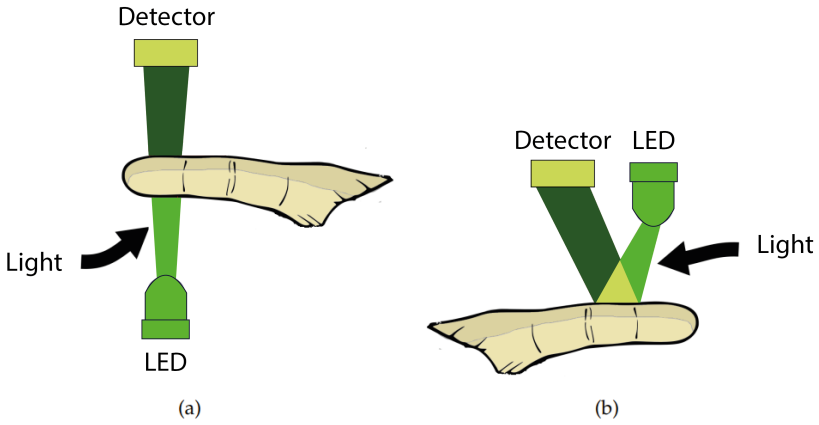


FIGURE 12: Representation of PPG sensors operation for finger application, by transmission (**a**) and by reflection (**b**) (Adapted from [97])

side of the tissue. This mode can be employed where the body parts are too thick to allow transmission of light such as the wrist or the forehead [97]. Reflection mode offers higher flexibility, as it allows for measurements on more body locations and are therefore more suitable for non-invasive long term vitality monitoring devices [107]. Different wavelengths of light penetrate the skin tissue to different depths, as visualised in Figure 13 [108]. Wavelengths in the range of 390-600 nm can penetrate until the dermis, which is the thickest layer of the skin. Longer wavelengths in the range of 600 - 1100 nm can penetrate further. Whilst testing infrared, red, green and blue light sensors, Han et al observed that the PPG onset of the pulse signal is observed first in the sensor data that can penetrate deepest into the skin and last in the sensor data that is the shallowest. This resulted in the order of detection being infrared - red - green - blue [108].

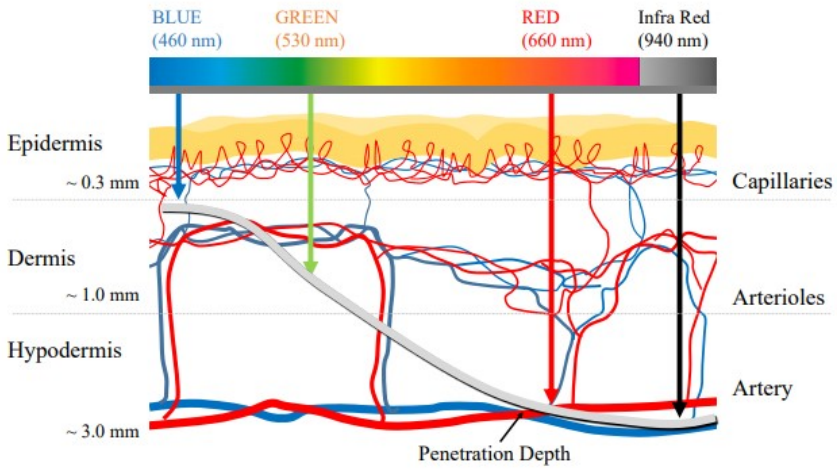


FIGURE 13: Mean light penetration depth according to the wavelength [108]

A typical signal from the PPG can be seen in the bottom part of Figure 14. It is a smooth signal with slow changes and relatively constant frequency content [98]. The signal is usually divided into two phases. The systole is associated with the rising edge of the pulse and describes

the first phase. The diastole is associated with the falling edge of the pulse and describes the second phase [105]. The dicrotic notch is usually seen in subjects with healthy arteries but its prominence dampens with age, arterial stiffness and also sensor location [94], [96], [105], [109].

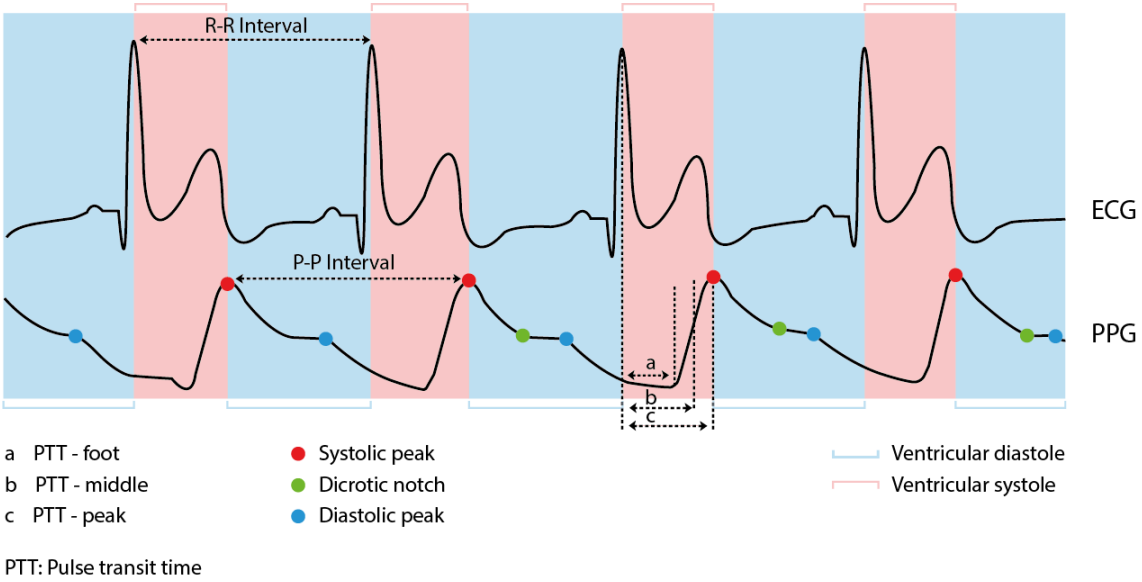


FIGURE 14: PPG wave characteristics (Adapted from [105], [110], [111])

PPG sensors have been used to detect, characterise and monitor somatic diseases, assess mental health, identify sleep stages and assess different markers of cardiovascular health [98]. PPG sensors are most commonly placed on the toes, earlobes, fingers, wrist and forehead [28], [96], [109], [112]. Different body sites differ by tissue thickness, vascularization, and skin pigmentation, which influence the shape of the waveform and therefore also its accuracy in estimating the HRV [112]. The finger is the most practical and most sensitive to blood volume fluctuations and is therefore the most used body site for clinical applications [96], [112].

The limitations of PPG signals is that they are very perceptible to motion artifacts, environmental and power-line noise and low amplitude signals if there is bad connectivity between the body part and the probe (too tight / too loose) [95], [105]. PPG signals are also perceptible to physiological changes such as vascular aging and blood pressure changes, as well as postural changes and have shown different results to HRV with different pre-processing techniques and different fiducial points [98].

Pulse Rate Variability

Pulse Rate Variability (PRV) refers to the changes in pulse rate and has been widely employed as an alternative to heart rate variability (HRV) in the last years by using PPG sensors [98]. PRV has been used largely as a surrogate of HRV [113]–[115], however there is no scientific consensus that this should be done [94], [110], as the relationship between the two is not yet fully understood [98]. The major difference between the two is the pulse transit time (PTT). This describes the time the blood takes to travel to the peripheral site where the pulse wave is being measured and can be separated into three time intervals as seen in Figure 14, namely the foot, the middle and the peak. Thus, the location of the PPG sensor could affect the relationship between PRV and HRV, as PRV measured from different body sites holds different information regarding the vascular path the blood had to travel [98]. Studies

have shown that signals from the finger and earlobe are most reliable due to their convenience of use and tissue thickness [116] with the forehead to be the least analyzable PPG location [112].

As the PPG signal is a relatively slow changing signal, identifying the inflection points is crucial for a thorough analysis. Most studies that concluded that PRV was not a valid surrogate for HRV used the peak points / systolic peaks of the PPG signal to identify cardiac cycles [98], [105]. Furthermore, it has been shown that the systolic peaks show the lowest agreement between PRV and HRV in comparison to other fiducial points, as depicted in Figure 15. In a study conducted by Peng et al. the maximum second derivative and the tangent intersection point was shown to have the least bias between the five points when compared to the ECG signal [106]. The second derivative is more commonly used than the first and is also called the acceleration photoplethysmogram because it is an indication of acceleration of the blood at the sensor location [96], [105]. When the participants are healthy, young individuals in a supine position at rest, PRV is a good substitute for HRV [94], [98].

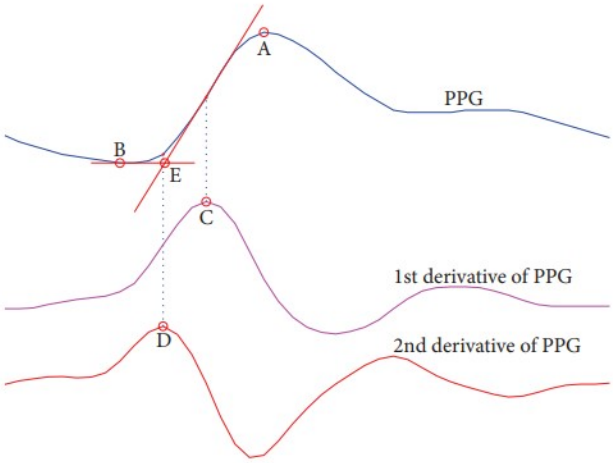


FIGURE 15: Illustration of five characteristic points of PPG signal analysis including A, the peak point; B, the valley point; C, the maximum first derivative; D, the maximum second derivative; and E, the tangent intersection [106])

Georgiou et al conducted a systematic review researching whether wearables can accurately measure HRV and found that the sampling rates used in PPG recordings is much lower (20Hz) than the sampling rates used in ECG measurements (125 - 250 Hz) [101]. Sun et al compared different sampling rates of PPG (200, 100, 50, 20 Hz) and found no significant differences between them after using cubic spline interpolation [117]. Schäfer and Vagedes conducted a review comparing PPG technology with ECG technology and listed many studies using a sampling rate of 1000 Hz for their PPG sensors with the result of moderate to high correlation between the two [94]. Moreover, when comparing PPG signals to ECG signals a Bland Altman analysis should be used as opposed to any correlation measure because the former is a direct way to quantify agreement between two measures whereas correlations are unable to detect bias [94], [106]. This method of plotting will be elaborated upon in section 5.

3.4 Development of the wearable

The Creative Technology Design Process will be employed to develop the wearable. It was introduced through Mader and Eggink [118] in 2014. The four phases of this design process are ideation, specification, realisation and evaluation. The ideation phase encompasses the process of going from a user need or creative inspiration to a product idea and will be elaborated on in section 4. The specification phase describes the making of multiple prototypes to explore the design space that includes a short evaluation and feedback loop. These prototypes are subsequently discarded, improved or (partially) merged into new prototypes with help of evaluations and comments from user testing [118]. Chapter 5 will go more into depth about this and will conduct sensor, algorithm and preliminary user tests. The realisation phase is characterised by combining the knowledge acquired in the previous phases to construct and realise the final prototype and is described in chapter 6. The evaluation phase consists of functional and user testing to evaluate the prototype under the requirements of the specification stage. This is implemented in chapter 7.

3.5 Evaluation Procedure

This section presents the main methods used in this thesis to gather and evaluate data. TOPIS, a feature selection method and linear mixed models, a statistical evaluation method are introduced as quantitative techniques. Interviews and surveys are listed as the qualitative techniques used in this thesis.

3.5.1 TOPSIS for resonance frequency determination

The TOPSIS (The Technique for Order of Preference by Similarity to Ideal Solution) method, is founded on the idea that the best solution is that which is closest to the ideal solution. For this thesis the TOPSIS calculator accounts for the varying optimums of the resonance frequency categories in RMSSD, LF power, SDNN and $HR_{max} - HR_{min}$.

To use this method, the positive ideal and negative ideal solution need to be set and all distances from alternatives will be ranked according to this. The Euclidean Distance will be used for all calculations. The highest closeness value is selected as the best alternative [119]. This method is both simple and logical, completely uses all allocated information and has no need for the information to be independent of each other [119]. Even though strong deviations of one indicator from the ideal solution may strongly influence the results, this can be prevented beforehand by outlier detection techniques. The application of this technique is described in section 6.3.

3.5.2 Linear Mixed Model (LMM)

Linear mixed models are tools for modeling continuous correlated hierarchical / multilevel data and are an extension of linear models [120].

Linear models describe the relationship between two or more variables but only allow for fixed effects. They require independence between the variables for their output to be valid [121]. Linear mixed models extend linear simple linear models to allow for both fixed and random effects. Fixed effects describe effects of the intercept that are the same for all units of analysis. Random effects describe the random error term or the residual in the regression that is different for every unit [122]. The incorporation of random effects account for there being more similarity between

responses of the same person than between responses from different people [73]. Furthermore, LMMs are particularly used when there is non-independence in the data that can occur in a hierarchical structure such as patients from within doctors or students from within schools [123].

Analysis of variance (ANOVA) is a widely used statistical technique to analyse the differences among means of two or more groups. Similar to the linear model, an assumption that ANOVA makes, is that the data are independent and the residuals are not correlated. A repeated measures ANOVA is an extension of ANOVA but allows for correlated samples. The repeated measures ANOVA and the mixed linear model can be used interchangeably when there is no missing data in the dataset. When there is data missing, the repeated measures ANOVA uses listwise deletion, which can reduce power and cause bias. LMMs can account for unbalanced datasets, model correlations between observations to allow for more in-depth clustering and allow for unequal variances between groups.

In this thesis, the LMM approach will be used because of their superior flexibility in clustering data and in dealing with unbalanced classes. For this use case, the LMMs will produce quantitative parameter estimates that describe both how the response variable (e.g heart rate variability) changes as a function of the fixed predictor variables (e.g. body placement and pattern), and the variability among the levels of the random effect (e.g. subject differences) [73].

3.5.3 Surveys

As described in section 2.3, haptic wearables that have the purpose of breath regulation should let the user personalise their feedback, have stimuli for progress, be adaptable, present a clear task for the user to do and come in more comfortable and ergonomic forms and materials. More requirements will be set up in chapter 4.

To evaluate requirements, different scales can be used. Janidarmian et al evaluated their wearable with a 10-point survey scale on comfort, evoked sensation and helpful instructions [58]. A 10-point scale provides a wider resolution than traditional 5 or 7 point Likert scales and offers the participant more choices for a response that reflects their opinion. Likert scales have the feature of bi-directionality. The categories of response may be increasingly positive or increasingly negative [124]. In this thesis, a bidirectional 10 point survey scale will be used to evaluate the participants' perceptions of the wearable and can be seen in the section 72.

3.5.4 Interviews

Interviews can be classified into three techniques, namely the fully structured, semi-structured and unstructured interviews [125]. Unstructured interviews do not have a list of questions but may have a list of topics, called an interview guide. The objective of this technique is to let the interviewee focus on the topics they find important by enabling them to lead the conversation. All interviews in this proposal and thesis will be semi-structured interviews, as they allow the interviewer to follow up on comments of the interviewee to gain additional insights and increase knowledge of the subject. This technique was chosen as the goal of the interviews was to get as much relevant information as possible in a constricted time period.

4 Ideation

"If you want to find secrets of the universe,
think in terms of ***energy, frequency and vibration****".*

The ideation phase describes the process of taking inspiration to a product idea. This chapter presents this phase by firstly introducing a section on design guidelines for wearable devices and then presenting the initial brainstorming results on body placement of the device. It then puts forth a small literature review on haptic patterns used in previous research before showing the results of the brainstorm conducted on haptic patterns of the wearable. It concludes by a section on the actuators used in this thesis. This chapter answers the design question of *"Where is the most suitable placement for the wearable to stimulate resonant breathing?"*

4.1 Body placement for wearable devices

Over the span of seven years, Gemperle et al made 13 design guidelines for wearable devices and published the work in 1998 [126]. In this work, they underlined that the human body is active and its form is diverse and changing. Wearability is defined by a design that has an active relationship with the human form by being comfortable, manageable, unobtrusive and can integrate with the body in motion [126]. Zeagler et al updated these guidelines 20 years later to adapt to the technology advancements of today [127]. Today, devices are a lot smaller and are able to sense and measure more than their older counterparts. More wearable devices are now used as body sensors and our understanding of how we perceive and interact with wearable devices has also grown. Most choices on wearable body placement come down to a balance between the desired use of the device and the affordances different parts of the body offer [127].

Haptic feedback, as described in section 2.3.1, falls under passive touch, when talking about wearability. Passive touch describes a stimulation of the skin brought by some outside agent and differs from active touch, which refers to the exploratory action of touching [127]. Use of wearable technology and body placement has quite a large correlation with the social acceptability of the system. Uncomfortable social situations can arise from interaction with the wearable device which can make the bystander as well as the user feel awkward [127]. Figure 16 shows a social acceptability bodymap for wearable devices and possible PPG sensor locations, as this is the sensor that will be used to measure HRV. The PPG sensor locations were determined at body parts where blood vessels are close to the surface of the skin. As illustrated in Figure 16, all PPG sensor locations are at socially acceptable places for passive touch. However, at the illustrated PPG sensor locations, the average distance in two-point discrimination is < 0.28" (< 0.71cm) with the inside of the fingertips being most sensitive at < 0.15" (< 0.38 cm) [127]. This indicates that body locations where blood vessels are close to the surface of the skin are also quite sensitive and good at discriminating touch from two different points, even when they are close together.

It is important to mention that for the use case scenario of this thesis, the sensor and actuation need to be on separate body locations, else they will interfere with each other. PPG measurements are extremely sensitive to movement artifacts, as mentioned in section 3.3.2. The fingertip is an interesting location as it has the highest two-point discrimination factor [127] and also the most reliable sensor readings [112], [116]. The earlobe follows as a close second for a clean and reliable signal acquisition with the forehead resulting as the least analysable PPG signal [112], [116]. For this reason, priority will be given to the finger tip for sensing and

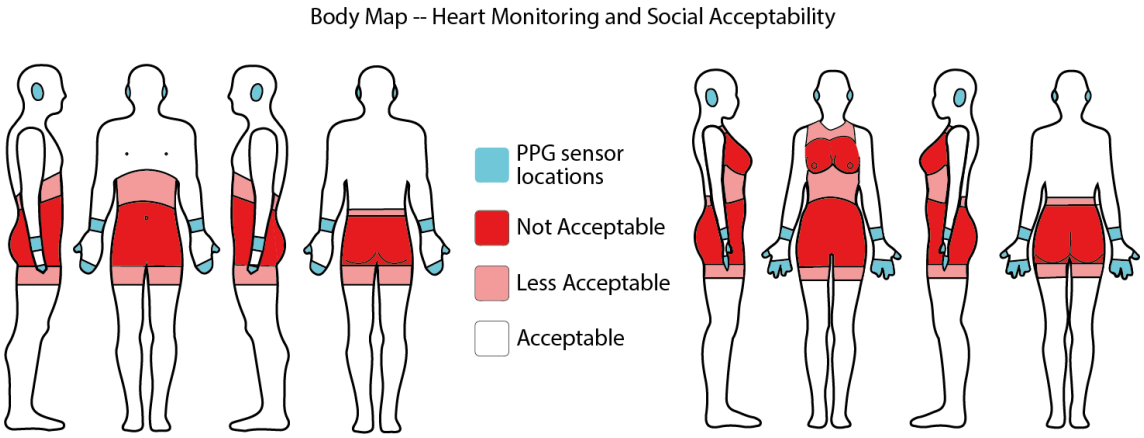


FIGURE 16: Body Map – Possible PPG sensor locations (Adapted from [127])

the actuation will happen elsewhere.

Sigrist et al stated that there is an initial advantage in placing actuators on locations that represent specific information, due to its naturalness but this could also dissolve if users are given enough time to become familiar with less intuitive sites [1]. This thesis has shown that deep breathing happens primarily in the chest-to-abdominal area with the diaphragm acting as the main muscle, as can be read in section 2.1. This area covers some less acceptable body parts, as illustrated in Figure 16 but this should not form too large a restriction, as many health wearables are also worn in this area.

4.1.1 Requirements

This section provides an overview of the requirements the wearable of this thesis will have to comply to. Francés-Morcillo et al put together a roadmap providing a classification of design requirements and evaluation for wearability designers and their model includes all aspects of Gemperle et al [126] and Zeagler [127] with additional human factor considerations [128]. An illustration of this wheel model can be seen in Figure 54 in section 10.

The wheel model has 9 main parameters that should be evaluated during user tests and be iterated upon during the design process. Francés-Morcillo et al stress that the user tests concerning the safety, durability, usability, reliability and engagement should be conducted in a real scenario for the optimum results for the evaluation of the wearable. Other methods of evaluation include washing experiments for the comfort parameter, focus group evaluations for the aesthetics parameter, co-design workshops for the privacy and satisfaction parameter [128]. For the scope of this thesis, the focus of the wearable will lie in the cognitive ergonomics section with usability and reliability but the comfort of the wearable for the participants will also be considered. The parameters chosen from the wheel model of Francés-Morcillo et al [128] can be seen in Table 7.

The requirements listed in Table 7 have quite some overlap with the preliminary requirements stated in section 2.3. The usability requirement is a more concise description of the better understanding of the task at hand requirement. The comfort requirement summarises the adaptability, research into materials and personalised feedback requirement. The engagement requirement has some overlap with the stimuli for progress. In this way, it can be seen that

Table 7 complements the requirements listed in section 2.3, and that the state of the art in haptic wearables align with the wearable design requirements of Francés-Morcillo et al [128].

Requirement	Parameter	Definition
Usability	Intuitiveness	The user understands the interaction with the device in an intuitive way.
	Simplicity	The device is easy to use and the feedback is presented in a simple manner.
Reliability	Precision	The device is accurate.
	Effectiveness	The device meets the function and the final result is achieved.
Engagement	Engagement	The device is appealing for the user and he/she feels the need of having it.
	Long-term use	The device has long-term use.
Comfort	Sizing	The device adapts to all the target users' size.
	Obtrusiveness	The device does not cause fatigue or decrease the comfort.
	Movement	The device is sufficiently flexible to allow the natural movement on the body region.
Functionality	The wearable works properly (components work individually and all within the wearable)	
Satisfaction	The user is satisfied with the wearable.	

TABLE 7: Wearable design requirements, parameters and definitions (Adapted from [128])

Section 3 stated that breathing is habitually measured by respiratory inductance plethysmography (RIP) or spirometry. RIP, similar to extracting the breathing rate from the PPG sensors, can only estimate the breathing phases of the participant by measuring the expansion and contraction of the abdomen or chest. It does not provide true insight into the air volume of the lungs as spirometry does. A drawback of spirometry, despite it being the most accurate measurement method of breathing, is that it cannot be integrated into a wearable. The participants would need to use a very obvious and possibly also obtrusive device to blow into to measure their breathing, such as the Airofit device presented in Figure 10f. The use-case for this project is to create a wearable that can be used in an every-day setting, without being too obvious, to support breathing. This requirement is under the umbrella of the comfort parameter shown in Table 7.

4.1.2 Brainstorm on body placement

This subsection will present the different ideas that were played with on placement of the wearable before concluding on the four main placements that will be taken forward to the experiment.

As stated by Sigrist et al [1], there is advantage in placing the actuators on locations that are in accordance with the activity that should be supported. Shafiqul Islam and Lin add that localising vibrotactile feedback to the target body site can potentially decrease response times as participants would perceive feedback and initiate movement from the same locations [129]. The main actions of breathing happens in the lower torso area. The skin covering the torso provides an extensive haptic space for presenting tactile information as it covers approximately half the total surface area of the body and contains hundreds of mechanoreceptors, which are capable of precise discrimination [130]. The contraction of the diaphragm and expansion of the lungs leads to an enlargement of the entire upper body. According to Figure 16, there would be some violations if the wearable were to be placed on the chest or the lower abdomen. However, as mentioned above, Figure 16 was intended to display the social acceptability of wearables imitating social touch, rather than health guidance actuation. There have been studies that have created belts, abdomen stickers and adjustable fanny packs that were placed in different locations marked in red in Figure 16 [76], [77], [79], and are referenced in Table 3.

Preliminary sketches can be seen in section 10.1. These sketches were made before the importance of the placing actuators on body locations that are in accordance to "where

breathing happens" were established. As mentioned in the studies above [1], [73], [129], [130], placing tactile feedback on the torso to assist breathing simulates where physiotherapists would touch patients to help them breathe and could decrease the response time of the users, as the actuation and movement is performed at the same location. These arguments resulted in four positions, which are illustrated in Figure 17. The diaphragm is drawn twice. This was to research the perception of the users on the direction of the actuation. To add this direction to every position would have resulted in a very long experiment, which is why it is only present once.

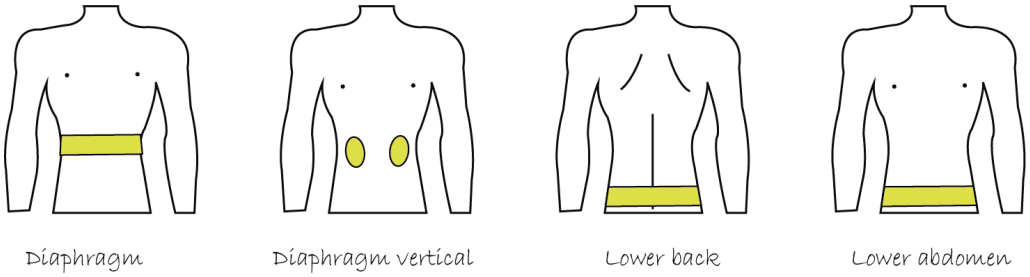


FIGURE 17: Choice of positions for experiment

Knowing the spatial acuity of these chosen body positions is important in determining how far apart the individual motors need to be. Jóhannesson et al researched the relative vibrotactile spatial acuity of the torso and found that the discrimination accuracy is still well below their lowest experiment of 13mm [131]. Jones et al state that the average spatial acuity of the torso averages 20 - 40mm [130], which is substantially worse than the findings of Jóhannesson et al. Jones et al add that the lower back has a spatial acuity that considerably smaller than the torso at 10 - 11 mm, and is the same regardless of whether the stimuli are delivered simultaneously or successively [130]. Shafiqul Islam and Lim oppose Jones et al's statement that the lower back is more sensitive than the torso and argue that the lower back is the least sensitive body site with a spacial acuity of 37mm at 138 Hz [129].

Stronks et al showed in their study that training can help improve spatial acuity on the lower back and suggest that this training can also be translated to other body parts [132]. In a 10 min training session, the participants of the study were able to decreased the two-point discrimination distance on their lower back from 58mm to 37mm [132].

The findings of these studies are not consistent, but they all show that different body parts have different two-point discrimination thresholds for haptic feedback. Stronks et al have shown that it is possible to train spatial acuity [132], however this is not the focus of this thesis. For this reason, the motors will not be placed closer together than 37mm to ensure that the lowest spatial acuity mentioned in the above stated studies is taken into consideration.

4.2 Patterns in wearable devices

There is very little literature on haptic patterns in wearables for breathing. This subsection will firstly present the few findings of literature before introducing the results of the brainstorming process and will conclude with the chosen patterns for this thesis.

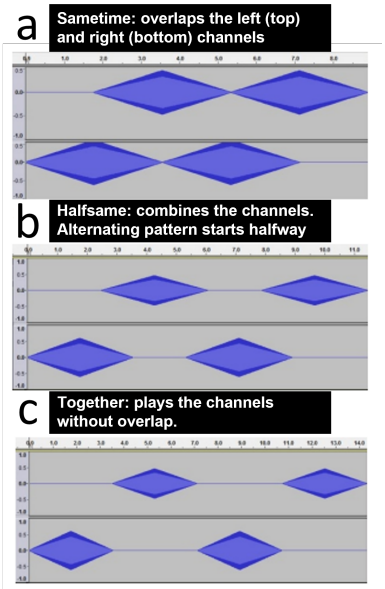
Kelling, Pitaro and Rantala made a haptic sleeve to aid users deal with stressful situations by using dynamic vibration patterns to soothe them [133]. This study did not evaluate breathing but did explore different haptic patterns. The created sleeve was placed around the elbow of the users and the patterns used in their study can be seen in Figure 18a. There was no significant preference out of the three patterns as most users rated the patterns as neutral on the Likert scale (1 - 7) [133]. The study revealed that participants who received haptic feedback had a lower heart rate than those that did not [133].

Choi et al compared a synchronised pattern to a sequential pattern, visualised in Figure 18b for a pneumatic clippable belt to assist breathing [77]. Out of their 15 participants they found that 53% preferred the sequential pattern and 27% preferred the synchronised pattern [77]. The other 20% did not know. Users said that they felt their pattern more clearly which made it easier to recognise and for them to match it with their breathing. Open ended comments stated that the participants favourite pattern could also depend on their mood [77].

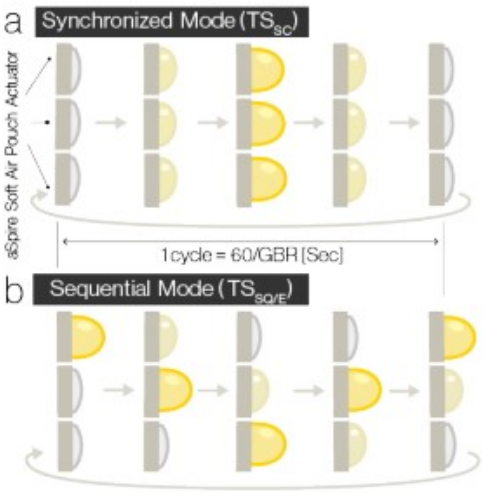
Parades et al [10] made a haptic car seat to calm down drivers whilst commuting with patterns as seen in Figure 18c. This study did not make a wearable but did explore perception of haptic patterns in relation to breathing. The results showed that the haptic system reduced the drivers' breathing rate and provided a sustained post-intervention effect without affecting driving safety.

Other studies have simply let the participants adjust the vibration parameters themselves (frequency, intensity, pattern) [134] or suggest to do this in further studies, as described in section 2.3.3. Miri et al stated very clearly in their study that breathing is a symmetrical experience as we have two lungs and two nostrils [73]. Their research assistants and biofeedback practitioners agreed with the line of reasoning that the placement and pattern should therefore also be symmetrical. The biofeedback practitioners of the same study stated that they use both their hands to touch patients at symmetrical places to feel the breathing movement of their patients, rather than just using one hand [73].

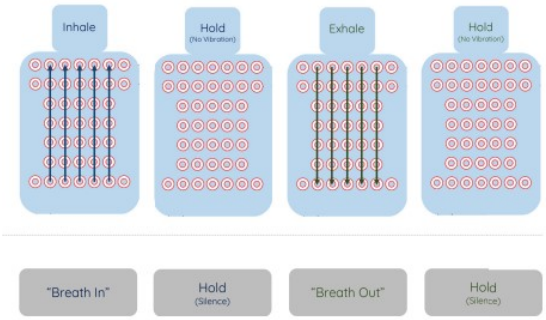
Apparent motion is a phenomenon in which two different stimuli are perceived as the motion of a single object when they occur in sequence [135]. This perception of motion consists out of distance between the actuators, the duration of the individual actuators and the interstimulus onset interval, the time between the first and second point of actuation being presented [135], [136]. Wilson et al proposed guidelines for ultrasonic haptic feedback where they state that the use of larger distances, larger number of stimulus points and longer stimuli improve the sensation and quality of movement [136]. In particular, they state that across larger distances actuators should vibrate in the range of 50 - 100ms each and across shorter distances in the range of 200 - 300 ms, to improve movement perception [136]. Furthermore, there are two main types of vibrotactile illusions that can be created by changing the spatio-temporal parameters of the actuators [137], [138]. Saltation creates the feeling that a signal travels between two or more actuators which are activated with different time intervals. Funneling describes the feeling where the user perceives a signal in the middle of two simultaneously activated actuators [137], [138].



(A) Sleeve patterns [133]



(B) Belt patterns [77]



(C) Car seat pattern [10]

FIGURE 18: Haptic patterns from literature

All studies showing the state of the art in section 2.3 and section 2.4 use guiding haptic feedback during the movement to support breath training. Guiding feedback can create a dependency on the user similar to concurrent feedback, but may not hamper motor learning if the user only uses this for the attention-demanding phase and refinement phase of motor learning. The further sections of this chapter will describe the process of making guiding haptic patterns for breath training.

In this world, symmetry is pervasive in many living things. From radial symmetry of flowers to the mirror symmetry of animals, symmetry in nature is usually a sign of good health [139]. Decades into research has shown that both men and women are more attracted to symmetrical faces than asymmetrical ones, as severe physical asymmetries are indicative of genetic disorders [140]. Humans recognise symmetrical patterns to be inherently familiar and usually also perceive them to be pleasant to our brains [139], [140].

Breathing is a natural activity and the patterns that should help guide this activity should also feel natural. This can be pursued by making the patterns symmetrical, but this brings the

requirement of having at least two motors, one on either side of the body's midline. Having one motor vibrate on either side of the body really constrains making multiple patterns as the only parameter that can be controlled is intensity. Placing two motors on either side of the body (4 motors total), adds in the additional direction parameter. However, this would only allow for left/right pulses on either side of the body but still not feel very natural. The wave motion is a phenomenon that is found both in nature and in science. Breathing and meditation practices are often tied to envisioning waves or soft breezes. These patterns have oscillatory behaviour on top of being perceived symmetrically (on both sides of the body). The patterns can be recreated on the human body by having at least three motors on either side (6 motors total). The parameters that can be influenced in this setup are not only intensity and direction but also the flow of the vibration motors, which could simulate a symmetrical wave. Six motors are the minimum requirement for this. Furthermore, as mentioned above, having more stimulus points has been shown to improve the the sensation and quality of movement [136].

The microcontroller to be used in this project is the Arduino UNO [141]. Pulse Width Modulation (PWM) is a technique to get an analog output with digital means. The pins on an Arduino either give out a 5V signal or a 0V signal. However, the PWM pins can simulate voltages between 0 - 5V by changing the segment of the time that the signal spends on as opposed to the segment of time it spends off [142]. The pulse width describes the "on-time" of the signal. When writing analog values to the actuator, the pulse width is modulated. If this pattern is repeated with a high enough speed, the actuator will seem like it functions at a voltage between 0 - 5V, even though the actual operating voltage stays the same. The Arduino UNO has six PWM pins, which is a perfect fit for the amount of ideated motors.

The results of these studies show that there is no clear design for the best perceived haptic pattern for a breathing wearable and that there are many differences in preferences of users. The requirements stated in Table 7 will serve as the foundations of this thesis. The patterns should be intuitive, effective, comfortable, function properly and satisfy the user. The engagement aspect will be evaluated at the end of the experiment but will not be the main focus as the product at the end will still only be a prototype. Six vibration motors will be used for the prototype.

4.2.1 Brainstorm on patterns

For this thesis, three patterns were made to be tested. The preliminary sketches can be seen in Figure 57. The patterns are seperated in the two breathing phases of inhale and exhale. Every row downwards indicates a change in time. Pattern 1 is quite similar to the synchronised pattern of Choi et al [77]. All motors increased in intensity until the pulse, which indicated the state change to exhale. Pattern 2 had a biological explanation, the right side would motors of the belt would switch on for an inhale and the left side would switch on for an exhale. This corresponds to the more fuller atria described in Figure 2 and 3. However, pattern 2 did not have a symmetrical aspect to it and was therefore discarded. Pattern 3 moved inwards with the actuation for the inhale and outwards for the exhale. This was thought to mimic the natural movement of the abdomen whilst breathing. The pattern actuated one motor after the other symmetrically.

A pilot test was conducted on 5 users (4f, 1m) to get some insight on the user perception of these patterns. The test was only performed on the abdomen as the feedback in question was meant for the patterns and not the position. The feedback was gathered in an informal interview process. The main purpose was of this pilot test was to research whether the patterns are understandable. It was found that 100% of the users did not appreciate the pulse of Pattern

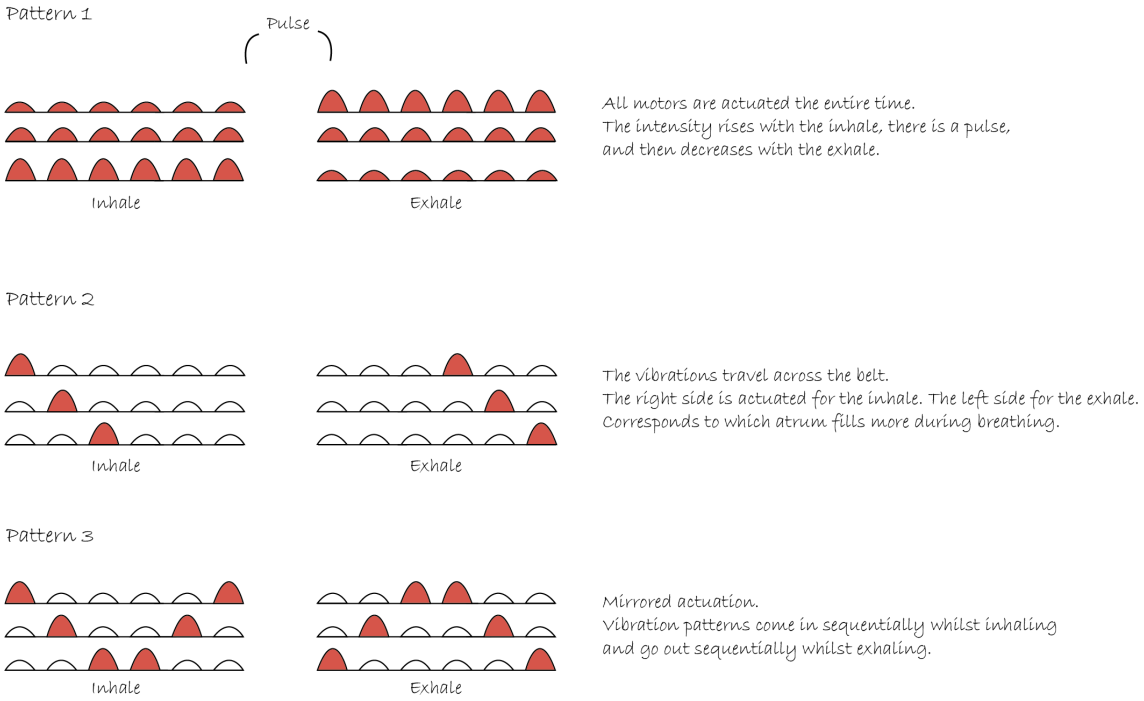


FIGURE 19: Pattern Ideation

1. They did not know whether they were supposed to stop breathing or hold their breath or contract their stomach. Pattern 2 was not tested due to its lack of symmetry. Pattern 3 was considered "blocky" and rigid, as every motor was actuated after the previous one rather than having a smooth transition. However, the pattern was well understood as participants were easily able to follow the haptic cue.

The second iteration of patterns fixed these issues. The pulse of pattern 1 was removed and an overlap between the actuating motors was added for a smoother transition. The transitions in Pattern 3 were modified to be smoother by adding overlap between the two actuated motors. The pattern went from together to halfsame as seen in Figure 18. A third pattern was created to replace the removal of pattern 2. This pattern was the inverse of the previous pattern 3. Now the if the pattern moved outwards, it signified an inhale and if it moved inward it signified an exhale. This pattern was ideated because people can interpret the haptic cues differently. It could be that the spatial awareness of the motors going backwards helped people visualise that their stomach needs to expand and vice versa. Furthermore, this meant that pattern 2 and pattern 3 did not have an interstimulus onset interval anymore because of the added overlap. It is important to note that the duration of the stimulus points for all patterns vary with the five different resonant frequency rates, as they all have different periods. A visualisation of the second iteration of the haptic patterns can be seen in Figure 20.

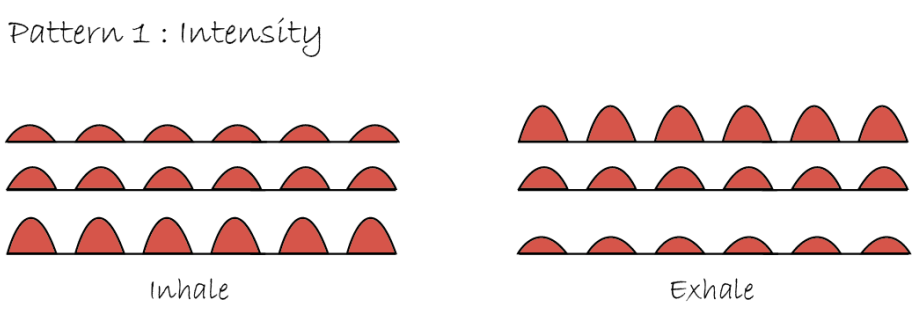


FIGURE 20: Final Patterns

4.3 Actuators

This section will briefly describe the functioning of the actuators in this thesis. It concludes by presenting a circuit diagram for the user tests.

Eccentric Rotating Mass vibration motors, as seen in Figure 21, commonly known as ERMs have shot up in popularity with the growth of the mobile phone industry. They are also used in pagers, tablets, handheld medical instruments, watches and automotive displays and dashboards. ERM coin motors are affordable, energy-efficient and easy to implement. They rely on the rotation of an unbalanced load to create vibration effects [143]. The vibration is elicited due to the rotation of the mass around the central motor shaft and its speed (frequency) is determined by the DC voltage.

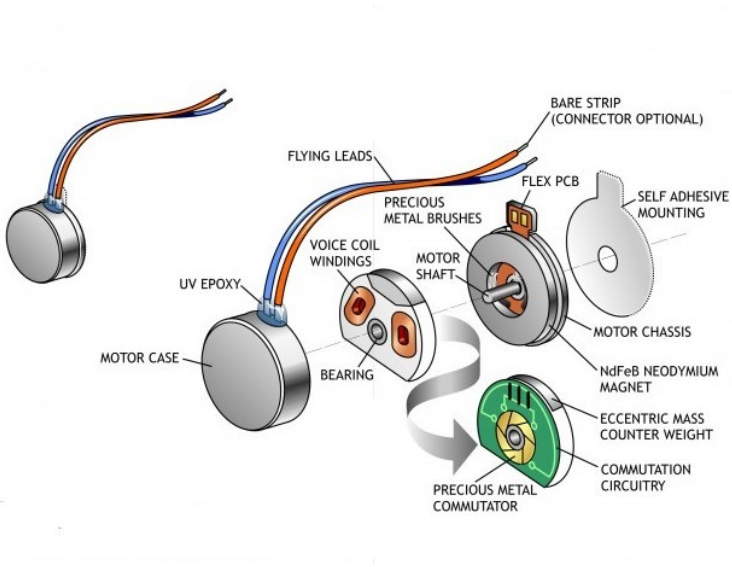


FIGURE 21: Coin Vibration Motor

The vibration motor has two terminals, namely positive and negative. In order to control the motor, it should be connected to a micro-controller. However, most DC vibration motors have a start current and operating current that is greater than the output current of micro-controllers. A transistor can act as a switch to turn the motor on and and off and can also connect a low current source (Arduino) with a higher current source (battery), without damaging any parts in between [144], [145]. Furthermore, they can also switch on/off rapidly, which allows for speed modulation with PWM [144], as described in section 4.2. The transistor chosen for this project was the NPN C33775. Using an N-channel MOSFET implies that the load will switch on when the microcontroller output is high. These MOSFETS generally have lower on-resistance, which means that if there is enough drive voltage, they will be be more efficient than P-channel MOSFETS.

Additionally, a $10k\Omega$ resistor was placed at the base of the transistor to limit the current to the transistor but to still allow enough base current to ensure that it gets fully saturated when switched on [145].

A 10uF capacitor was used as a decoupling capacitor to help to stabilise the voltage through the circuit. They filter out voltage spikes and absorb noise to make the DC signal from the

Arduino as smooth as possible. Decoupling capacitors behave like a reservoir, meaning if the input voltage drops, they will be able to provide enough power to the board to keep it stable. If the input voltage increases, they absorb the additional energy, which in turn, keeps the voltage stable [146].

The wires used in for this prototype were braided and twisted per actuator. Through twisting wires that carry an equal and opposite amount of current through them, the interference produced by one wire is cancelled out by the other one, and therefore leads to a cleaner signal [147]. Furthermore, twisting wires also cancels out external electromagnetic interference from other equipment. The potentiometer signal and the PPG sensor signal were also separated as far as possible on the Arduino UNO board to prevent additional cross-talk between the two input signals. The potentiometer was attached to pin A0 and the PPG sensor to pin A5. The full setup schematic can be seen in Figure 22.

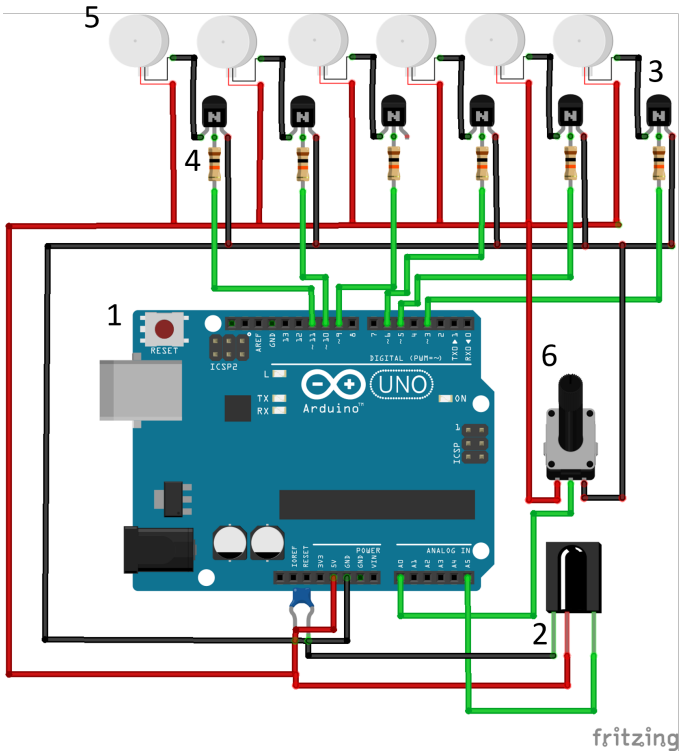


FIGURE 22: User test prototype setup schematic

Component List:

1. Arduino UNO
2. Grove earclip sensor (shown as IR LED)
3. 6 NPN C33775 transisors
4. 6 $10k\Omega$ resistors
5. 6 ERM coin motors
6. Potentiomenter
7. Arduino Uno protoboard
8. Wires
9. Laptop

This section has shown that suitable placements for the wearable should ideally be connected to the body parts that play a part in breathing. Ideally this is around the chest-to-abdomen area. Moreover, the placement and the pattern of the actuators should be symmetrical for a natural feeling. Previous studies as listed in Table 3 have used the wrist, abdomen, elbow for haptic wearables to support breathing. This section has shown that four positions as illustrated in Figure 17 will be taken further to the experiment stage and thus answers the first design question of *Where is the most suitable placement for the wearable to stimulate resonant breathing?*

5 Specification

"Ideation without execution is delusional."

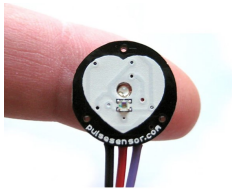
The goal of this chapter is to select a PPG sensor and to explore the time and frequency domain characteristics of breathing at the rates of 4.5 breaths/min, 5 breaths/min, 5.5 breaths/min, 6 breaths/min and 6.5 breaths/min. This is approached in the form of two experiments that are presented in this chapter. This chapter builds upon chapter 3 and answers the sixth knowledge question of *"How can heart rate variability be measured and what sensors should be employed?"*

5.1 Experiment 1: Sensor Tests

This section describes the measurement set-up, plan and results of the tests conducted to evaluate the suitability of PPG sensors to estimate the heart rate. This experiment compared three different PPG sensors to an ECG signal over a 5min recording period. The result of these experiments shows that the Grove earclip PPG sensor along with the rising edge algorithm for peak detection will be used for the further stages of this thesis.

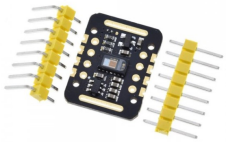
5.1.1 PPG Sensors

The three sensors that were compared can be seen in Figure 23. All sensors work with different wavelengths of light. The pulse sensor in Figure 23a emits green light, the grove earclip emits infrared light and the MAX30102 sensor emits both red and infrared light. The penetration depth of every light wavelength can be seen in Figure 13. All these sensors were compared to a reference ECG measurement that was taken using the AD8232 sensor. As mentioned in section 3.3.2, PPG signals are highly variable, have low amplitudes and noise and environmental factors heavily affects the quality of the signal. This was especially the case from the pulse sensor, seen in Figure 23a. It should be noted that on occasion the sensor would show very large deviations in the signal due to unknown disturbances, despite all measurements being from the same person, on the same finger. For this reason, other photoplethysmographic sensors were acquired as shown in Figure 23b and 23c.



(A) Pulse sensor PPG

(B) Grove earclip PPG sensor



(C) MAX30102 PPG sensor

FIGURE 23: Photoplethysmographic sensors to compare

The grove earclip sensor, as seen in Figure 23b, contains an ear clip and a receiver module. The receiver module has internal circuitry that converts the sensor reading into a square wave if the value it picks up is above a certain threshold. It does therefore not provide a "continuous" signal but only indicates when it detects a pulse. As a consequence, it does not have amplitude fluctuation issues like the pulse sensor, but provides less information about what it measures, as no characteristics as described in Figure 14 can be detected.

The MAX30102 sensor, as seen in Figure 23c combines an infrared and a red LED and can be used to estimate oxygen levels of the blood as well as heart rate. This is because deoxygenated blood absorbs more red light, whilst oxygenated blood absorbs more infrared light and by taking the ratio of the two the oxygen level can be estimated. The sensor also communicates with an I2C protocol.

Preliminary Experiment Description
Originally, all experiments would have been conducted with the pulse sensor on different body locations to evaluate their feasibility for creating a wearable. This was executed by using the AD8232 ECG sensor and two pulse sensors on an Arduino UNO. Conductive gel was used in combination with the electrode pads to reduce electrical impedance with the skin for a better signal. The sampling rate was chosen at 200Hz. The body locations that were tested were fingertip, fingerstem, bottom of the wrist, top of the wrist and earlobe. However, measuring these three signals using the Arduino UNO introduced quite some crosstalk between the pins, resulting in the signals to synchronise even though they were measuring different signals. This was also seen when measuring the heartbeat of two separate people on the same Arduino.

Furthermore, the calculation of the second derivative for peak detection according to Peng et al. [106] introduced a lot of additional noise to very high amplitudes, rendering the second derivative futile for analysis. Smoothing the raw signal for better computation of the derivative was also tried, however, this introduced a double delay of the peak detection in real time. This is due to firstly, the computation of the smoothing filter, secondly, due to the calculation of the derivative and thirdly, the detection of the peaks of the derivative, which did not improve significantly from the raw signal. The results of this sensor were not always reproducible which is why stabilisation circuits with a pull-down resistor and op-amp were also tried. The pull-down resistor introduced high frequency oscillations that did not allow the sensor to measure anything anymore. This could be because the output resistance of the pulsesensor was too high. For this reason, an operational amplifier was added to the circuit to lower the impedance of the signal and to amplify it if needed. From these experiments, the operational amplifier and a larger Arduino will be added to use in combination with the pulse sensor.

5.1.2 Setup

All sensors could be interfaced using a supply voltage of 3.3V or 5V, both which an Arduino can supply. Through testing, it was found that the supply voltage of 3.3V gave more stable measurements than 5V. The circuit of the measurement setup can be seen in Figure 24 and was made in Fritzing [148]. The TLC272 was taken as the operational amplifier for this circuit. It is a dual supply op-amp which allowed for a signal comparison between two inputs. It was powered by a supply voltage of 5V. As can be seen in Figure 24, the left side of the op-amp circuit results in a gain of 2 and the right side has the configuration of a unity buffer.

Three signals were recorded from the pulse sensor, namely the raw, the unity gain and the amplified signal. The grove earclip sensor was connected to an analog pin to read its raw data, as was the AD8232 sensor. New electrodes patches were used in combination with OneStep clear gel for this experiment. Two patches were placed on the chest and one on the left side of the abdomen. The pulse sensor was connected to the fingertip on the left index finger, the MAX30102 was placed underneath the fingertip of the left middle finger and the grove earclip was connected to the left little finger, as no discernible heartbeat was measurable from the researchers' earlobes, as they are pierced.

The purpose of these experiments are two-fold. Firstly, the goal of this experiment is to select a suitable sensor for this thesis based on its performance in comparison to the ECG baseline. The second goal is to assess whether there is a measurable difference in heart rate variability when breathing at the resonance frequency breathing rates and how to determine this.

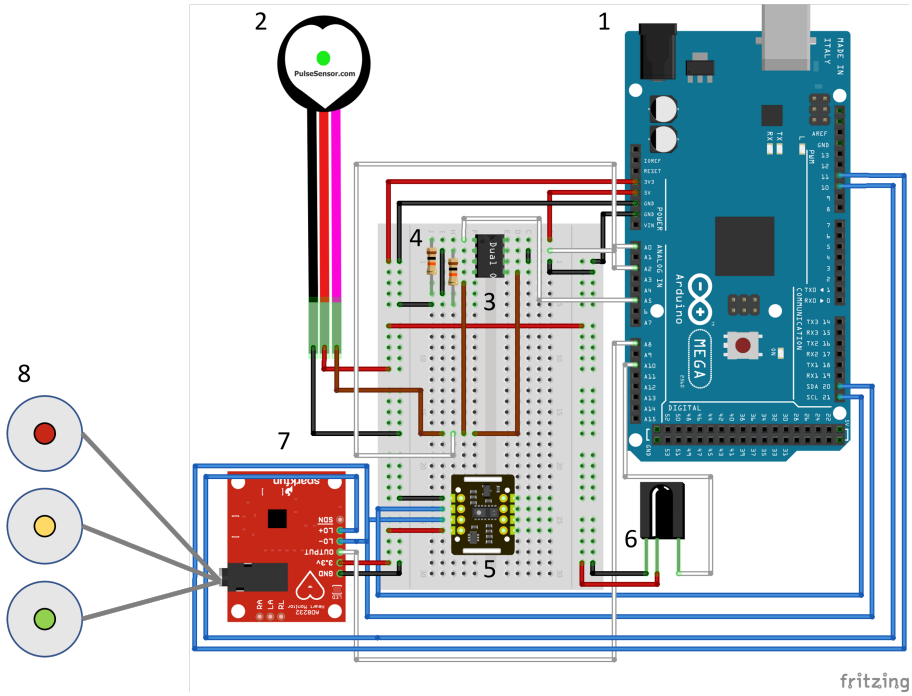


FIGURE 24: Sensor test setup schematic

Component List:

1. Arduino MEGA
2. Pulse sensor
3. TLC272 operational amplifier
4. 2 $10k\Omega$ resistors
5. MAX30102 biosensor
6. Grove earclip sensor (shown as IR LED)
7. AD8232 ECG sensor
8. Electrode pads
9. OneStep Cleargel electrode gel
10. Breadboard
11. Wires
12. Laptop

5.1.3 Methodology

This subsection describes the methodology to determine the most suitable PPG sensor for this thesis by comparing all sensors shown in Figure 23 an ECG baseline with a Bland-Altman analysis. Pre-processing steps include a missing beat analysis and linear interpolation of outlier values.

The data was recorded at 200Hz. It was saved in a .csv file that later was read from Jupyter Notebook. The data was first visually inspected and inconsistencies were manually removed. The visual inspection was in forms of distribution plots such as histograms and boxplots. Peak detection of the points was performed through the the scipy.signal library [149]. The peaks were detected with a 125 horizontal sample distance requirement, which corresponds to a maximum detectable heartbeat of 96 beats per minute.

The methodology for the breathing rate estimation can be seen in Figure 25. The extracted RR intervals firstly undergo a cubic spline interpolation to 1000 Hz. This step is needed in order for the frequency calculations to have a better resolution. Secondly, a bandpass filter with cut-off frequencies of 0.05 Hz - 0.4 Hz is applied on the interpolated signal. These frequencies correspond to a breathing rate of 3 - 24 breaths per minute, which accounts for all the breathing rates that will be tested and the higher end of respiratory frequencies at which humans usually breathe. A fourier transformation is executed on the filtered signal. This step transfers the time data to the frequency domain, which allows changes in frequencies to be analysed more clearly. The power spectral density complements the fourier transform and measures the power of the frequency components. The frequency with the largest power in the range of 0.05 Hz - 0.4 Hz is selected and output as the breathing rate. This function was used from the heartpy library [150].

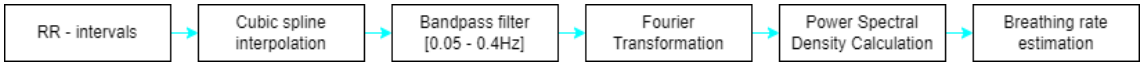


FIGURE 25: Methodology for breathing rate estimation

To assess the agreement between two quantitative measures of agreement the Bland-Altman method has been proposed from studies that have previously compared ECG to PPG signals [98], [151], [152]. The Bland-Altman method studies the mean difference between measurements and constructs an agreement interval (usually within two standard deviations of the mean difference) within which 95% of of the differences between measurements can fall. It is visualised a scatter plot where the x-axis represents the average of the two measurements and the y-axis shows the difference between the two measurements [153]. Correlation measures have been used quite often in studies as an indicator of agreement, however, correlation studies the relationship between variables, not the differences and is not recommended as a method for assessing the comparability between methods [98], [153]. A high correlation does not automatically imply that there is a good agreement between the methods, it simply states that there is a linear association between two sets of observations [153]. The assumption of normality has to be verified before using the Bland-Altman method and the limits of maximum acceptable differences should be defined a priori, as this analysis does not state whether the limits are acceptable or not, it simply sets them.

Preprocessing steps

Heart rate variability signals extracted from RR interval time series often contain different amounts of artifact [154]. The false beats can either stem from physiological or technical

errors. Examples of physiological errors can be ectopic beats and atrial fibrillation. An ectopic beat describes a inter-beat interval that deviates from the normal heartbeat interval including missed and additional beats [155]. Atrial fibrillation describes irregular heartbeats due to the upper chambers of the heart contracting irregularly. It may happen in brief episodes or be a permanent condition. Examples of technical errors can be poorly fastened sensors and motion artifacts. Both these errors can lead to inter-beat intervals that are either too long or too short [155]. Since these beats are caused by abnormalities in cardiac conduction or movement rather than effects of the autonomic nervous system, HRV results in assessment of the ANS can be distorted and misleading insights concerning the health status of the individual could be drawn if these beats are not removed [155], [156]. Several studies have presented interpolation methodologies to to handling false beats present in the R-R interval series, which has slowly come to be an important and integral part of these analyses [154]–[157].

In this project, linear interpolation is used to fill in the gaps where ectopic beats are detected to produce a cleaner signal for analysis in the time and frequency domains. There is an inbuilt function for this in the hrvanalysis library for python [158]. The boundaries of outlier selection were chosen between 450ms and 1500ms, which corresponds to an average heartrate range of 40 - 133 beats per minute. These boundaries are larger than what is considered to be the range for average human heartbeats, but were chosen to account for physiological abnormalities and to ensure that the range is not too narrow. Values that fell outside these margins were firstly removed and then replaced by a linear interpolated value for continuity. Ectopic beat correction was also performed using Malik's rule, which marks a beat as ectopic if it falls outside 20% of the inter-beat interval preceeding it [159]. The logic for this rule can be seen in the equation 2. Figure 26 summarises the methodology for the sensor testing experiment.

$$Outlier = abs(rr\ interval - next\ rr\ interval) >= 0.2 * rr\ interval \tag{2}$$

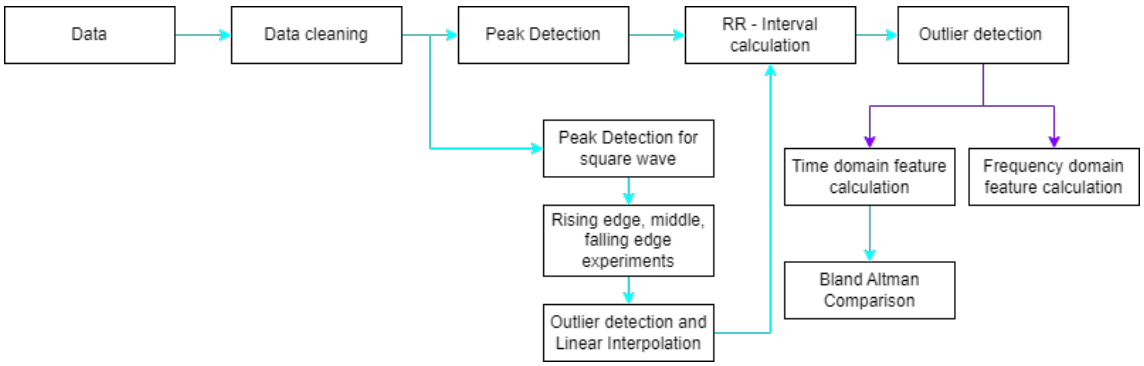


FIGURE 26: Methodology for sensor tests

Correlation analysis

In research, correlation analysis is a statistical method used to measure the strength of the linear relationship between two variables and compute their association [160]. The Pearson correlation coefficient (r) is the most common way of measuring a linear correlation. It ranges between –1 and 1 which indicates the strength and direction of the relationship between two variables [160]. A high correlation (closer to 1 or -1) points towards a strong relationship between the two variables, while a low correlation (closer to 0) indicates that the variables are weakly related.

5.1.4 Results

This section describes the results of the sensor tests experiment. It shows that the grove earclip sensor, together with the rising edge algorithm performs best in the Bland-Altman analysis as compared to the ECG signal and will therefore be selected as the sensor of choice for this thesis.

All sensors have different scales for their raw output as seen in Figure 27. All photoplethysmographic sensors peak with a delay to the ECG sensor. This phenomenon is in accordance with the theory as the delay in the PPG peaks in Figure 27 correspond with what is described in Figure 14.

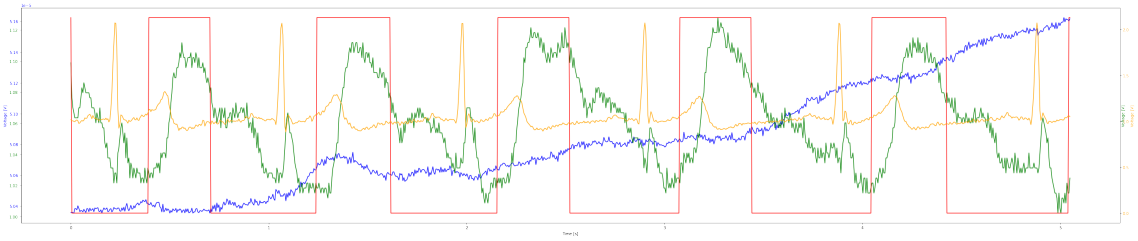


FIGURE 27: Data readings from all sensors for 5 seconds - ECG signal: yellow, Grove earclip sensor: red, Pulse sensor signal: green, MAX30102 IR sensor: blue

Visually, it can already be seen that the MAX30102 IR sensor (blue) has a very low sensitivity compared to the others, as it is quite difficult to see where there is a pulse. The pulse sensor (green) does not output a clean signal either, as there is quite some high frequency noise for the amplitude changes. The grove earclip signal (red) is very clean in the comparison to the others, but this is because it only changes between two values. However, the grove earclip signal seems to alternate value at the tangent intersection when compared to the signal of the pulse sensor. This can also be seen as point E in Figure 15, which Peng et. al showed to be one of the best fiducial points of the PPG signal with the least bias when compared to the ECG signal [106].

Signal	Nr. of detected peaks	BPM	IBI [ms]	SDNN [ms]	RMSSD [ms]
ECG	360	100.17	834.81	135.28	179.13
Pulse sensor	358	72.37	839.57	97.62	104.40
MAX30102 IR	373	76.29	806.33	131.32	178.89
MAX30102 red	363	73.78	828.29	113.34	138.95
Grove earclip	351	71.48	856.63	148.13	168.57

TABLE 8: Comparison of all sensors across a 5min recording. BPM: beats per minute, IBI: inter-beat-intervals, SDNN: standard deviation of the NN intervals, RMSSD: root mean square of successive differences between normal heartbeats

As described in the preliminary experiment description section, taking the second derivative of a signal sampled at 200Hz introduced a delay when calculated real-time, but also resulted in a signal with high noise and was therefore discarded. A low pass filter with a cut-off frequency at 10 Hz was applied eliminate the high frequency noise but did not improve the peak detection functionality and was therefore removed as it introduced a further calculation step, which could eventually slow down the real-time processing if implemented.

Table 8 shows the results of all sensors across a 5 min recording of breathing at 6 breaths/min (0.1Hz). Even though the all sensors recorded data from the same person at the same time,

they all detected a different amount of peaks. This did not allow for direct comparison of the beats as time-shifted errors would have been introduced. Therefore, the missing beats had to be manually identified and deleted to ensure a valid analysis.

Grove earclip sensor peak detection

This section will present the three different algorithms tested for peak detection on the Grove earclip sensor wave for the best correlation with the ECG. It will further elaborate on the missing peaks detection methodology and provide examples with the grove earclip sensor. Plots of the other sensors can be seen in section 10.2.1.

The three different algorithms tested for peak detection on the grove earclip sensor are visualised in Figure 28. As the wave is a square wave pulse, the detection of the pulses were separated into the rising edge, the middle of the pulse and the falling edge of the wave. The rising edge was taken by only considering the rising slope of the first derivative of the square wave. The heartpy library's inbuilt peak detection algorithm [150] marked the middle point of the square wave. This is due to their use of cubic spline interpolation to reconstruct a clipped signal. The square wave is therefore constantly identified as clipped and therefore reconstructed through their library with an identified peak in the middle. The falling edge was identified through the findpeaks function of the scipy.signal library [149]. Similar to the rising edge, here only the falling edge of the first derivative of the signal was considered.

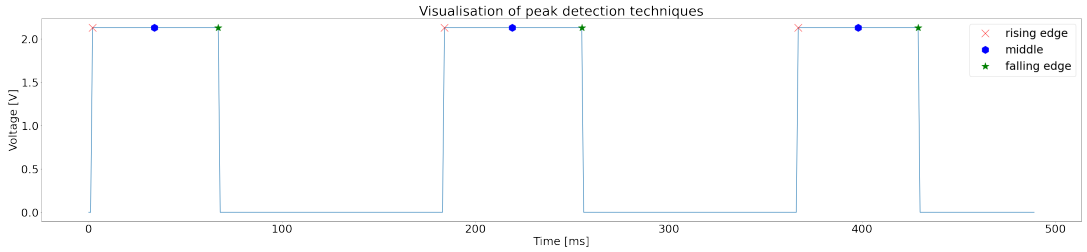


FIGURE 28: Visualisation of rising edge (red), middle (blue) and falling edge (green) of a square wave

To detect which algorithm performs the best, a correlation analysis can be run between the inter-beat intervals of the Grove sensor with every algorithm and the ECG sensor. For this, it is important that the same inter-beat intervals of the same peaks are compared to each other for accurate results. However, as seen in Table 8 the Grove earclip sensor detected 9 peaks fewer than the ECG. These were detected by plotting the subtracted inter-beat intervals between the ECG sensor and the Grove earclip sensor and can be seen as the red line in Figure 29 below. The blue signal shows the ECG recording over 5min (300 s) of the author breathing at 6 breaths a minute (0.1 Hz). This can further be detected by the 30 peaks (breaths) seen in the span 5min recording of Figure 29. Respiratory sinus arrhythmia, as explained in section 2.1.3 can be detected in the ECG signal as the oscillatory behaviour of the peaks. The troughs of the peaks represent an inhale as the heart beats are closer together. The peaks of the peaks represent an exhale as the heart beats are further apart. 30 breaths can be seen in Figure 29 which corresponds to the 0.1Hz breathing rate of the participant. There are 9 artefacts in the ECG signal and these can be seen as as points where the voltage falls to 0.6V.

Ideally, the red line should be horizontal to indicate that the difference between the detected interbeat intervals of both sensors are in phase. This seems to be the case except at 9 points

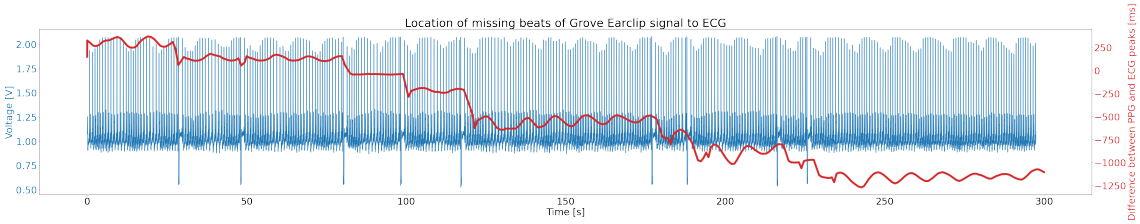


FIGURE 29: Visualisation of missing beats between ECG and grove sensor

where the red line drops which indicates a missed beat. Most of the drops correspond to the artefacts of the ECG signal. The detected ECG beats at these points were removed so that both signals had detected the same amount of beats that corresponded to each other in order for an accurate correlation analysis to be run. As photoplethysmography has a delay in detecting the heartbeat relative to electrocardiography, the first detected PPG beat and last detected ECG beat were removed to match the range of detected beats between the two sensors. A visualisation of this can be seen in Figure 58 in the Appendix.

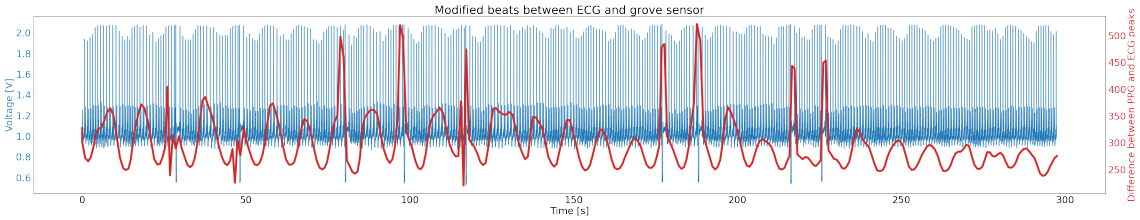


FIGURE 30: Modified beats between ECG and grove senor

The red line in Figure 30 shows the differences between both sensors with the 9 removed ECG beats. The range of the signal has decreased from 1500ms in Figure 29 to 250ms which indicates a 600% increase in relative accuracy. It can be observed that the red signal oscillates periodically which suggests that there is a constant delay between both sensors.

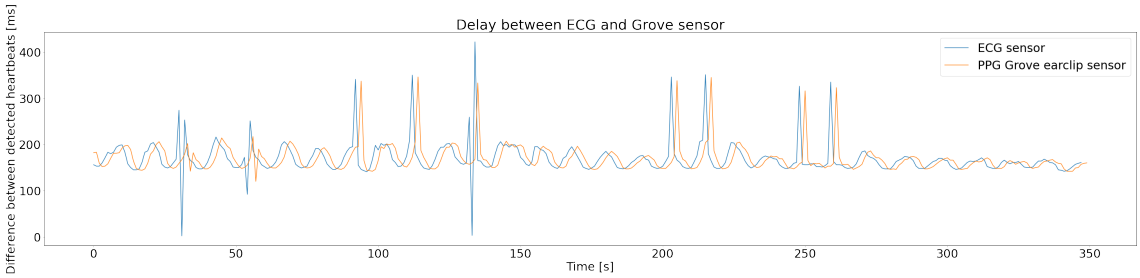


FIGURE 31: Delay between ECG and Grove signals

Figure 31 confirms the delay as it visualises the detected time differences between heartbeats over the 5 min recording shown in Figures 29 and 30 above. These characteristics are aligned with the theory illustrated in Figure 14, as there is always a certain delay between electrical signal of the heart and the detection of a pulse anywhere on the body. This is called the pulse transit time and was explained in Figure 14.

The same procedure of peak matching was run on the other sensors and all plots can be seen in section 10.2.1. There were varying delays between the different PPG sensors to the ECG sensor and can be seen in Table 9. These delays can be attributed to the different internal

circuitry in the sensors themselves.

	Pulse sensor	MAX30102 IR	MAX30102 red	Grove earclip
Delay [ms]	1.5	4	1	2

TABLE 9: Delay between ECG and Grove signals

Correlation analysis

The detected 350 inter-beat-intervals of the grove sensor were run through all three algorithms and compared to the inter-beat-intervals extracted from the ECG. The highest correlation of the raw extracted intervals to the ECG was with the rising edge peak detection algorithm. This correlation was 0.642, as can be seen in Table 10. The middle and falling edge algorithms had very similar performances of around 0.63. The algorithms had very high correlations within themselves with a 0.99 correlation coefficient. These results indicate that the choice of algorithm would not make a significant difference on the inter-beat intervals as the correlation between the algorithms themselves and the correlation with the ECG is similar.

	rising edge	middle	falling edge	ECG
rising edge	1	0.998	0.994	0.642
middle	0.998	1	0.998	0.634
falling edge	0.994	0.998	1	0.633
ECG	0.642	0.634	0.633	1

TABLE 10: Correlation Matrix for square wave raw

To better these results, only inter-beat-intervals larger than 450ms and shorter than 1500ms were kept. These correspond to an average heartrate range of 40 - 133 beats per minute. Similarly to the justification above, these values are larger than the average human heart beat values. A larger margin was taken to account for physiological abnormalities and to not constrict the range too narrowly. Values that fell outside these margins were firstly removed and then replaced by a linear interpolated value for continuity. Ectopic beat correction was also performed using Malik's rule where the beats were first removed and later replaced through linear interpolation by using the hrvanalysis library [158]. Figure 32 illustrates how these preprocessing steps worked by depicting the inter-beat intervals of the rising edge and the preprocessed signal. It can be seen that the large peaks are 7 large peaks of the blue signal are removed and interpolated as is the large rising slope from 0. These preprocessing steps smoothen the raw signal out for better readability but also more reliable results, which can be seen in Table 11.

	rising edge	middle	falling edge	ECG
rising edge	1	0.889	0.873	0.834
middle	0.889	1	0.996	0.754
falling edge	0.873	0.996	1	0.746
ECG	0.834	0.754	0.746	1

TABLE 11: Correlation Matrix for square wave with linear interpolation

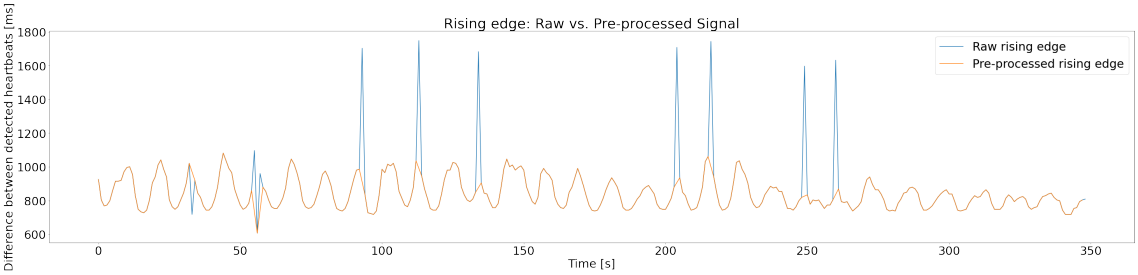


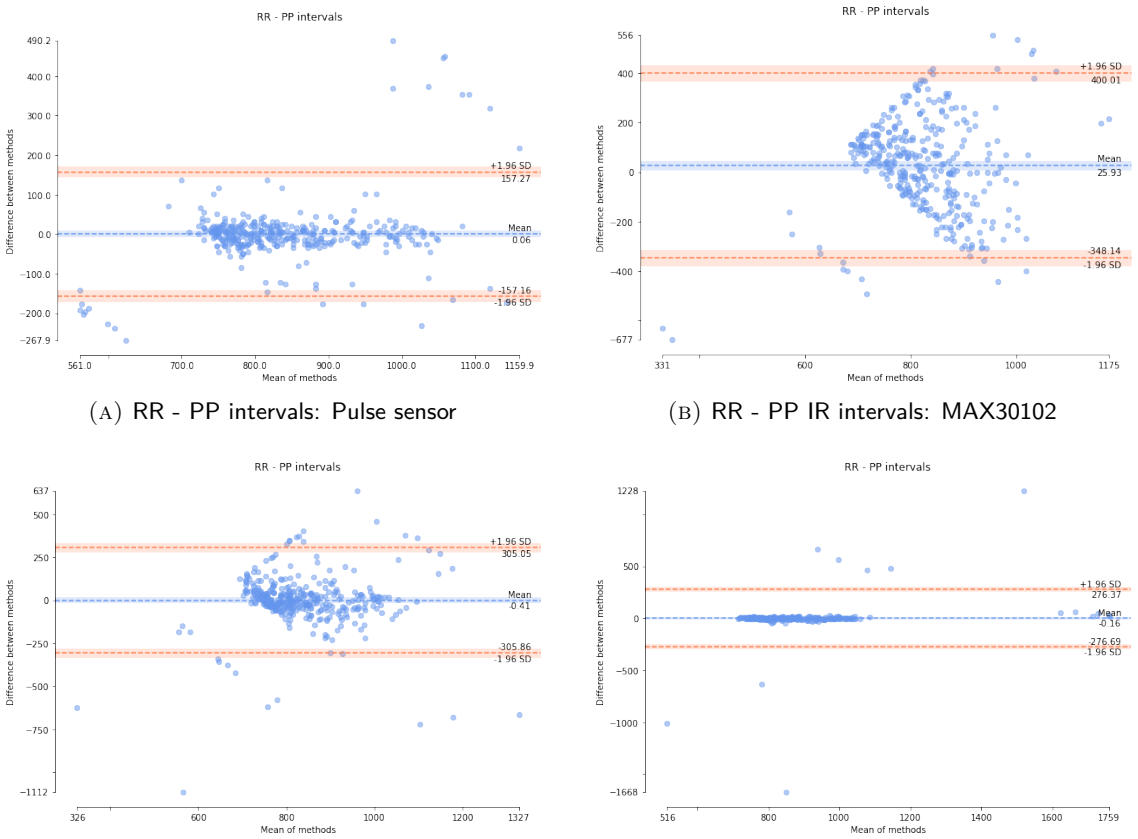
FIGURE 32: Linear Interpolation on raw signal

Correlation analyses are sensitive to outliers and removing the abnormal peaks seen in Figure 32 improved the correlation results of all three algorithms. 350 inter-beat-intervals were kept for every algorithm in this method. The rising edge algorithm performs the best with a correlation coefficient of 0.83 which is a 0.19 point improvement from the raw values. The middle and falling edge algorithms are slightly worse as they only have a 0.75 correlation coefficient. However, this is still a 0.12 point improvement from the raw values seen in Table 10. The correlation between the algorithms themselves have worsened slightly, as they are now around 0.87.

The rising edge algorithm had the highest correlation with the ECG intervals on both the raw and the interpolated data. Even though the performance of all algorithms seems to be quite similar, both raw and interpolated, the rising edge will be chosen for the continuation of this thesis since it seems to be the most robust out of the three. Furthermore, the rising edge peak point aligns with the tangent intersection point as described in Figure 14 which was described to be the point with the least bias when comparing the PPG waveform to the ECG [106]. Moreover, the linear interpolation and ectopic beat correction using the Malik method will be performed using outlier cleaning between 450ms and 1500ms as it yields the best results as seen in Table 11.

Agreement Analysis

The measurement points on the Bland Altman graph represent how much one method measures against the other one. The y-axis of all plots have been made in the form of $ECG\ sensor\ measurements - PPG\ sensor\ measurements$. If the measurement point is positive, it indicates that the ECG signal measures more milliseconds in the inter-beat intervals and if it is negative, if indicates that the PPG sensor it was compared to measures more. The mean, drawn through the blue line, indicates how much more on average one sensor measures against the other. Ideally, this number should as close to 0 as possible to indicate that there are fewer differences between the two sensors. The pulse sensor and the MAX30102 IR sensor both measure shorter inter-beat intervals as compared to the ECG sensor. This can be seen through both sensors having a positive mean value in Figures 33a and 33b. Alternatively, the MAX30102 sensor and the grove earclip sensor measure larger inter-beat intervals than the ECG as they have a negative mean value as seen in Figures 33c and 33d. The orange horizontal lines indicate the confidence interval limits for mean and agreement limits. They are calculated by multiplying the standard deviation by 1.95 on both side and therefore account for 95% of all measurements. This is done with the assumption of a normal distribution of the data. Ideally, these limits should be minimised as the highest plot of agreement would have a mean of 0 and all measurements would be on a horizontal line.



(A) RR - PP intervals: Pulse sensor

(B) RR - PP IR intervals: MAX30102

(C) RR - PP red intervals: MAX30102

(D) RR - PP intervals: Grove earclip

FIGURE 33: Bland-Altman plots for all 4 sensors

The mean and standard deviations are the largest for the MAX30102 IR sensor followed by the red sensor. Their distribution on the plot also indicates that there is a random bias after inter-beat intervals above 830 ms. The pulse sensor has the smallest confidence intervals and the smallest deviation of the mean from 0. The mean of the grove earclip sensor has a larger deviation from 0 and larger confidence intervals but fewer outliers outside the bounds when compared to the pulse sensor. The distribution of both sensors seem to be clustered relatively horizontally on the blue line which indicates good agreement of both sensors with the ECG.

	Pulse sensor	MAX30102 IR	MAX30102 red	Grove earclip
Correlation with ECG sensor	0.750	-0.022	0.308	0.643

TABLE 12: Correlation coefficients of PPG sensors with ECG sensor

The correlation coefficients of the different PPG signals with the ECG can be seen in Table 12. These results align with the Bland Altman plots in the sense that the performance of the sensors can be ranked best to worst pulse sensor, grove earclip sensor, MAX30102 red sensor and MAX30102 IR sensor in both analyses.

A rigourous manual selection of the peaks had to implemented for extracting the inter-beat intervals of the pulse sensor. To program a dynamic algorithm that can properly detect the peaks of the pulse sensor real time and through its noisy and unpredictable signal would

extend the time scope of this project. The grove earclip sensor has a more reliable and robust signal, peaks when it detects an upward slope of arterial blood which aligns with the tangent intersection point stated in Figure 14 and has acceptable sensor performance when compared to the ECG signal as depicted in Figure 33d. Moreover, the performance of the sensor can be boosted by using linear interpolation for ectopic beat removal as seen in the grove earclip sensor peak detection section. All of these reasons together lead to the grove earclip sensor to be chosen as the PPG sensor for this project.

5.2 Experiment 2: Breathing rates comparison

This section describes the measurement set-up, plan and results of the tests conducted to explore the time and frequency domain characteristics of breathing at the rates of 4.5 breaths/min, 5 breaths/min, 5.5 breaths/min, 6 breaths/min and 6.5 breaths/min. It shows that there are differences in both domains between all breathing rates and that there is need for a methodology to choose one.

5.2.1 Methodology

All tests were conducted on the author of this thesis. The participant was female and 24 years old. The data was recorded at 200 Hz. The previous section finalised on the choice of selecting the grove earclip sensor as the PPG sensor for this thesis. This sensor shall be employed for this experiment and the measurement setup schematic can be seen in Figure 22. Firstly a baseline measurement was taken where the participant breathed at their habitual rate with the PPG sensor attached to their left little finger. Thereafter, the participant breathed for 2 min each at 6.5 breaths/min with audio cues from [161], 6 breaths/min [162], 5.5 breaths/min [163], 5 breaths/min [164] and 4.5 breaths/min [165]. Between every session a two minute break was taken. This methodology of decreasing breathing rates and breaks is described in the paper of Shaffer and Meehan [28]. The processing of the data was done in the same manner as illustrated in Figure 26. The first 30s of data was removed to get rid of the participant getting accustomed to the breathing rate. Thereafter, the peaks were detected with the rising edge algorithm. Outliers outside the range of 450 - 1500ms were removed and interpolated linearly. This range was taken with the same reasoning mentioned above of allowing for a larger range beats per minute than the habitual range to account for abnormalities. The time and frequency domain results were calculated using the pyHRV library [166].

5.2.2 Results

The extracted time and frequency domain results of all different breathing rates are summarised in Table 13. No statistical hypothesis testing could be done on these results as all tests were conducted on the author and would therefore violate the assumption of independence. Moreover, with a sample size of only 5 measurements, statistical inferences would not have a large valid meaning. The breathing rates were calculated using the scheme in Figure 25.

	4.5 breaths/min	5 breaths/min	5.5 breaths/min	6 breaths/min	6.5 breaths/min	Baseline
NN [ms]	914.95	715.48	765.86	838.59	867.81	900.5
SDNN [ms]	128.51	48.84	55.71	87.54	110.27	60.25
RMSSD [ms]	61.17	18.72	27.45	49.05	66.83	60.08
Mean HR [bpm]	66.93	84.25	78.75	72.29	70.27	66.94
PNN50 [%]	48.28	2.34	7.2	29.3	47.22	39.59
VLF [ms^2]	6.53	5.05	6.81	7.35	7.28	6.13
LF [ms^2]	9.58	7.3	7.31	8.77	9.2	6.25
HF [ms^2]	7.34	4.69	5.43	6.05	6.18	7.04
Breathing rate [breaths/min]	4.51	5.08	5.43	6.23	6.39	15.79

TABLE 13: Results: Time and frequency domain measures of 5 breathing rates

All metrics described in section 3 can be been in Table 13. Heart rate variability has no singular metric, which is why it is important that both time and frequency domain features are inspected. There is no consensus in literature about which metric should be chosen to determine which breathing rate should be chosen as the resonance frequency of the participant. The SDNN describes the standard deviation of the NN intervals and is a measure of how dispersed the

data is relative to the mean. A lower number would indicate that the data is clustered around the mean and a higher number indicates that the data is more spread out. As the choice of the breathing rate for the resonance frequency should maximise heart rate variability a higher number would indicate more variability. Yu et al followed this line of reasoning in their experiment [167]. However, the SDNN is heavily affected by outliers and may not be the most robust option.

RMSSD describes the root mean square of the successive differences (inter-beat intervals). This is a very commonly used metric in heart rate variability studies and reflects the beat-to-beat variance in heart rate [92]. Previously the average peak-trough amplitude was considered as a metric to describe HRV, but the RMSSD outperforms this as it has a superiour resolution due to the additional data points.

Based on visual inspection of Table 13, it can be seen that the 4.5 breaths/min category has the largest SDNN, RMSSD and largest low frequency power out of all categories. If compared to the baseline, the SDNN has experienced a 2.28 factor growth and the RMSSD a 1.2 factor growth. The frequency domain values did not experience such a drastic change but have also shown different factors of growth when compared to the baseline. This experiment suggests that breathing slower already shows a difference in both time and frequency domain metrics.

To get further insight on which metric should be chosen for resonance frequency determination, an interview with Fredric Shaffer, biological psychologist and professor of Psychology at Truman State University, was conducted over Microsoft Teams.

Interview with Dr. Fredric Shaffer

Mr. Shaffer stated that there is still a dispute over a singular measure for heart rate variability and that there is no consensus of a particular method to determine the resonance frequency of a human. He mentioned that there are studies that have used the LF power as a measure of parasympathetic activity and have concluded that it does indeed get boosted after an intervention of slow breathing. However, Mr. Shaffer postulates that this change is only temporary and does not cause long-term effects to the vagus nerve. He states if the intention is to train the vagus nerve, breath training experiments should be at least twice a day for 20 minutes each. If the intention is to increase respiratory sinus arrhythmia (RSA), any intervention will help, as the heart is and functions as a muscle. Any activity or exercise will strengthen it.

Mr. Shaffer added that in the biofeedback field, a lot of training nowadays is done using pacers. Doing this removes the need for additional sensors to determine the users individual resonance frequency. He mentioned that there are not many studies that have addressed the topic of choosing a resonance frequency in a controlled setting and therefore not a lot can be said about their influence. A pacer could very well have the same effect.

When asked recommendations for an outcome variable, Mr. Shaffer strongly advocated looking at both the RMSSD as a time domain feature and the logarithm of the low frequency band as a frequency domain feature. The baroreflex system's resonance falls within the LF band and therefore reflects its activity. Moreover, Mr. Shaffer adds that the logarithm of the lower frequency band would also reveal how consistently the participants breathed in the LF range.

With this new knowledge, it could be postulated that the resonance frequency that should be chosen out of the choices presented in Table 13 is 6.5 breaths per minute as it exhibits the largest RMSSD. However, this choice would be one-dimensional as it would not consider any other characteristic. RMSSD should be the factor with the largest weight but the logarithms of the LF power should also be considered. For this reason, a methodology was developed to choose a resonance frequency with multiple parameters by using the TOPSIS method to include the suggestions by Mr. Shaffer. This will be further described in section 6.3.

To summarise, this chapter has shown experiments conducted with three different PPG sensors and five different breathing rates. The first experiment selected the grove earclip sensor to be the most suitable sensor for this project. The second experiment explored various heart rate variability metrics and has concluded on RMSSD of the RR intervals to be the most important feature through data analysis and an interview with Mr. Fredric Shaffer. The logarithm of the low frequency band will also be analysed in future data analyses. This section has thereby fully answered the sixth research question of *How can heart rate variability be measured and what sensors should be employed?*

6 Realisation

"Prototyping is the conversation you have with your ideas".

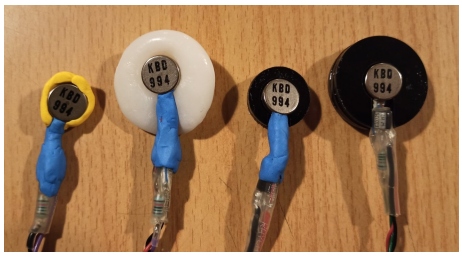
The goal of this chapter is to develop the prototype to a standard that can be taken forward to the user testing stage. These steps will be presented in five stages. Firstly, the hardware choices will be shown. Secondly the software programs will be listed up. Thirdly, findings on influences on heart heart rate will be presented. Fourthly, a methodology on the experiment design to select resonance frequencies for multiple participants will be discussed. This chapter will conclude with a section describing the full experiment design.

6.1 Hardware

This section will describe the choices and iterations done on the hardware of the wearable. It will conclude with images of the final product.

Table 7 sets the requirements for the wearable. The comfort parameter together with the functionality parameter is the focus of the hardware section. Comfort in table 7 is defined as the wearable being adaptable to all the target users' size, not obtrusive and allowing natural movement on the body region. The functionality parameter is defined as all individual components working properly within the wearable.

The motors needed to be attached to the wearable and therefore casings and attachments were required. Figure 34 shows the encasing iterations. The first iterations employed Sugru, a mouldable glue that turns from flexible putty into durable silicone rubber, was used to protect the connections of the motor head with the wires. However, Sugru turned out to be too firm for the vibrating wires and was also not smooth enough to be attached to the wearable neatly. Polymorph are mouldable plastic pellets that solidify at room temperature. The motor head case with this material was solid and could have been attached to the wearable, however presented a risk of deformation with prolonged usage.



(A) Encasing Experiments from front

(B) Encasing Experiments from back

FIGURE 34: Encasing Experiments (left to right: Sugru, Polymorph, Acrylic)

Acrylic, also known as plexiglass, is a strong, light and easy to shape material. Next, experiments were conducted with laser cut acrylic cases. These had three different layers to account for the height difference of the sugru-ed wire and the motor head, so that the latter was the first component that made contact with the user's skin. The smaller case was sturdy but did not protect the wires and did not seem to be "user-test-proof". Therefore, the final design was the large acrylic case for the motor head, which dampened more sound than the other cases and provided some support for the motor wires. The motor wires were firstly attached with hot

glue to the acrylic cases, which was a very unsustainable solution. When the motor attachments came loose, due to the user tests and long vibration times, the solidified hot glue had to be scratched out and the Sugru neck had to be destroyed in order to reach and troubleshoot the wires. Therefore, whenever repair work needed to be done, adhesive patty was used as an alternative. This remains flexible during the entire period of use but is still sturdy enough to keep the wires and motor head in the case. These are visible as the white patches on the case in Figure 36.

It was important that the motor cases had a flat back so that they could easily be attached to the belt wearable using velcro. Using velcro in the prototype made it adjustable for the different shapes of different users but also suitable for different body positions, as stated in the comfort requirement of Table 7. Moreover, the distance of the motors could also be adjusted on the horizontal as well as vertical axis, as seen by the horizontal white velcro strip in the middle and the individual velcro stickers on the top and bottom of this strip. This corresponds to the ideated placements illustrated in Figure 17. The vertical constellation can be seen in Figure 35 and the horizontal constellation can be seen in Figure 36.

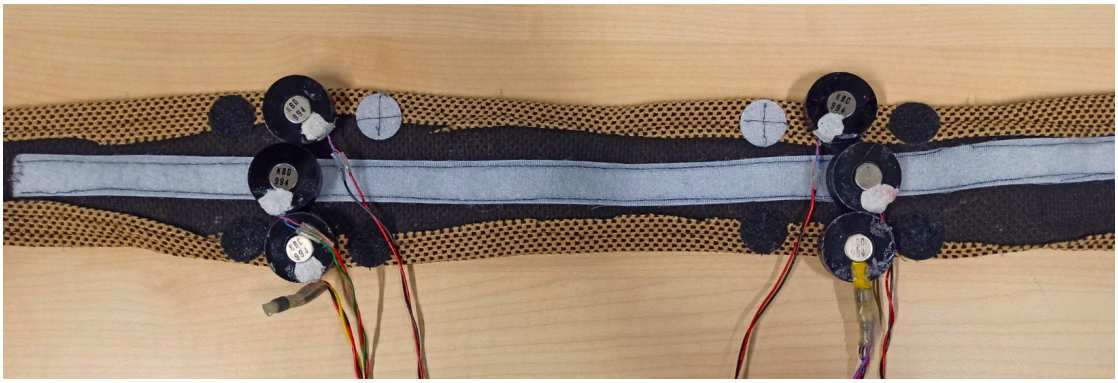


FIGURE 35: Vertical motor constellation

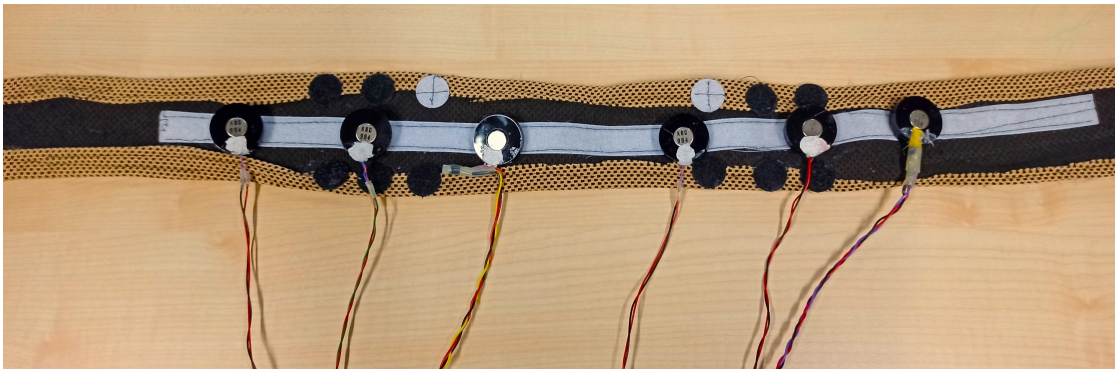


FIGURE 36: Adjustable Belt Prototype

6.2 Software

This section will provide a brief description of the software programs used for the entire development and data processing of the wearable. The links for the code and output from the individual programs can be found here: https://github.com/1997radhika/MScThesis

- **Python:** Python is a general-purpose programming language, which is often used to build websites and software, automate tasks, and conduct data analysis [168]. All data cleaning data processing in this thesis will be done in Python. Three main heart rate processing libraries are used in this thesis and will be described below.
  - *heartpy library:* This library was made with the purpose for analysing heart rate signals, especially with focus on the PPG signals, collected in noisy settings [150]. This library can extract features from a heart signal by taking the raw signal as its input. In this thesis, this library was used for the breathing rate calculation from the heart signals. The peak detection function from this library will be used for experiments on the Grove earclip sensor, described in section 5.1.4.
  - *hrvanalysis library:* This library serves as a python module for heart rate variability analysis of RR-intervals [158]. It can extract features from a heart signal but needs the RR-intervals as its input. It has sophisticated outliers and ectopic beats filtering methods for cleaning of the RR-intervals. In this thesis, the outlier detection and filtering methods of this library will be employed, as described in section 5.1.3 and 7.
  - *pyHRV library:* This library also serves as a heart rate variability toolbox for python [166]. Similiar to the hrvanalysis library [158], it also needs RR-intervals as its input. The advantage of this library over the others, is that it outputs frequency domain plots in addition to the feature calculation, which simplifies the verification process of the data. In this thesis, the time domain and frequency domain features of the heart rate signal will be extracted by using this library.
- **R:** R is a language and environment for statistical computing and graphics [169]. It offeres a wide variety of statistics-related libraries and is a useful tool for data importing and cleaning, as well as visualisation. The statistical tests of this thesis will be conducted in R.
- **Arduino:** Arduino is an open-source electronics platform based on easy-to-use hardware and software [170]. The language is based on C and can be expanded through C++ libraries. As the prototype will be controlled with an Arduino, the Arduino software is used for development of the breath guidance wearable.
- **Excel:** Microsoft Excel is the industry-leading spreadsheet program, a powerful data visualization and analysis tool [171]. In this project it shall primarily be used to store and visualise the heart data acquired from Arduino. In later stages of the project, it shall also be used to sort and store data acquired from surveys and to merge data into a readable format for usage in Python and R.

6.3 Resonance Frequency Selection

This section describes the procedure for the resonance frequency selection of the participants. The choices made for this procedure come from Shaffer and Meehans' paper [28] and Mr. Fredric Shaffers' interview, summarised in section 5.2.2.

Methodology

To recruit participants for this study. an interest message was sent out to various WhatsApp group chats with an interest form, attached in section 69. Only people who were interested, did not have respiratory problems and did sport fewer than three times a week were contacted. The trials either took place in the authors home or in the Empathise room in DesignLab. The resonance frequency procedure was conducted on 18 participants (9f, 9m). The ethical permission number for these experiments is 220016.

As shown in Figure 37, the participants were firstly briefed about the project and asked to sign a consent form that can be seen in section 70. Thereafter, the grove earclip sensor was attached to the participant either on the left little finger or their left ear. The left side of the body was chosen, as the distance from the heart is closer than from the right side. As described in section 4.1, both finger and earlobe are body locations for the PPG sensor that provide the most reliable results. Most female participants had pierced earlobes which did not allow for a reading from the sensor. Their ears were also generally smaller than the male participants which added difficulties in attaching the sensor. In these cases, the fingertip was taken. The male participants, generally had thicker fingers and the sensor could not get a reading from the fingers. In these cases, the earlobe was taken. The sampling rate was 200Hz.

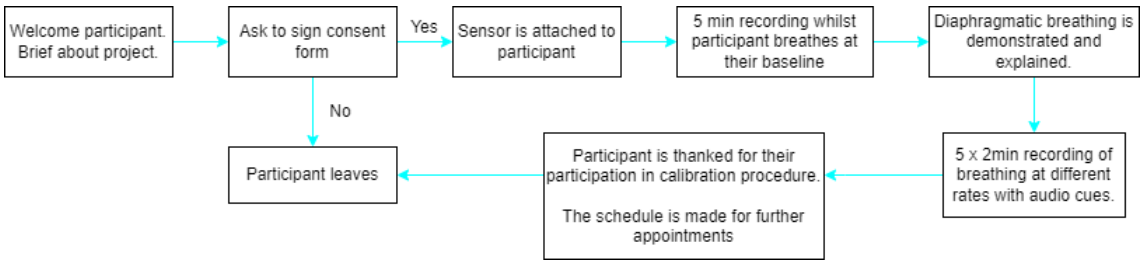


FIGURE 37: Methodology for resonance frequency selection

The participants were asked to breathe as they habitually do for 5min. This recording served as the baseline recording before any intervention with the haptic wearable. Thereafter, they were instructed on the technique of diaphragmatic breathing. They were told that during inhalation, the abdomen should expand and during exhalation it should contract. The participants were asked to breathe for two minutes each at the following breathing rates: 6.5 breaths/min, 6 breaths/min, 5.5 breaths/min, 5 breaths/min and 4.5 breaths/min. The inhale-exhale ratio was kept to 1. There was a 1min break in-between every session for the participants to recover. The different breathing rates were guided through scale of pentatonic notes that indicated an inhale when rising and exhale when falling [161]–[165]. After completing this procedure, the participant was thanked for their time and participation. They were asked about their coffee, drug and alcohol intake in the past 24h and an appointment was scheduled for the following session.

Processing

The data from all participants and all breathing rates were processed using python and the methodology can be seen in Figure 38. In the data cleaning step, the first 30s of data were removed to ensure that the participant was familiar with the breathing rhythm in the signal. The peak detection was done on the rising edge of the grove sensor. In the outlier detection step, RR-intervals lower than 450ms and higher than 1500ms were removed. These bounds correspond with an average heartbeat from 40 bpm - 133 bpm. These bounds account for some abnormality as the resting heartbeat for most humans lies between 60 - 100 bpm [30]. The time and frequency domain features were calculated using the hrvanalysis library [158].

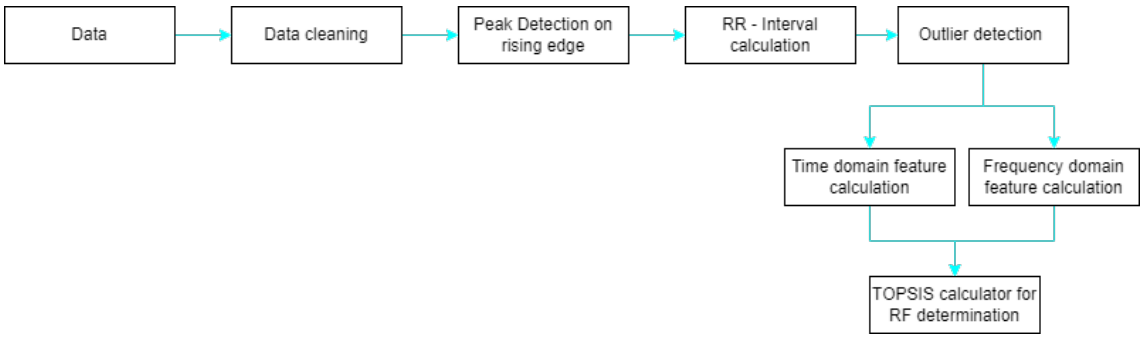


FIGURE 38: Methodology for RF determination

The output of the TOPSIS calculator was a ranking of the alternatives based on their performance score. The highest ranked alternative was taken as the resonance frequency for the participant. The weights for the TOPSIS method can be seen in Figure 39.

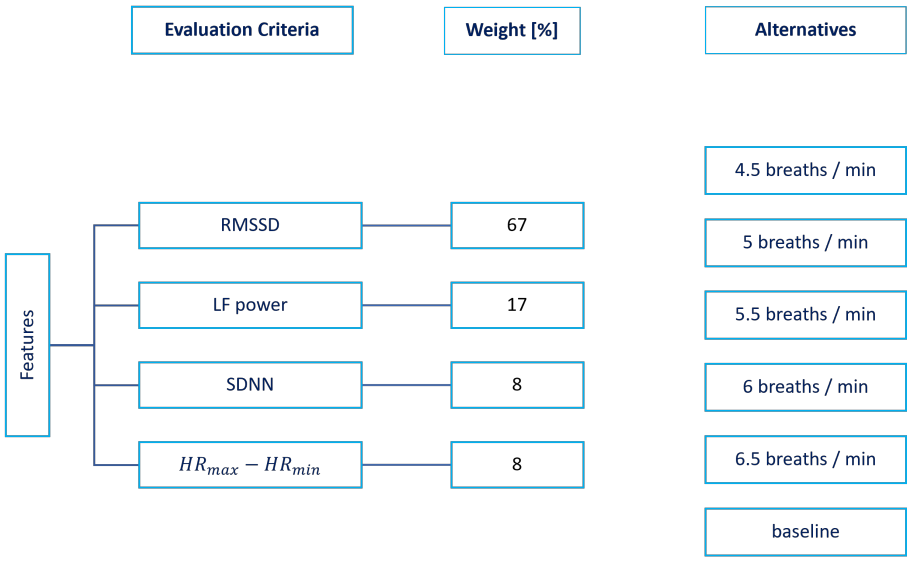


FIGURE 39: Value Tree of Evaluation Criteria

These weights were assigned based on the interview with Mr. Shaffer, who concluded that RMSSD alone could be taken as the determining factor for the resonance frequency selection. This is also stated in the paper of Shaffer and Meehan [28]. The paper lists six different criteria for resonance frequency selection and very clearly state that the weights given to the criteria have not yet been validated by other researchers [28]. Mr. Shaffer also said that there is still no consensus of a particular method to determine the resonance frequency of a human. The first criteria in the paper is the phase synchrony between the different respiration rates and the heart rate. Ideally this phase synchrony should be 0°, as shown in Figure 7. For this, a respirometer is needed, which does not fit into the non-obtrusive requirement of a wearable. Therefore, this criteria cannot be included into the RF selection. The peak-trough amplitude defined as $HR_{max} - HR_{min}$ and the LF power are the following criteria and will be taken into the TOPSIS calculator to evaluate adult breathing rates in the range 4.5 - 6.5 breaths/min [28].

RMSSD was given the highest weight in Mr. Shaffers' interview, with the LF power following second. SDNN was included due to its use in previous studies as an important HRV parameter [167], [172]. The peak-to-trough amplitude of $HR_{max} - HR_{min}$ was also included because of its importance in the criteria list proposed by Shaffer and Meehan [28]. However, this amplitude is already in part accounted for in the RMSSD calculation, which is why its' weight is so low.

6.4 Resonance Frequency Training

This section will describe the procedure for the resonance frequency training of the participants. This experiment combines the results of the patterns and position choices of section 4, and hardware, software and resonance frequency choices from this section.

6.4.1 Experiment Design

As described in section 4, three patterns and four body placements were be taken forward to the user tests. There were three 10 min sessions every week. The experiment took four weeks to complete to iterate through every pattern for every participant. At every session either the position of the belt or the pattern was changed. This was randomised through the participants to cancel out any learning effect the participants may experience. During every session, the PPG sensor recorded heart beat data. The resonance frequency, determined per participant and described in section 6.3 was used for every one of the next sessions with the belt. Once all iterations of pattern and position were tested, a 5 min baseline measurement was taken to compare with the original baseline before the RF selection. The ethical permission number for these experiments is 220016.

To randomise the order of experiment conditions every combination of pattern and position was given a number. The resulting list had 12 values. This list was put in an online random set generator [173] to generate 18 sets with 12 unique random integers in each, taken from the [1,12] range. 18 sets were generated for the 18 participants (9f, 9m) that wished to go further with the study from the RF selection stage.

The user test procedure can be seen in Figure 40. At the beginning of every session, the participants were briefed about where the belt would be placed and which pattern would be actuated so that they understood the inhale and exhale cues. The sensor was be attached to the participant, either on the left little finger or the left earlobe. The belt was then be attached to the participant based on the output of the randomised matrix and actuated with the corresponding pattern vibrating to the participants calculated resonance frequency. The

actuation of the belt only started once it recognised the participant was in an inhalation (the heart beats were closer together). The participant breathed with the haptic cues for 10min. After the breathing session, the participant was asked to fill out a short evaluation form which also screened them for their alcohol, coffee and drug intake in the last 24h. The questions on the form were meant to evaluate the comfort, pleasantness, intuitiveness and effectiveness of every pattern and every position, as these are the requirements listed in Table 7. The form can be seen in section 72. Once the form was filled in, the participants were thanked for their participation and an appointment was scheduled for the following session.

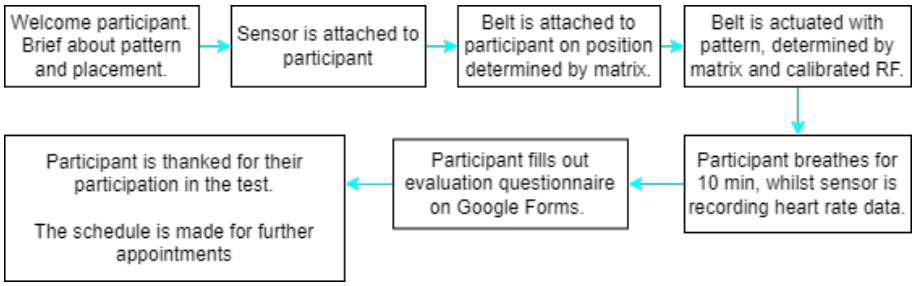


FIGURE 40: User test procedure

6.4.2 Modifications to the experiment

During the experiment, it was found that the participants had a lot of difficulty discerning the direction of vibration patterns in the diaphragm vertical position, as shown in Figure 17. The motor constellation is shown in Figure 35. The vertical distance between the motors was 80mm and the motors themselves had a 12mm diameter. According to the literature mentioned in section 4.1.2, the two-point discrimination distance of the torso ranges from 13mm - 40mm. The 80mm distance between the motors should therefore have been sufficient to recognise adjacent vibrations of motors. However, when the motors vibrated, the housings vibrated with them and the distance between the individual housings were 0cm. Moreover, determinants of perception of motion are not only the distance between the actuators but also their duration, the number of stimulated positions and interstimulus onset interval as mentioned in section 4.2.

(A) Diaphragm placement (B) Lower abdomen placement (C) Lower back placement

FIGURE 41: Experiment Placements

The fact that people were unable to discern the direction of the haptic actuation could be due to a problem with the spatial acuity but also due to the fact that there was no interstimulus onset interval, as there was always at least one actuator active. To add on to this, the different resonance frequencies required different actuation times of individual motors which led to a range of 150 ms - 220 ms of individual actuation across the small vertical distance of the belt.

This duration may have been too short to clearly perceive a change in motion. Another factor that could have contributed towards the difficulty of discerning the direction of the actuation is the saltation illusion that could have come into play across the small distance. This may have summarised the three pulses into two, which again would have made it more challenging to determine direction.

For these reason, the diaphragm vertical position shown in Figure 17 was discarded after six training sessions. All participants that had experienced this motor placement were unable to find the pattern with which to synchronise their breathing. Although Stronks et al have shown that it is possible to train spatial acuity of different body parts [132], improving this was not the focus of this thesis and can be reserved for further research. Discarding a placement also meant that the experiment duration was shortened from four weeks to three. The participants were briefed about this change and the matrix described in 6.4.1 was adjusted from a list of 12 randomised sessions to 9. The final body positions with the prototype implementation can be seen in Figure 41.

7 Evaluation

"Continuous improvement is better than delayed perfection".

This chapter will evaluate the prototype and its effect on the participants by usability test. The requirements stated in Table 7 will also be evaluated in this chapter. The purpose of this chapter is to answer the second design question of *Which type of patterning of feedback is most effective to stimulate resonant breathing?*

7.1 Evaluation Procedure

This section describes the evaluation procedure of the user test. As mentioned in section 6.4.2, the experiment spanned over the course of five weeks. The first and the last week were reserved for the baseline measurements, and the weeks in between were reserved for the breathing sessions with varying patterns and positions.

Figure 42 shows the software processing steps taken to evaluate the data from all the breathing sessions. The steps are very similar to the processing methodologies mentioned section 5.1 and 6.3 with the addition of the analysis in R. 15 participants (8f, 7m) within the age group 20 - 28 took part in the experiment until the end. 129 sessions were recorded during the experiment with six sessions being discarded due to the diaphragm vertical placement on the participants. Outliers on the PP-intervals were declared on measurements outside the bounds of 450ms and 1500ms. These are the same bounds that were taken for the resonance frequency determination measurement. Measurements that fell outside these bounds were interpolated linearly using the Malik method described in equation 2. All statistical tests are conducted using mixed linear models as described in section 3.5.2. he lmerTest package was used in R [120] and the model was fit by using the Maximum Likelihood (ML) algorithm. The Satterthwaite-approximation method is used in order to approximate degrees of freedom and p-values. P-values below 0.05 are considered statistically significant.

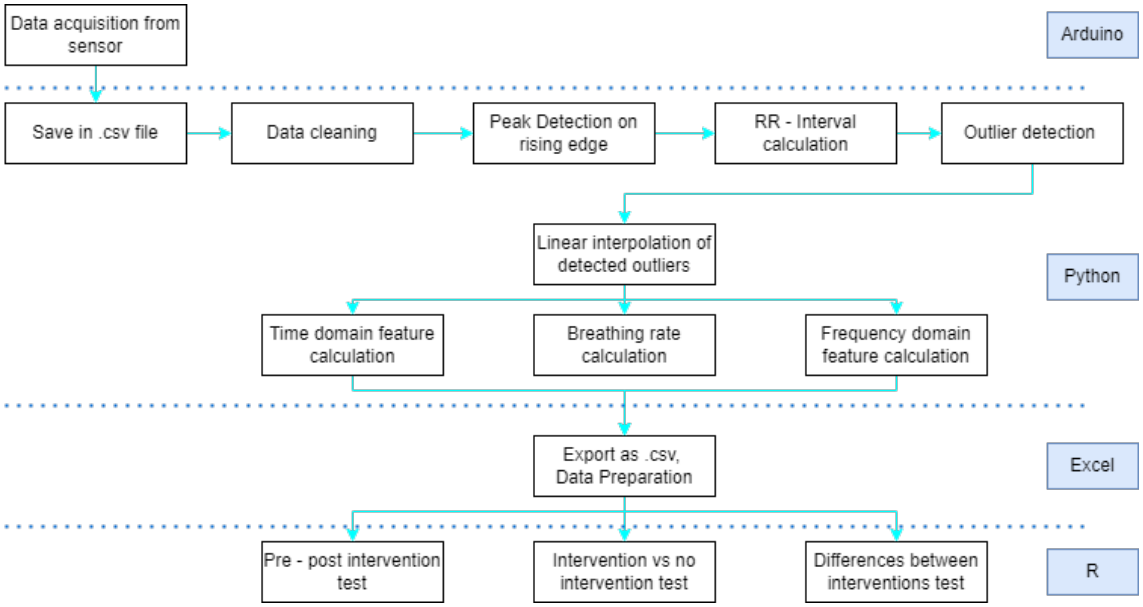


FIGURE 42: Evaluation Procedure Diagram

7.2 Quantitative Results

This section describes the results achieved from the processed sensor data and presents the results of the conditions shown in Figure 42. There are no significant differences between the patterns and positions for heart rate variability or effective breathing. All conditions perform similarly. All R outputs for all tests can be seen in section 10.4. The corresponding pictures will be mentioned explicitly in the matching sections.

A dependent variable that summarises heart rate variability needed to be chosen to conduct all analyses with. As the root mean square of the successive N-N interval differences (RMSSD) was assigned the largest weight due to the interview of Mr. Fredric Shaffer and through the data analysis, it was selected as the corresponding HRV measure.

In order to have comparable values of the participants to each other, the relative increase of the RMSSD throughout all the experiments was calculated. This was done through subtracting the baseline RMSSD value from every intervention measurement to show the change in heart rate variability. The equation for this can be seen below. This variable serves as the dependent variable for the models to explain the difference in heart rate variability.

$$Difference\ in\ RMSSD = RMSSD_{invervention} - RMSSD_{baseline} \tag{3}$$

In order to compare the relative deviation from the actuated breathing rate, the calibrated resonance frequency values were subtracted from the breathing rate values. The absolute value of this number was the dependent variable for the breathing rate and can be seen in the equation below. This was done in order to show the deviation of the participants from the rate they should have breathed at to the rate at which they did breathe.

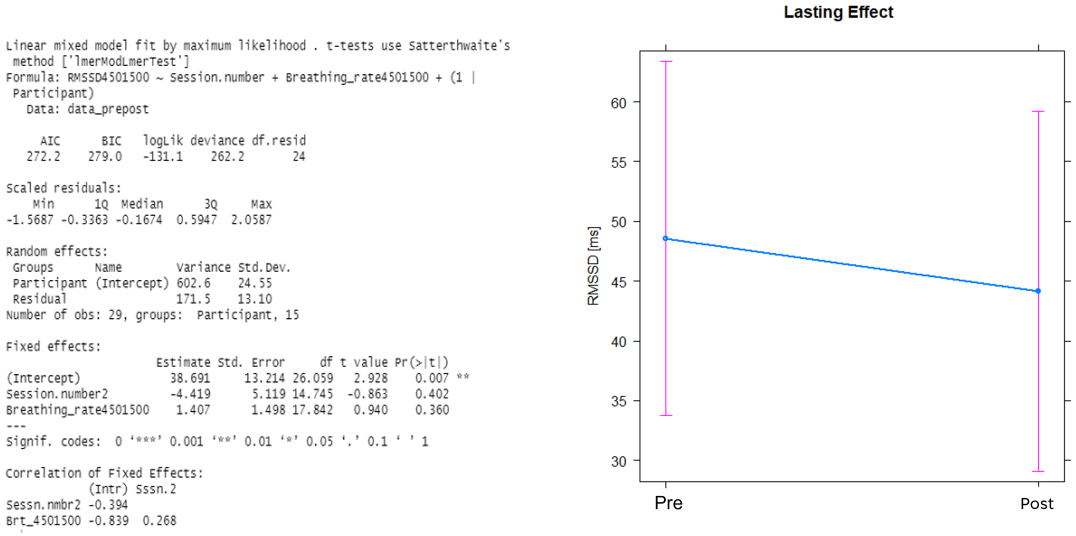
$$Deviation\ breathing\ rate = |Breathing\ rate - resonance\ frequency| \tag{4}$$

7.2.1 Pre - post intervention test

This test compares the baseline RMSSD values for every participant from before and after the intervention to investigate whether there was a lasting difference in heart rate variability (RMSSD). The R output can be seen in Figure 43 A and the lasting effect in RMSSD is visualised in Figure 43. The model includes the explanatory variables of the session number (pre and post) and the breathing rate. The random effects of this model are the participants. The mean RMSSD of the participants is 46.7 ms and the standard deviation is 28.85 ms. These values are in the normal ranges of HRV studies according to a literature study of HRV norms by Shaffer and Ginsberg [92]. The mean breathing rate of the participants is 6.78 breaths per minute and the standard deviation is 2.54 breaths per minute. This is slightly slower than expected as studies have found that the resting rate for respiration is around 9 - 24 breaths per minute [4], [13]. The model shows that there is no significant difference between the pre and post intervention RMSSD values ($p = 0.402$) or the breathing rate values ($p = 0.36$). This indicates that the intervention was not able to make a lasting change in the baselines of the heart rate variability of the participants with a 3-week intervention.

The standard errors of are quite large in comparison to the β coefficients. A large standard error indicates that the sample means are widely spread around the population mean, implying that the sample does not represent the population well. The R output in Figure 43 A suggests that amongst the 15 participants, the second session decreases the RMSSD value by 4.2ms [*CI(95%) = (-15.09; 6.35)*]. This can also be seen in Figure 43 B in the negative slope from

the pre to post intervention group. The model also suggests that for every additional increase in breath per minute the RMSSD value would increase by 1.4ms [*CI(95%) = (-1.68; 4.51)*]. However the results of this model cannot be suggested about the population, as the p-values are not significant and the standard errors are as large as the β coefficients themselves. This model will be discussed more in section 8.



(A) R output (B) Lasting Effect

FIGURE 43: R output: Lasting effect (A) and Lasting effect on RMSSD (B)

7.2.2 Intervention vs. no intervention test

The previous test showed that there was no significant lasting difference between the two RMSSD baseline measurements. This allowed for both baseline measurements to be grouped together to be tested against all measurements with the belt. This model tests whether there was a difference between the 15 participants breathing with the belt in a specifically actuated haptic rhythm and them breathing without the belt (their baseline measurements). The mean RMSSD for these conditions is 54.65 ms and the standard deviation is 24.73ms. The mean RMSSD for this test is 7.95 ms higher than the pre - post interventions test and the standard deviation is 4.12 ms smaller. These results can already suggest that including the intervention measurements made a difference in the RMSSD of the participants due to the larger mean value. The R output can be seen in Figure 44 A and a visualisation of the intervention effect on RMSSD between the baselines of the participants and with them breathing with the belt in Figure 44 B.

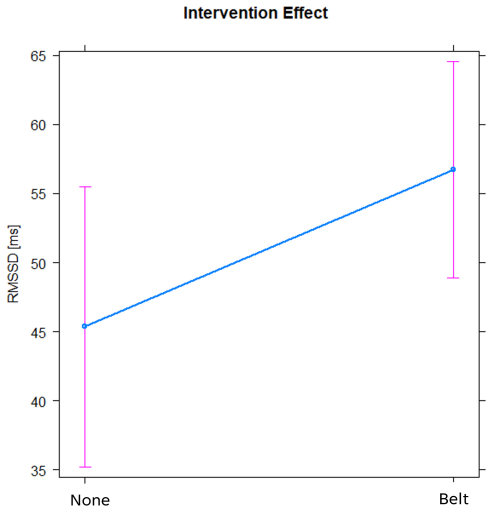
The test shows a significant difference between the no intervention and intervention group ($p = 0.006$), suggesting that the intervention had a difference on the heart rate variability or RMSSD of the participants. The breathing rate of the participants also exhibits a significant difference on the RMSSD of the participants ($p = 0.046$).

The results of this test suggest that the intervention with the belt led to an 11.35ms [*CI(95%) = (3.25; 19.46)*] increase in RMSSD in contrast to breathing without the belt. This can also be seen with the positive slope between the none and belt group in Figure 44 B. The

results also suggest that the breathing rate has a significant effect on the RMSSD ($p = 0.046$), which is confirmed by Steffen [20], Vaschillo [21], Lehrer et al [31], and Shaffer et al [28]. Interestingly, it suggests that at every additional breath per minute, the RMSSD will increase by 1.84 ms [$(CI(95\%) = (0.04; 3.65))$]. This is not in line with the theory shown in chapter 2.1, as there it shown that slow breathing increases heart rate variability. These results will be discussed further in section 8.

```
Linear mixed model fit by maximum likelihood . t-tests use
  Satterthwaite's method [lmerModLmerTest]
Formula:
RMSSD4501500 ~ Intervention + Breathing_rate4501500 + (1 | Participant)
   Data: Interventions

     AIC      BIC   logLik deviance df.resid
  1417.1   1432.4   -703.5   1407.1      152

Scaled residuals:
    Min      1Q  Median      3Q     Max
-2.0590 -0.6422 -0.1556  0.4050  3.2747

Random effects:
 Groups      Name        Variance Std.Dev.
 Participant (Intercept) 190.5    13.80
 Residual                383.9    19.59
Number of obs: 157, groups:  Participant, 15

Fixed effects:
                    Estimate Std. Error       df t value Pr(>|t|)
(Intercept)          33.6845     8.1870 120.4688   4.114 7.13e-05 ***
InterventionYes      11.3552     4.1053 142.6780   2.766  0.00643 **
Breathing_rate4501500  1.8433     0.9151 153.8252   2.014  0.04571 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
            (Intr) IntrvY
IntervntnYs -0.541
Brt_4501500 -0.783  0.188
```

(A) R output



(B) Intervention effect

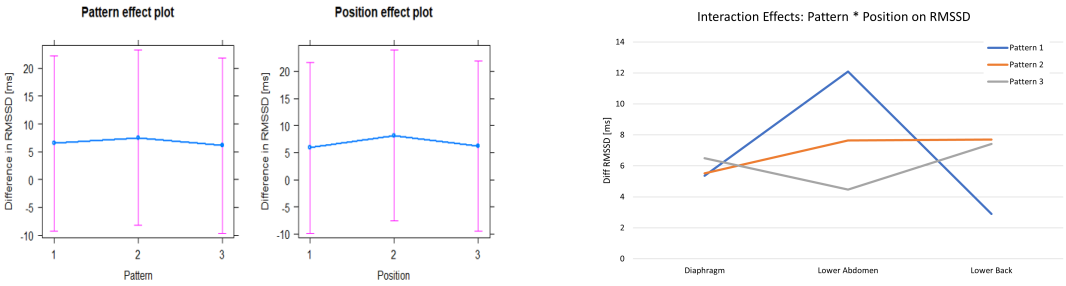
FIGURE 44: R output: Intervention Effect (A) and Intervention Effect on RMSSD (B)

7.2.3 Differences between interventions test

Two tests are discussed in this section. The first test determines the most effective pattern and position to boost RMSSD with the dependent variable described in equation 3. The mean difference in RMSSD across all experiments with the belt is 6.7ms and the standard deviation is 34.86 ms. The second test determines the most effective pattern and position so that the participant breathed at the breathing rate of the belt, with the dependent variable described in equation 4. The mean difference in breathing rate is 0.86 breaths per minute across all experiments with the belt and the standard deviation is 1.73 breaths per minute. The R output for both tests can be seen in the section 10.4.

The first test showed that the breathing rate had a significant effect on the RMSSD of the participants between all interventions with the belt ($p = 0.03$). The results of this model suggest that every breath per minute leads to a 2.39ms [$CI(95\%) = (0.25; 4.52)$] increase in RMSSD. No particular pattern or position is shown to have a significant effect, as visualised in Figure 45 A. The corresponding R output can be seen in Figure 73 in the Appendix. No interaction effects are shown to be significant either, which suggests that no combination of a particular pattern and position were better or worse than the rest. A visualisation of the non-significant interaction effects can be seen in Figure 45 B and the corresponding R output in Figure 74 in the Appendix.

The pink lines in Figure 45 A depict the 95% confidence intervals for every condition and the blue lines show the mean value. The overlapping of confidence intervals between

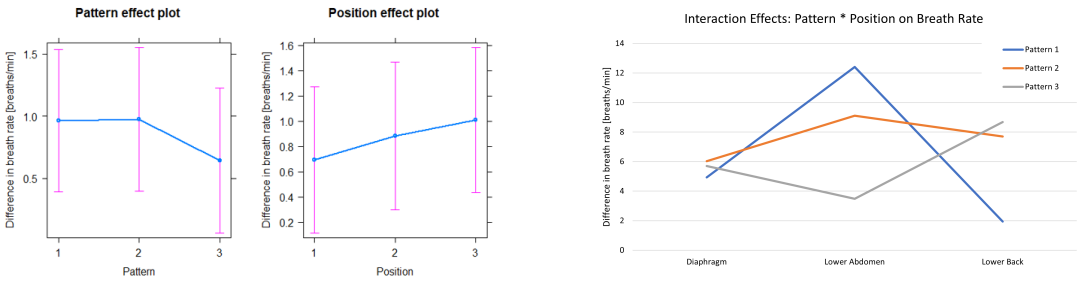


(A) Effect on RMSSD (B) Interaction Effects

FIGURE 45: Effects of pattern and position on RMSSD (A) and Interaction Effects (B), where Pattern 1 = Intensity, Pattern 2 = Inhale, In, Exhale, Out and Pattern 3 = Inhale, Out, Exhale, In

the conditions visually depicts why there is no significant effect between the patterns and positions on RMSSD or breathing rate. For an ideal result, in Figure 45 A, a particular pattern or position should be higher than the others to suggest it being the most effective by having the largest relative difference on RMSSD. Only position 2, corresponding to the lower abdomen, seems to be slightly higher than the other two. However, the difference is not significant. The interaction effects depicted in Figure 45 B reflects this finding also, and shows that Pattern 1 on the lower abdomen had the largest relative difference in RMSSD. However, these small effects do not hold significant results should therefore be looked at with caution.

The results of the second test can be seen in Figure 46. There are no significant results to report, which suggests that similar to the test above, no particular pattern or body placement or combination had a stronger effect on breathing better or worse. The graphs shown in Figure 46 A should be interpreted in the opposite way as Figure 45 A. As the dependent variable is the difference in breath rate between the belt and the participant, this variable should be closest to 0. Pattern 3 and position 1 (diaphragm) have the lowest difference in breathing rate values in comparison to the other categories. This occurrence does not hold true for the combination of pattern 3 and the diaphragm as seen in Figure 46 B. The best performing combination seems to be pattern 1 on the lower back (position 3). However, these differences are not significant as this test did not show any significant results. The R output for the fixed effects can be seen in Figure 75 and for the interaction effects in Figure 76 in the Appendix.



(A) Effect on breath rate (B) Interaction Effects

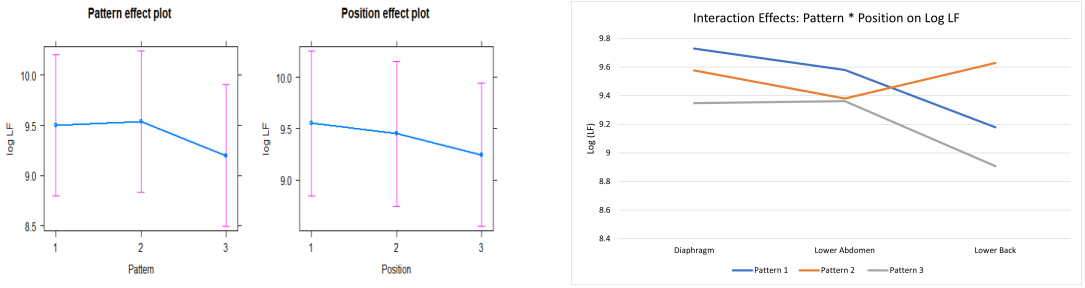
FIGURE 46: Effects of pattern and position on breath rate (A) and Interaction Effects (B), where Pattern 1 = Intensity, Pattern 2 = Inhale - In, Exhale - Out and Pattern 3 = Inhale - Out, Exhale - In

7.2.4 Log LF analysis

Mr. Shaffer mentioned in section 5.2.2 that the logarithm of the low frequency band can indicate how consistently the participant breathed in the low frequency range (0.04 - 0.15 Hz), and that this metric can be used as a measure for parasympathetic activity. The R output of the model can be seen in Figure 77 in the Appendix. The mean log LF power is 9.42 with a standard deviation of 2.1. The breathing rate has a significant effect on log LF power (p = 2.12e-06). The model suggests that with additional breath per minute, there will be a 0.32 increase in log LF [*CI(95%) = (0.19; 0.44)*]. The breathing rate has been shown to be significant across every test it was included in as an explanatory variable, except in the lasting effect test. This is an important finding and will be discussed further in section 8.

Figure 47 A shows that pattern 2 and position 1 (diaphragm) have the relative best performance as they have the highest low frequency powers, suggesting that the participants breathed most consistently at the rate they should have in these categories. Pattern 2 has the largest effect for the difference in RMSSD and in the log LF, however even though these results overlap, the difference is not significant and could be coincidental. However, similar to the results above, the differences are not significant as the confidence intervals have large overlaps between the categories. There were also no significant interaction effects between the patterns and positions, suggesting that there was no combination that had a significant difference in log(LF). These interaction effects are visualised in Figure 47 B.

Figure 47 B suggests that all three patterns might be comparable in their effect when used on the diaphragm and lower abdomen, as indicated by the parallel lines. It also suggests that breathing with Pattern 2 on the lower back may have caused more parasympathetic activity in the participants, however this result is not significant.



(A) Effect on log LF

(B) Effect of breathing rate

FIGURE 47: Effects of pattern and position on log LF (A) and effect of breathing rate on log LF (B)

This section has shown that with the current dataset, there was no significant lasting effect on RMSSD and no significant difference between either of the patterns, positions or combinations of both on RMSSD, breathing rate or log LF. There was a significant difference found in RMSSD between the intervention with the belt and no intervention (p = 0.006) and a significant difference found in the breathing rate (p = 0.046).

7.2.5 Survey Statistics

After every session, the participants were asked to fill out a survey as shown in section 72. The boxplots in Figure 48 - 50 show the metrics on comfort, pleasantness, intuitiveness and effectiveness for every pattern with every position. There does not seem to be a large difference between the patterns on the evaluation metrics. Pattern 1, as seen in Figure 48, seems to perform best in the comfort parameter, as it has the smallest inter-quartile ranges and largest median values. Pattern 3 seems to perform the worst in the effectiveness and intuitive parameter, as it has the largest inter-quartile ranges and largest whiskers. However, all patterns have an equal distribution of data values, ranging from very high on the survey scale (10) to very low (2).

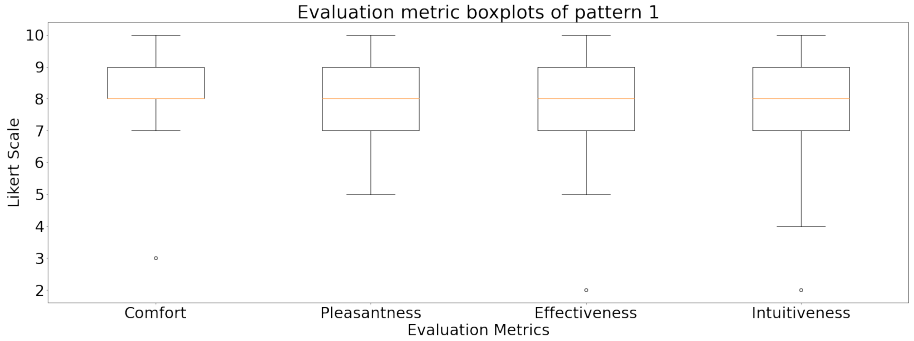


FIGURE 48: Pattern 1 Evaluation: Intensity

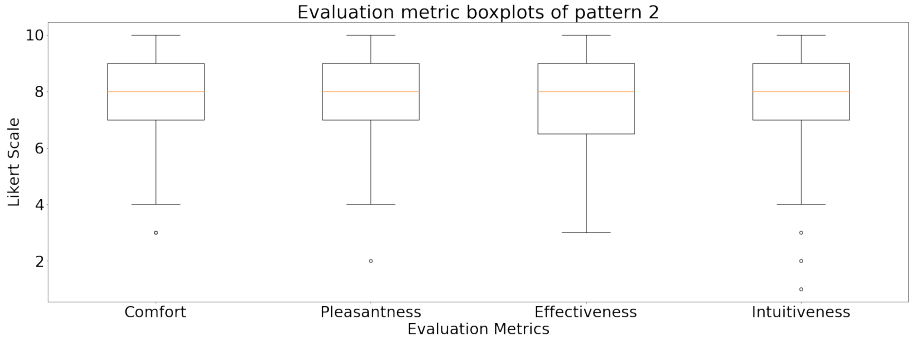


FIGURE 49: Pattern 2 Evaluation: Inhale - In, Exhale - Out

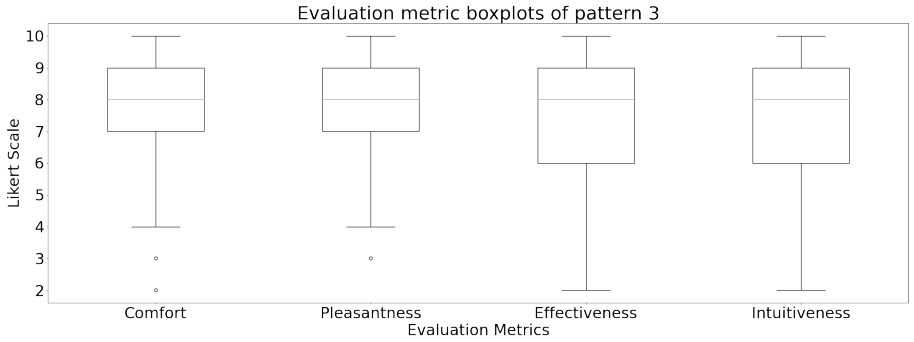


FIGURE 50: Pattern 3 Evaluation: Inhale - Out, Exhale - In

Upon completion of the experiment, the participants were asked about their most and least comfortable position and their most and least intuitive pattern. The answers of these results can be seen in Figure 51 and 52. The results show that 53.3% of the participants found the lower abdomen to be the most comfortable position. 46.7% of the participants found pattern 2 to be the most intuitive. There was no clear least comfortable position, there were 5 people who disliked every position. 53.3% of the participants found pattern 3 to be the least intuitive pattern. Controversially, the results shown in Figure 45 B suggest that pattern 3 was most intuitive, because the mean value of the difference on breathing was the closest to 0 in comparison to the other patterns.

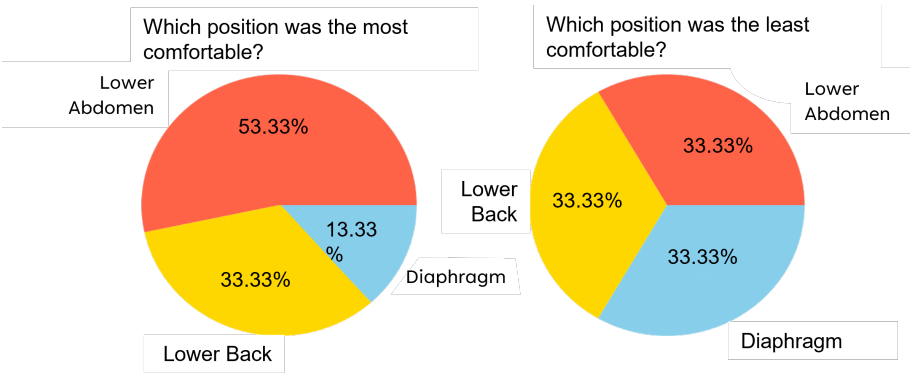


FIGURE 51: Evaluation: Comfort

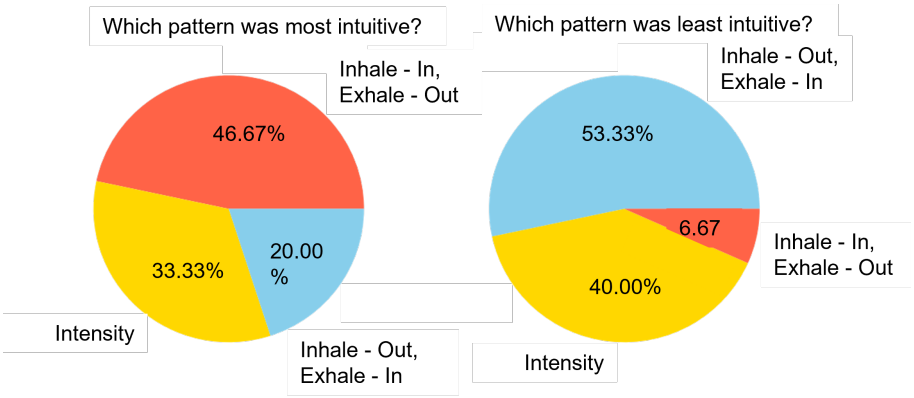


FIGURE 52: Evaluation: Intuitiveness

Figure 53 shows that the majority of the participants would not want to use the prototype if it were a product on the market. Section 7.3 will dive in depth into why these results look the way they do through evaluating the qualitative aspects of the survey and summarising interviews of the participants.

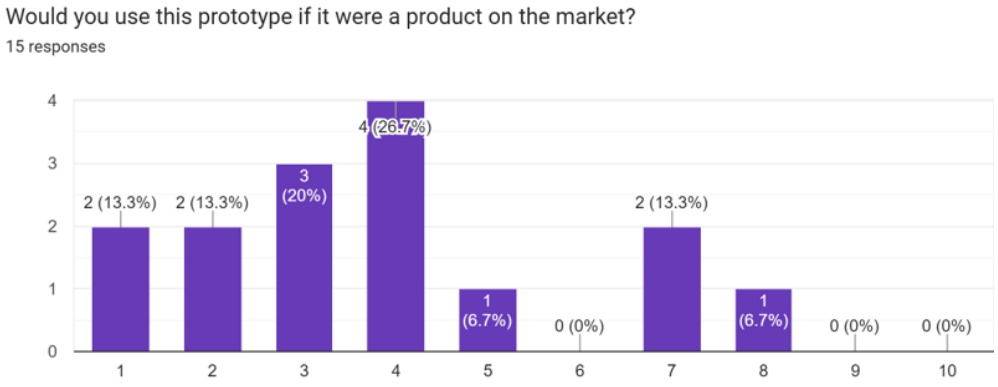


FIGURE 53: Evaluation: Purchasing Intent

7.3 Qualitative Results

This section will summarise the comments given in the survey during the experiments and the interviews that were taken with every participant at the end of the experiment to provide more insights to the results of section 7.2.

In general, the majority of the comments said that the participants felt calm, relaxed and at ease after the breathing sessions. There were mixed feelings about the lower back placement. Some comments mentioned that the participants were more aware of their back during breathing because of the placement on the lower back. Others added that the back must have more receptors because the vibrations were easiest to discern at that position. Some comments said the exact opposite, that vibrations were the most difficult to discern on the back. Further comments said that the lower back felt the least ticklish and less invasive than the lower abdomen position, however they understood that the front of the torso is a more meaningful placement for breathing. This led them to also state that the back was the most comfortable position. The diaphragm placement of the belt was mentioned twice in being restricting, especially as it can move to where bras are worn. The placements on the front of the body were preferred because the participant could easily touch the motors for additional feedback if they needed. A suggestion was also made to add physical visuals to the product in terms of light or audio to visualise breathing.

Pattern 1 was described as being very easy to follow as the vibration stayed in one place and the participants only had to concentrate on the intensity, rather than intensity and direction. Some participants commented that the pattern should have had a clearer distinction from the inhale phase to the exhale phase, perhaps in form of a gap.

Pattern 2 was described by some participants as the clearest pattern as the action fits the name. When the motors move in, it indicates an inhale, and when they go out, an exhale. The majority of the participants felt that the pattern made sense and was easy to follow. Pattern 3 was the opposite of pattern 2 and was many times described as being counter-intuitive and harder to follow in comparison.

Additional modifications of the belt would be to make sure that the contact area of the motors are evenly touching the body, as one participant mentioned that the contact was uneven. The heart rate sensor should not be placed on the finger as participants may want to multi-task and placing a sensor on a finger does not allow for the participant to simultaneously wash dishes whilst breathing. The idea of the wearable being a wristwatch was mentioned three times, as it is already familiar and a used accessory. One participant also mentioned that they would like to determine the length of the inhale and exhale themselves to be able to adjust it to what they feel like on the day.

Most participants did not feel the need to purchase the prototype if it were a product on the market because they did not feel like they had a need for the belt. Many interpreted the belt for potentials users who have physical breathing problems such as asthma or anxiety issues. They stated that if they were aware of the health benefits of the belt, it may change their minds but for now they would not use it. Other participants mentioned that they already practice breathing and meditation exercises and they cannot see the added benefit. Further comments included use cases for the belt for potential musicians or scuba divers to increase their lung capacity by slow breathing.

To summarise, the parameters evaluated in this section were the intuitiveness, effectiveness, long term use or purchasing intent and comfort of the wearable that were described in Table 7. There are many individual differences in preferences for a pattern and placement for the wearable. This translated into differences in all parameters across all participants. The users wanted clear cues from inhale to exhale and thought that the cues from pattern 2 and 3 were effective. Pattern 1 should have had a clearer transition from the inhale / exhale stage. The participants are interested in a multi-modal feedback form for breath training that is not solely restricted to haptics and should also allow them to multi-task.

This chapter has shown that there is no uniform answer to which pattern and placement is most effective to stimulate resonant breathing. There are too many individual differences between the participants of the study both in the qualitative and quantitative data to be able to draw conclusions about the sample and therefore also the population. However, it is noteworthy to mention that that the average deviation that the participants breathed at from the frequency of the belt was 0.86 breaths per minute. This fact, together with the statistical tests showed that the participants were able to understand and act upon the haptic cues, regardless of pattern and placement of the wearable. The second design question of *Which type and patterning of feedback is most effective to stimulate resonant breathing* can therefore not be answered with a quantitative number. The type and patterning of feedback is dependent on the individual and they should be able to adjust it to what they find comfortable.

8 Discussion and Recommendations

The more that you read, the more things you will know.
The more that you learn, the more places you'll go.

This chapter presents the discussion of choices made in this thesis and combines them with recommendations for further research.

8.1 Sensor Measurements

The sensor experiments compared PPG sensors to an ECG baseline. Chapter 5 shows that the chosen grove earclip sensor has a correlation of 83.4% with the ECG baseline. This is a high correlation, but could still be improved by a better PPG sensor or better pre-processing algorithms. Moreover, using a PPG sensor can estimate the breathing rate but it cannot show whether the heart rate variability and the respiratory phases align. This can only be checked with a respirometer. This sensor was not used during this thesis because of its obtrusive and non-wearable nature. However, for better resonance frequency selection, a respirometer should be used to validate the calibration stage.

During the experiments the grove earclip sensor was placed on the left earlobes of the male participants and left little finger of the female participants. The fingers of most males in this experiment were too large for the sensor and most females had pierced ears which did not allow the sensor to pick up a signal. These two positions have varying pulse transit times (PTT), but can measure heart rate variability. More body positions for better intergration of the sensor could be experimented with that can work for all genders. As stated in section 5.1.1, preliminary experiments tested various body parts but faced a large problem of crosstalk with the Arduino UNO. These experiments should be redone with more sophisticated isolation and perhaps noise cancelling circuits. PPG sensors are known for being very perceptible to motion artifacts, blood pressure changes and postural changes [95], [105]. Therefore the choice of the sensor and sensor placement needs to be robust and strong for non-clinical settings.

8.1.1 Data pre-processing and analysis

During the pre-processing steps of the data analysis, outlier detection bounds were set at 450 - 1500ms, corresponding to 40 - 133 beats per minute. These bounds were selected by inspecting a histogram of the collected data but there is very little literature that specifies the correct bounds to take, that also aligned with the data collected. Shaffer and Ginsberg suggest the range of RR intervals to be within the range of 758 - 1160ms (corresponds to 52 - 76 beats per minute) [92], however this range was not realistic for this thesis as the data recorded during the experiments had a significantly larger range and would have had to be significantly modified. This may have been due to movement artifacts, missed beats or blood pressure changes and more insight could be gained if these experiments were conducted with an additional ECG sensor. For this reason, two more outlier bounds were experimented with namely, 300-2000ms (corresponds to 30 - 200 beats per minute) and 500-1200ms (corresponds to 50 - 120 beats per minute), both with and without linear interpolation. The results for the pre-post intervention test and the intervention vs no intervention test show the same results as the tests in section 7. The differences between interventions test shows significance of the lower back being the worst position for keeping the correct breathing rate between the outlier bounds of 300 ms and 2000 ms with interpolation ($p = 0.04$). When testing this for interaction effects the combination

of Pattern 3 (Inhale - Out, Exhale - In) on the lower back had a significant difference ($p = 0.02$) to be the worst combination for effective breathing. However, these results should be interpreted with caution as the outlier bounds correspond to 30 - 200 beats per minute which is a very large range and may have many wrongly detected beats. Interestingly, the results of the qualitative data suggest that Pattern 3 was the least intuitive (53.33%), which may be a reason to not completely disregard this finding. During the interviews, the majority of the participants described this pattern to be unclear and harder to follow than pattern 2. This is an intriguing finding because it suggests that the participants focussed more on the instruction of the pattern rather than how it felt. Pattern 3 was designed follow the natural movement of the abdomen (expands on inhale, inwards on exhale) but was instructed to the participants by the term "The inhale cue is when the pattern moves outwards and the exhale cue is when it moves inwards." This may have biased the participants in making the pattern unclear, as making them aware of the way their body moves first may have made the pattern more intuitive and easier to follow.

In the pre-processing, the data outside the outlier bounds in this thesis were interpolated linearly with Maliks rule as shown in equation 2. However, there are other interpolation methods such as polynomial and cubic and other rules that can be experimented with, such as Karlsson, Acar and Kamath [158], that could show different results. These different methods may fit the data better and have better outlier filtering performance.

Lastly, as discussed in this thesis in chapter 5, there is no consensus for a singular metric for heart rate variability. The root mean square of the successive differences (RMSSD) of the inter-beat intervals was used as the dependent variable to evaluate the effect of the intervention but this would not be the only methodology. This approach was taken in this paper after consulting Mr. Shaffer who has also advocated for this metric together with Meehan [28]. However, another methodology combining both time and frequency domain features to get a "HRV score" could also be explored to get a fuller picture of heart rate variability.

8.2 Vibrotactile feedback design

The wearable was designed to fit on body parts where breathing explicitly happens. However, more body parts can be experimented with as quite a few participants had an apple watch and liked the haptic feedback it provided them on the wrist to guide their breathing. Furthermore, it could be insightful to let participants design their own haptic cues for inhaling and exhaling. This could make the participants more aware of the movements that happen in their bodies and trends could be analysed in intuitiveness. The design in this thesis let the participants adjust the intensity of the vibrations themselves and this feature was appreciated. Allowing participants to tune more parameters of the haptic feedback would lead to a higher degree of personalisation which could boost their engagement with the device. A key take-away to emphasise for further research is to ensure proper perception of motion. The spatial acuity between the motors should also include the motor housings, as they vibrate with the motors. Furthermore, more attention to detail should be given to the inter-stimulus onset interval as this together with the spatial acuity and duration of the individual pulses could contribute towards better perception of motion. In this thesis, the diaphragm vertical position had to be discarded because this consideration was realised too late.

As stated in section 5, an Arduino UNO has 6 PWM pins. Pins 1-4 have a maximum frequency of 490 Hz and pins 5-6 have a maximum frequency of 980 Hz. This could have been the reason that some participants felt some motors more strongly than others. This was not

the primary intention, but was discovered during this thesis and could not be changed anymore. This may have influenced the participants in how they felt and interpreted the patterns, as they may have just waited for the stronger vibration to understand the inhale / exhale cues. Future research could focus on a more consistent design.

Another consideration to be made for future research could be to implement fading feedback once the participants are able to breathe slowly. This thesis has shown that using the haptic belt has a significant difference on RMSSD when actuated with the resonance frequency of the participant. If for future research an application would be made that would train participants to consistently breathe at a slower rate but not make them dependent, fading feedback could be considered to help them internalise the proper technique.

8.3 Wearable design

The material of the belt was polyester and the motor housing were made of acrylic. This can be improved in further iterations by using breathable material that expands and contracts with movement of the abdomen. The acrylic housings can be better integrated into the belt by being sewn in next time as there was no particular need of having the motors be detachable. The belt could be made wireless for further iterations, to increase wearability and comfort for the participant during the experiment. An accelerometer could also be embedded for additional feedback of the phase of breathing if a respirometer is not used. However, the form of a breath guidance belt is still quite obvious. Smaller, less notable wearable forms could also be experimented with. Participants mentioned that multimodal feedback forms could be interesting addition, either with addition of audio or visual feedback.

8.4 Experiment design

The experiment was a within-subject design with 15 participants. The age group of the participants was 20 - 28. The sample size is quite small for the number of conditions and this can also be observed in the normality tests. The distribution looked normal in the histograms and Q-Q plots, but was not always calculated to be so with the shapiro-wilk rule. A larger sample size could improve validity of the results. Other studies that have researched heart rate variability have had ranges of 30 [174] - 487 participants [175].

After every session, the participants had to fill out a form stating whether they had any caffeine, alcohol or drug intake within the last 24h, so that these influences could be accounted for. They were not required to state the exact time or dosage, as these were only control variables. However, this resulted in a non full factorial design, which as a consequence leads to categories not having sufficient data to draw meaningful conclusions on their effect. Therefore, these variables were left out of all the analyses in section 7, as consistent usage over the experiment by the participants could have cancelled their effects out. Moreover, if they were included in their current form, they would have only introduced unnecessary noise into the analysis.

The baseline measurements of the participants could have been taken multiple times to ensure its robustness. In this thesis, every measurement in every condition was only taken once due to time constraints. If this study is repeated, more measurements should be taken in every condition to ensure stability of the measurements.

The result shows no significant lasting effect from before and after the intervention. This fact, together with information from Mr. Shaffers' interview suggest that the training time of

10 minutes three times a week was not sufficient to show a lasting change in physiology. Longer and more frequent training sessions could be conducted in further research to learn at which point a lasting change can be seen with slow breathing sesions. The experiments took place in a lab setting, where in the beginning some hesitancy and nervousness could be observed in the participants. Furthermore, every time the participants came in, they were asked synchronise their breathing pattern with the haptic pattern of the belt. Quite often, they also tried to start a conversation during the session, which may have influenced the results. A stricter experiment protocol should be enforced from the beginning of the experiment. Conversation can also be avoided if they are left alone in the room for the session. Lastly a comment from one of the participants on the interest form stated that there was no place to include that they did sport 0 times a week. This should be an option for next time as it is erroneous to assume that everyone does sport at least once a week.

The intervention vs. no intervention test showed a significant effect of 11 ms in RMSSD ($p = 0.03$). This is a plausible result, as it complies to the range of previous studies [92], [174]–[176]. Together with the non-significant test result of the differences between interventions test, this thesis has suggested that any position or pattern with haptic feedback has proved effective of boosting the heart rate variability of the 15 participants that breathed three times a week for three weeks for 10min with the belt actuated to the rate of their resonance frequency. This is interesting because it indicates that the different designs of haptic cues may not have been of great importance as the users still understood and processed them correctly. This opens doorways to other research possibilities to check whether similar results can be achieved with different training durations and in less "clinical" settings.

The effect of the breathing rate on the RMSSD and log LF do not show the expected results. Both variables should show decreasing trends with lower breathing rates, but instead show increasing trends where ever significance is shown. According to the theory described in section 2.1, low frequency breathing stimulates the baroreflex and thereby also the low frequency bands. A shortcoming of this thesis is that the breath rate of the participants was not measured directly, but was only estimated through the method described in Figure 25. Therefore, there is no other measurement of breathing to confirm whether the participants indeed breathed at rate of the PPG estimation. Additionally, the participants were grouped into having different resonance frequencies according to the TOPSIS calculation. The breathing rate variable does not take this into account and therefore does not model the effect correctly. The experiment design and evaluation developed into being a more complex design than initially intended by being a mixed design with the various grouping factors rather than a simple within-participant design. Further research should consider these choices in advance for a valid end result.

As mentioned above, there was no additional sensor used to confirm whether the breathing rate estimation corresponds to the actual breathing rate. Therefore, the results only depict how well the participants where breathing at the rate of the belt but not if the inhale and exhale phases aligned with the belt. For this use case, this information is not strictly necessary but could have provided additional insight into the usability of the device.

9 Conclusion

"The last breath one takes is not an end,
but a passing on to a new journey."

This thesis has contributed towards research in the areas of heart rate variability, breath guidance and haptic feedback through literature reviews, interviews and experiments. It has shown promising results for the haptic belt as the participants breathed with an average deviation of 0.83 breaths per minute from the actuated pattern and increased their RMSSD by an average of 11 ms when breathing with the belt. This chapter marks the end of the report and will address the main research question of this thesis:

How to design a haptic feedback wearable for breathing guidance through heart rate variability training?

This research has explored the field of breathing and heart rate variability to find the technique of resonant frequency breathing. This breathing technique determines an individuals' resonance frequency between the rates of 4.5 breaths/min, 5 breaths/min, 5.5 breaths/min, 6 breaths/min and 6.5 breaths/min. Various PPG sensors were explored due to their non-invasive nature, cost effectiveness and ever growing popularity in modern day wearables. The grove earclip sensor performed most reliably with a 83.4% correlation coefficient to the ECG sensor and was chosen as the sensor for this project. It's purpose in this project was to measure heart rate variability as well as to monitor the respiration rate of the participant.

Furthermore, this research has shown that it is possible to monitor heart rate and breathing through using PPG sensors. Quantitatively, this research did not find significant results between the patterns and positions on heart rate variability or effective breathing rate when the outliers outside the bounds of 450 - 1500 ms were deleted and interpolated. However, a significant result was found between breathing without the haptic cues from the belt and breathing with the belt ($p = 0.03$), which may suggest that patterns and position may not be the most relevant factors when training slow breathing to boost HRV. This opens doors to other research possibilities.

Qualitatively, the lower abdomen was found to be the most comfortable position by 53.3% of the participants and pattern 2 (Inhale - In, Exhale - Out) was found to be the most intuitive pattern by 46.7% of the participants. Due to there being no significant difference between pattern or position during the experiments, this research suggests that the type of pattern or position does not seem to affect performance but participants do seem to have a slight preference for pattern 2 and the lower abdomen as a placement.

The participants found the breathing sessions with the wearable relaxing and comfortable but were not inclined to purchase the prototype if it were a product on the market as they were not fully aware of the health benefits and thought that it would suit people with respiratory problems or anxiety issues more.

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10 Appendix

Not all bits have extra value.

10.1 Ideation

FIGURE 54: Wearable design requirements: Wheel Model [128]

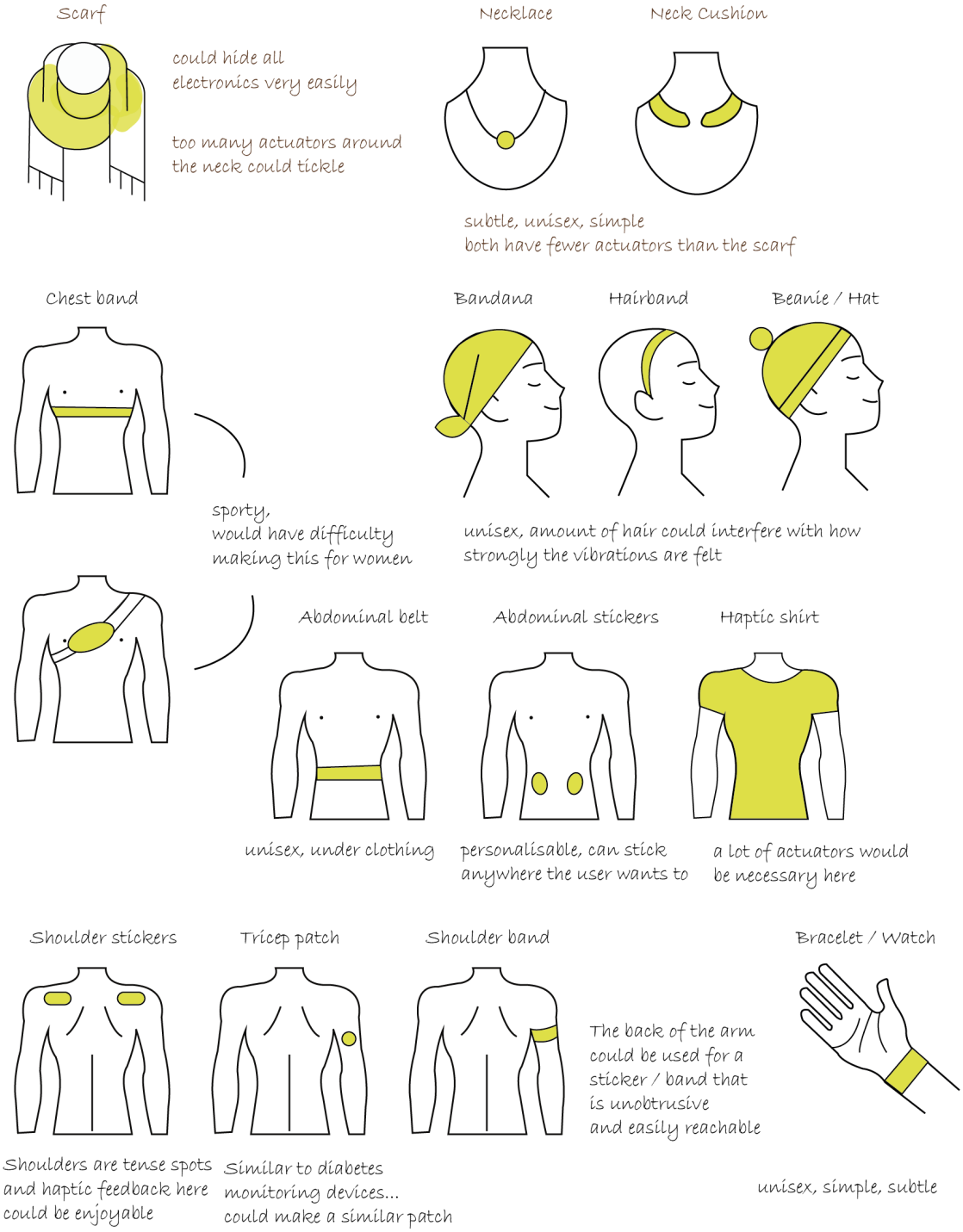


FIGURE 55: Sketches

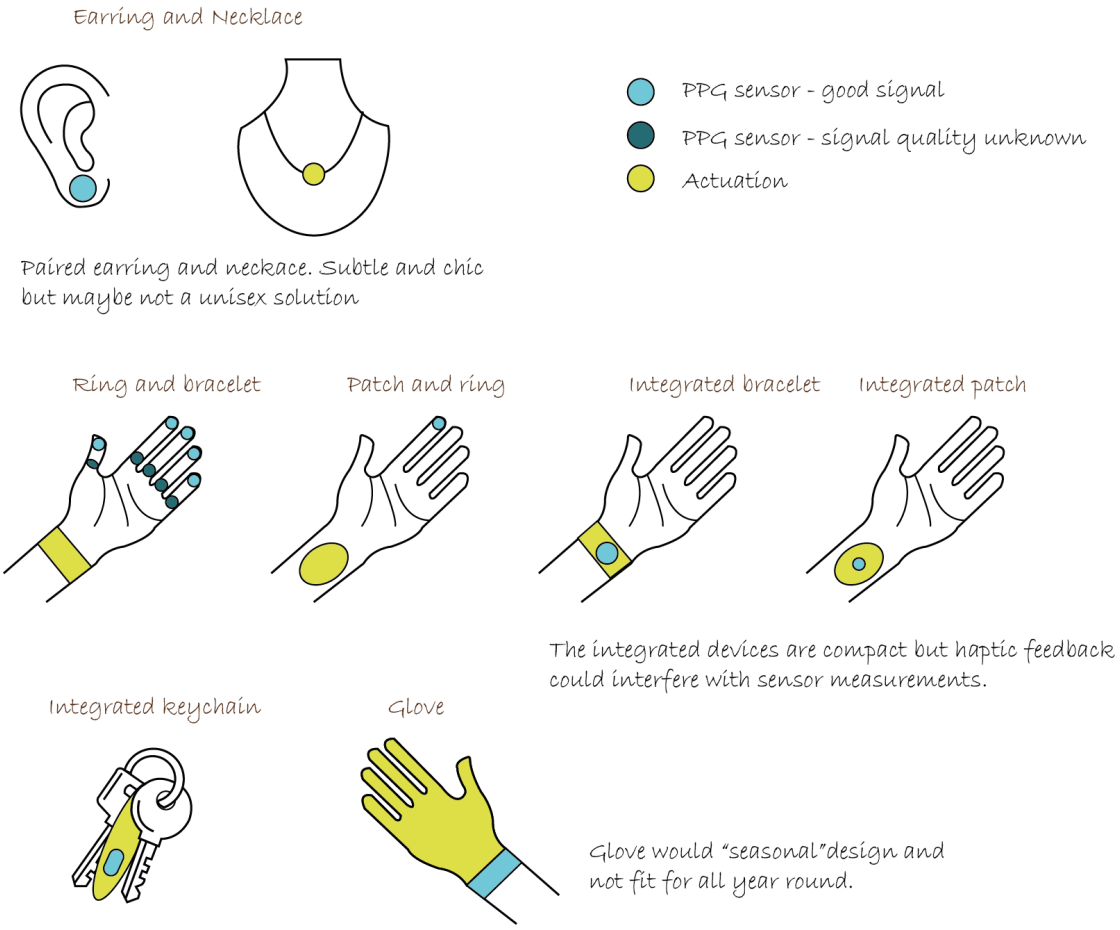


FIGURE 56: Sketches

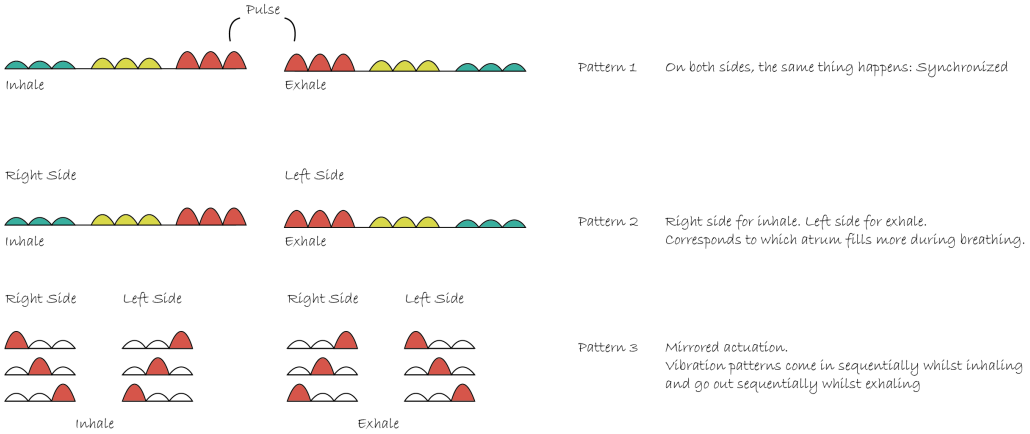


FIGURE 57: Pattern Ideation

10.2 Specification

10.2.1 Peak Matching

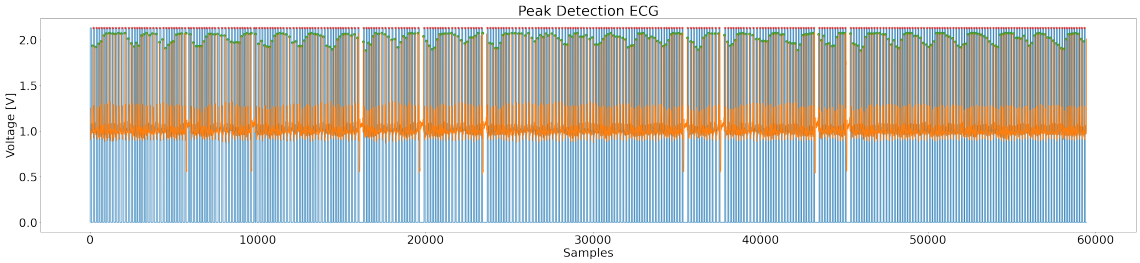


FIGURE 58: Visualisation of missing beats between ECG and grove sensor

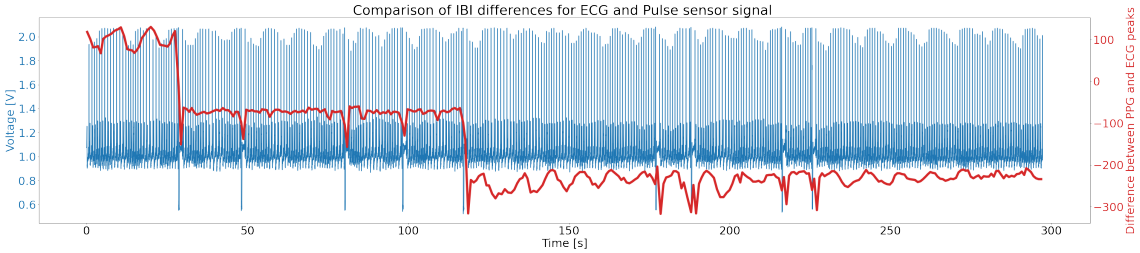


FIGURE 59: Visualisation of missing beats between ECG and pulse sensor

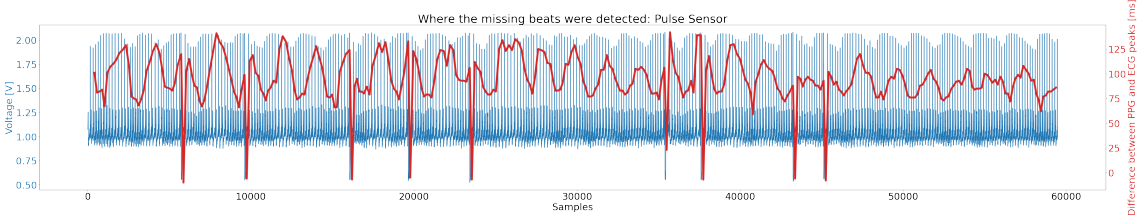


FIGURE 60: Modified beats between ECG and pulse sensor

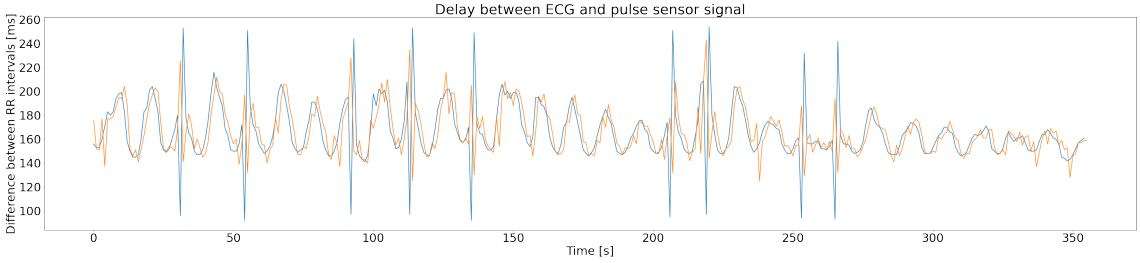


FIGURE 61: Delay between ECG and pulse signals

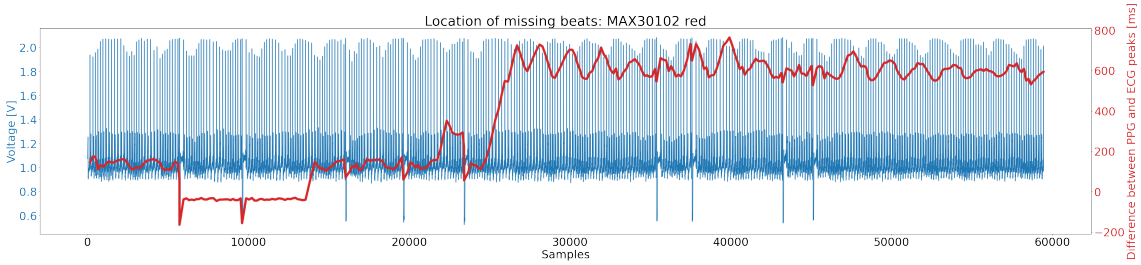


FIGURE 62: Visualisation of missing beats between ECG and MAX30102 red sensor

FIGURE 63: Modified beats between ECG and MAX30102 red sensor

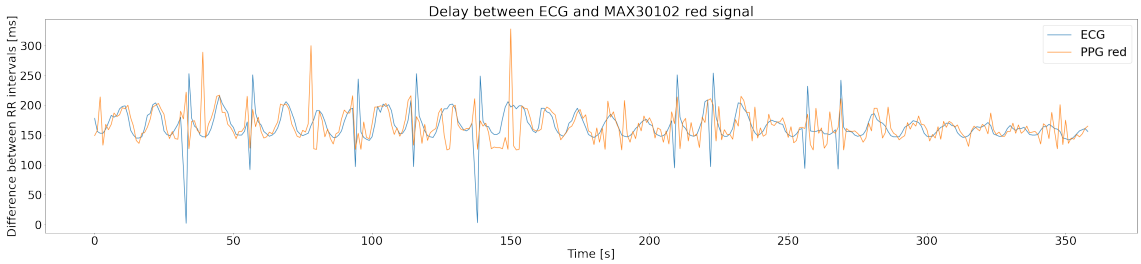


FIGURE 64: Delay between ECG and MAX30102 red signals

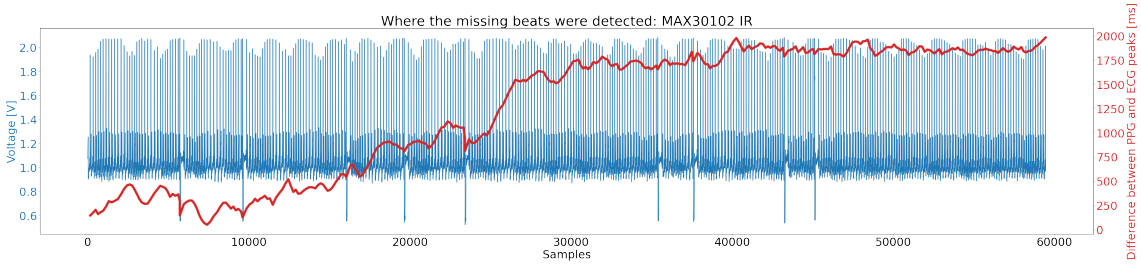


FIGURE 65: Visualisation of missing beats between ECG and MAX30102 IR sensor

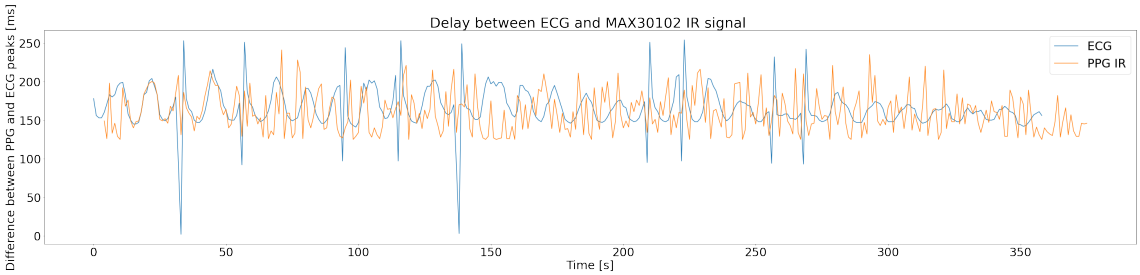
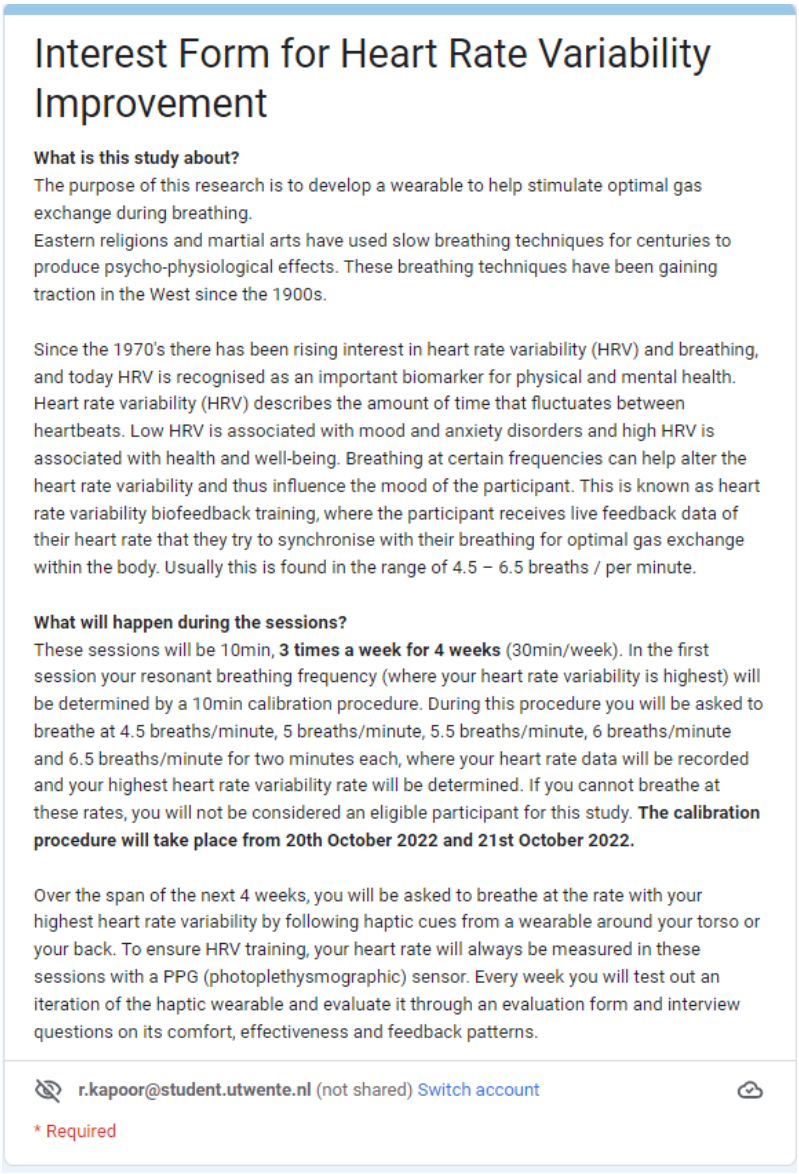


FIGURE 66: Delay between ECG and MAX30102 IR signals

10.3 Realisation

10.3.1 Interest Form



Interest Form for Heart Rate Variability Improvement

What is this study about?
The purpose of this research is to develop a wearable to help stimulate optimal gas exchange during breathing.
Eastern religions and martial arts have used slow breathing techniques for centuries to produce psycho-physiological effects. These breathing techniques have been gaining traction in the West since the 1900s.

Since the 1970's there has been rising interest in heart rate variability (HRV) and breathing, and today HRV is recognised as an important biomarker for physical and mental health. Heart rate variability (HRV) describes the amount of time that fluctuates between heartbeats. Low HRV is associated with mood and anxiety disorders and high HRV is associated with health and well-being. Breathing at certain frequencies can help alter the heart rate variability and thus influence the mood of the participant. This is known as heart rate variability biofeedback training, where the participant receives live feedback data of their heart rate that they try to synchronise with their breathing for optimal gas exchange within the body. Usually this is found in the range of 4.5 – 6.5 breaths / per minute.

What will happen during the sessions?
These sessions will be 10min, **3 times a week for 4 weeks** (30min/week). In the first session your resonant breathing frequency (where your heart rate variability is highest) will be determined by a 10min calibration procedure. During this procedure you will be asked to breathe at 4.5 breaths/minute, 5 breaths/minute, 5.5 breaths/minute, 6 breaths/minute and 6.5 breaths/minute for two minutes each, where your heart rate data will be recorded and your highest heart rate variability rate will be determined. If you cannot breathe at these rates, you will not be considered an eligible participant for this study. **The calibration procedure will take place from 20th October 2022 and 21st October 2022.**

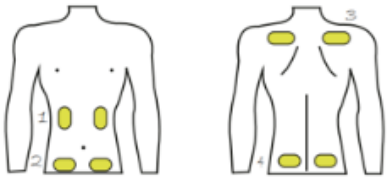
Over the span of the next 4 weeks, you will be asked to breathe at the rate with your highest heart rate variability by following haptic cues from a wearable around your torso or your back. To ensure HRV training, your heart rate will always be measured in these sessions with a PPG (photoplethysmographic) sensor. Every week you will test out an iteration of the haptic wearable and evaluate it through an evaluation form and interview questions on its comfort, effectiveness and feedback patterns.

r.kapoor@student.utwente.nl (not shared) Switch account

* Required

FIGURE 67: Interest form (page 1)

Body Positions



1: Diaphragm placement
2: Lower abdominal placement
3: Shoulder placement
4: Lower back placement

Benefits and Risks of Participating

Studies have shown that heart rate variability training can reduce the physiological dead space (space in your lungs that does not take part in the gas exchange), enhances pulmonary gas exchange and minimizes the energy expenditure for breathing. Higher levels of heart rate variability can lead to higher life expectancy and greater cognitive flexibility. However, it is possible that in the beginning you experience slight dizziness or fatigue because you are not used to breathing at such a slow rate (4.5 – 6.5 breaths per minute instead of 15 – 20 breaths per minute). This is perfectly normal and does not have any prolonged health effects. If you feel uncomfortable or discomfort you can stop breathing slowly and breathe "normally" at any time, and you are also free to stop your participation in this study at any time. This research project has been reviewed by the Ethics Committee Information and Computer Science for integrity and data protection.

Data Usage

Your data will be used for the purpose of this study and may be kept for future research. It will be kept anonymous the entire time and will not be able to be linked back to you. The only information regarding your person that will be collected is your age, gender, previous experience with breathing techniques, previous occurrences with respiratory distress (asthma), coffee or other drug intake 24h before the experiment. Quotes that you say during the interview sessions may be used in the thesis but will not be able to be traced back to you.

Contact details:

Researcher: Radhika Kapoor
Email: r.kapoor@student.utwente.nl
Phone: +31 61 403 5270

Supervisor: Angelika Mader
Email: a.h.mader@utwente.nl

If you have questions about your rights as a research participant, or wish to obtain information, ask questions, or discuss any concerns about this study with someone other than the researcher(s), please contact the Secretary of the Ethics Committee Information & Computer Science: ethicscommittee-CIS@utwente.nl

FIGURE 68: Interest form (page 2)

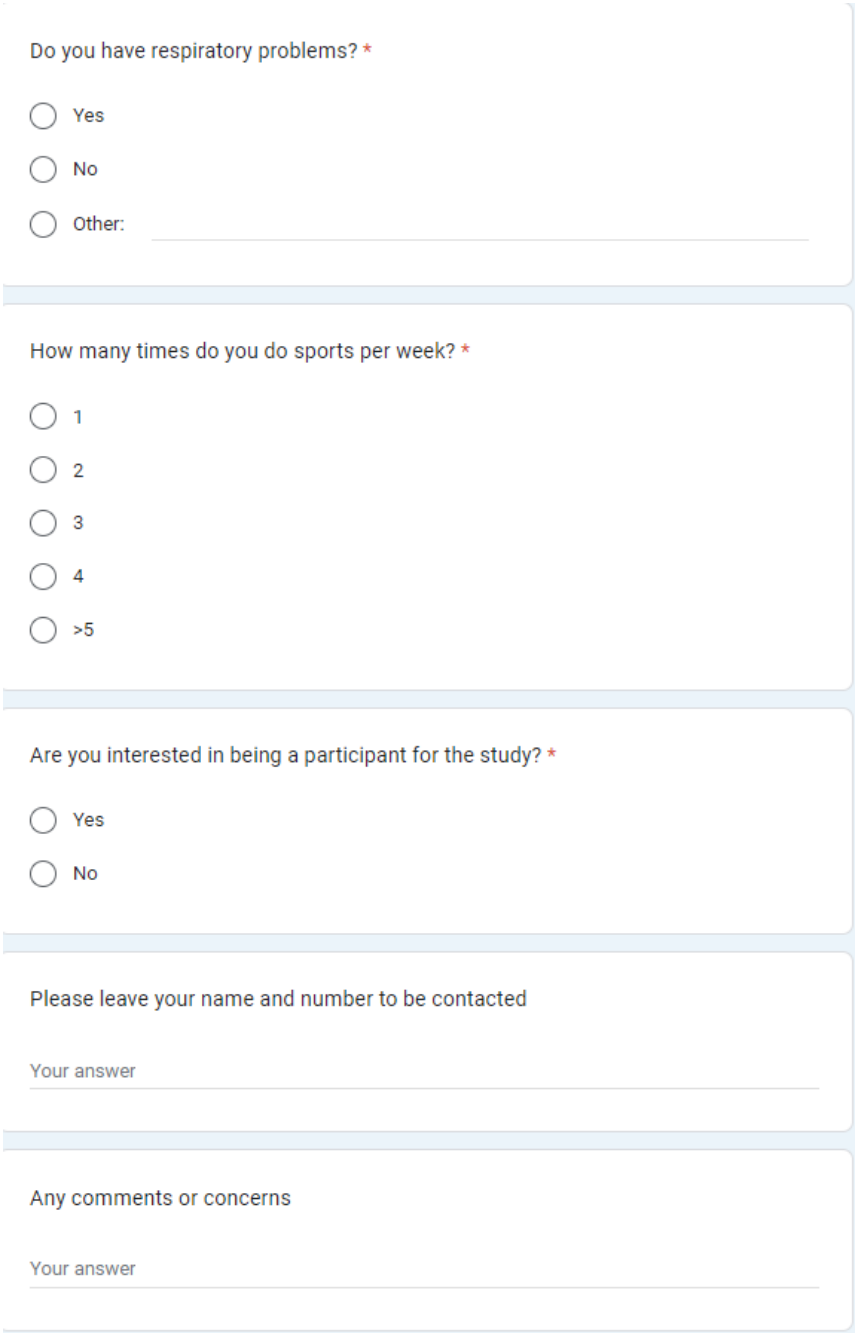


FIGURE 69: Interest form (page 3)

10.3.2 Consent Form

Consent Form for B R E A T H E

Please tick the appropriate boxes	Yes	No
Taking part in the study		
I have read and understood the study information dated 26/09/2022, or it has been read to me. I have been able to ask questions about the study and my questions have been answered to my satisfaction.	○	○
I consent voluntarily to be a participant in this study and understand that I can refuse to answer questions and I can withdraw from the study at any time, without having to give a reason.	○	○
I understand that taking part in the study involves capturing my heart rate data, a survey questionnaire and / or an interview on my opinion about the haptic wearable.	○	○
Risks associated with participating in the study		
I understand that taking part in the study involves the risks of slight dizziness and fatigue and possibility some discomfort and I consent to them.	○	○
Use of the information in the study		
I agree that my information can be quoted in research outputs but will be anonymised.	○	○
My data is allowed to be used stored for further research and I consent to this.	○	○

Signatures

_____ _____

Signature Date

I have accurately read out the information sheet to the potential participant and, to the best of my ability, ensured that the participant understands to what they are freely consenting.

_____ _____ _____

Radhika Kapoor Signature Date

Study contact details for further information:

Radhika Kapoor
r.kapoor@student.utwente.nl

UNIVERSITY OF TWENTE.

FIGURE 70: Consent Form

10.3.3 Feedback Form

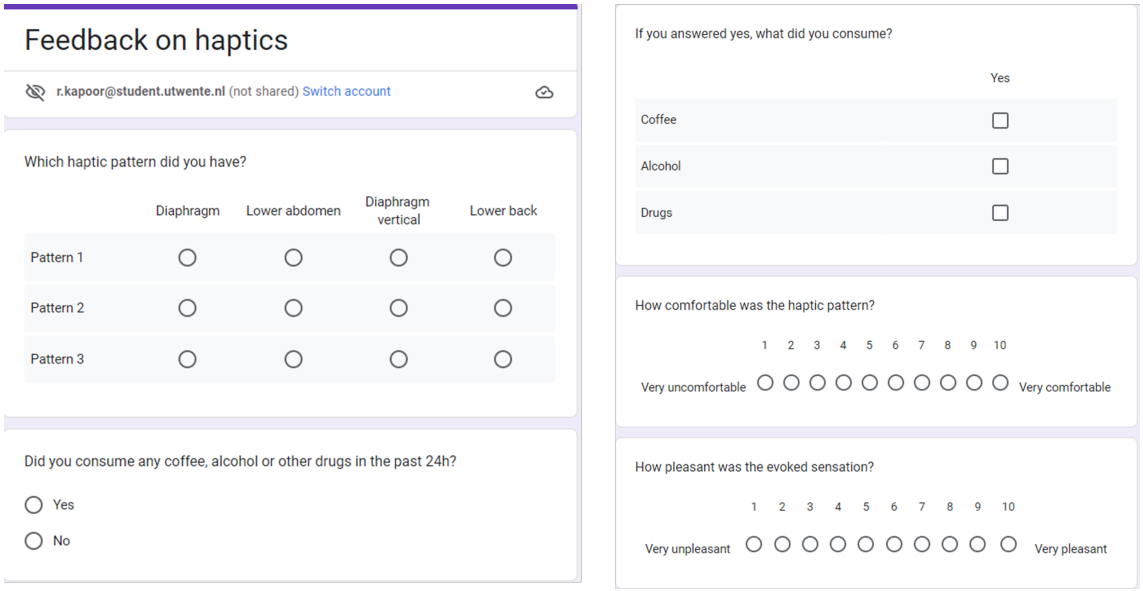


FIGURE 71: Feedback form per session (page 1)

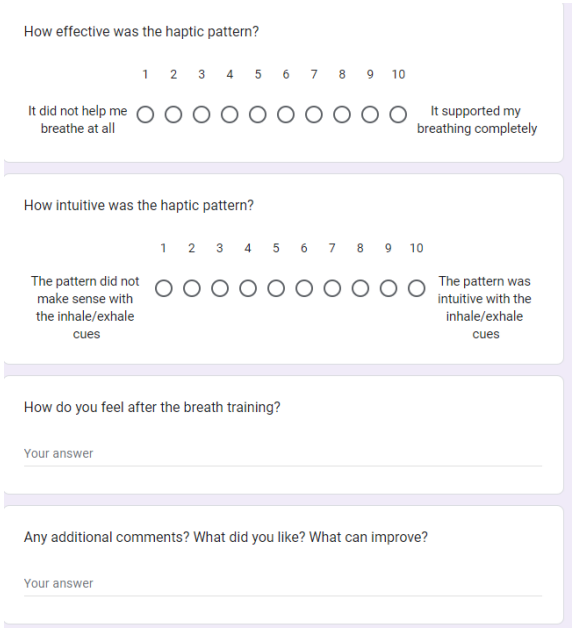


FIGURE 72: Feedback form per session (page 2)

10.4 Evaluation

```
Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's method ['lmerModLmerTest']
Formula: Diff_RMSSD4501500 ~ Pattern + Position + Breathing_rate4501500 +      (1 | Participant)
   Data: data_experiments

     AIC      BIC   logLik deviance df.resid
  1189.3   1212.2   -586.7   1173.3      121

Scaled residuals:
     Min       1Q   Median       3Q      Max
-3.13387 -0.58183 -0.07131  0.44650  2.61463

Random effects:
 Groups      Name        Variance Std.Dev.
 Participant (Intercept) 817.4    28.59
 Residual                368.4    19.19
Number of obs: 129, groups:  Participant, 15

Fixed effects:
                      Estimate Std. Error       df t value Pr(>|t|)
(Intercept)            -8.9654    10.4996  48.3467  -0.854   0.3974
Pattern2                1.0284     4.1214 114.0369   0.250   0.8034
Pattern3               -0.3500     4.1557 114.0961  -0.084   0.9330
Position2               2.2278     4.1950 114.1410   0.531   0.5964
Position3               0.2658     4.1325 114.0858   0.064   0.9488
Breathing_rate4501500   2.3883     1.0813 119.7174   2.209   0.0291 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:
            (Intr) Pttrn2 Pttrn3 Postn2 Postn3
Pattern2    -0.190
Pattern3    -0.197  0.489
Position2   -0.149  0.026 -0.017
Position3   -0.163 -0.010 -0.040  0.503
```

FIGURE 73: R Output: Difference on RMSSD within interventions

```
Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's method ['lmerModLmerTest']
Formula: Diff_RMSSD4501500 ~ Pattern * Position + Pattern + Position +      Breathing_rate4501500 + (1 | Participant)
   Data: data_experiments

     AIC      BIC   logLik deviance df.resid
  1195.7   1230.0   -585.8   1171.7      117

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.2673 -0.5456 -0.0421  0.4897  2.5448

Random effects:
 Groups      Name        Variance Std.Dev.
 Participant (Intercept) 814.0    28.53
 Residual                363.3    19.06
Number of obs: 129, groups:  Participant, 15

Fixed effects:
                     Estimate Std. Error       df t value Pr(>|t|)
(Intercept)           -8.4662    11.0494  56.8243  -0.766   0.4467
Pattern2               0.5057     6.9657 114.0282   0.073   0.9422
Pattern3               1.6021     7.2647 114.1370   0.221   0.8258
Position2              6.1969     6.9879 114.0690   0.887   0.3770
Position3             -2.6898     7.1006 114.0893  -0.379   0.7055
Breathing_rate4501500  2.2379     1.1032 119.9831   2.029   0.0447 *
Pattern2:Position2    -3.6209    10.0603 114.0865  -0.360   0.7196
Pattern3:Position2    -8.7420    10.1615 114.1306  -0.860   0.3914
Pattern2:Position3     5.3460     9.9471 114.0540   0.537   0.5920
Pattern3:Position3     3.1086    10.2429 114.2153   0.303   0.7621
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:
            (Intr) Pttrn2 Pttrn3 Postn2 Postn3 B_4501 Pt2:P2 Pt3:P2 Pt2:P3
Pattern2    -0.289
Pattern3    -0.336  0.476
Position2   -0.260  0.501  0.472
Position3   -0.321  0.489  0.470  0.486
Brt_4501500 -0.598 -0.042  0.057 -0.090  0.021
Pttrn2:Pst2  0.195 -0.693 -0.330 -0.692 -0.335  0.038
Pttrn3:Pst2  0.188 -0.344 -0.710 -0.686 -0.334  0.046  0.476
Pttrn2:Pst3  0.200 -0.700 -0.333 -0.351 -0.713  0.034  0.483  0.241
Pttrn3:Pst3  0.296 -0.334 -0.714 -0.326 -0.695 -0.138  0.228  0.499  0.490
```

FIGURE 74: R Output: Interaction Effects RMSSD within interventions

```
Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's method ['lmerModLmerTest']
Formula: Diff_breathing4501500 ~ Pattern + Position + (1 | Participant)
   Data: data_experiments

     AIC      BIC   logLik deviance df.resid
   513.7    533.7   -249.8    499.7      122

Scaled residuals:
    Min      1Q  Median      3Q     Max
-1.4523 -0.3888 -0.2300  0.0370  5.9070

Random effects:
 Groups      Name        Variance Std.Dev.
 Participant (Intercept) 0.3849   0.6204
 Residual                2.5582   1.5994
Number of obs: 129, groups:  Participant, 15

Fixed effects:
            Estimate Std. Error        df t value Pr(>|t|)
(Intercept)  0.79469    0.35039  79.57800   2.268    0.026 *
Pattern2     0.01141    0.34333 114.44080   0.033    0.974
Pattern3    -0.31930    0.34582 114.89662  -0.923    0.358
Position2    0.18731    0.34795 115.06491   0.538    0.591
Position3    0.31427    0.34364 114.77563   0.915    0.362
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:
          (Intr) Pttrn2 Pttrn3 Postn2
Pattern2  -0.488
Pattern3  -0.464  0.490
Position2 -0.494  0.025 -0.014
Position3 -0.481 -0.011 -0.037  0.501
```

FIGURE 75: R Output: Difference in breathing rate within interventions

```
Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's method ['lmerModLmerTest']
Formula: Diff_RMSSD4501500 ~ Pattern * Position + Pattern + Position +      (1 | Participant)
   Data: data_experiments

     AIC      BIC   logLik deviance df.resid
  1197.7   1229.2   -587.8   1175.7      118

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.6598 -0.5734 -0.0082  0.4904  2.7925

Random effects:
 Groups      Name        Variance Std.Dev.
 Participant (Intercept) 809.6    28.45
 Residual                376.5    19.40
Number of obs: 129, groups:  Participant, 15

Fixed effects:
                   Estimate Std. Error       df t value Pr(>|t|)
(Intercept)          4.9300     8.8923  28.4312   0.554    0.584
Pattern2             1.1040     7.0854 114.0214   0.156    0.876
Pattern3             0.7678     7.3841 114.1332   0.104    0.917
Position2            7.4740     7.0854 114.0214   1.055    0.294
Position3           -2.9933     7.2275 114.0905  -0.414    0.680
Pattern2:Position2  -4.3987    10.2350 114.0871  -0.430    0.668
Pattern3:Position2  -9.6925    10.3346 114.1142  -0.938    0.350
Pattern2:Position3   4.6633    10.1213 114.0566   0.461    0.646
Pattern3:Position3   5.9681    10.3286 114.0999   0.578    0.565

Correlation of Fixed Effects:
            (Intr) Pttrn2 Pttrn3 Postn2 Postn3 Pt2:P2 Pt3:P2 Pt2:P3
Pattern2    -0.398
Pattern3    -0.382  0.480
Position2   -0.398  0.500  0.480
Position3   -0.391  0.490  0.470  0.490
Pttrn2:Pst2  0.276 -0.692 -0.333 -0.692 -0.336
Pttrn3:Pst2  0.273 -0.343 -0.715 -0.686 -0.336  0.475
Pttrn2:Pst3  0.279 -0.700 -0.335 -0.350 -0.714  0.482  0.240
Pttrn3:Pst3  0.273 -0.343 -0.714 -0.343 -0.699  0.236  0.511  0.499
```

FIGURE 76: R Output: Interaction Effects in breathing rate within interventions

```
Linear mixed model fit by maximum likelihood . t-tests use Satterthwaite's method ['lmerModLmerTest']
Formula: LF4501500_ni ~ Pattern + Position + Breathing_rate4501500_ni +      (1 | Participant)
   Data: data_experiments

     AIC      BIC   logLik deviance df.resid
   517.6    540.4   -250.8    501.6      121

Scaled residuals:
    Min      1Q  Median      3Q     Max
-3.8747 -0.3719  0.0010  0.2906  7.1238

Random effects:
 Groups      Name        Variance Std.Dev.
 Participant (Intercept) 1.049    1.024
 Residual                2.383    1.544
Number of obs: 129, groups:  Participant, 15

Fixed effects:
                           Estimate Std. Error        df t value Pr(>|t|)
(Intercept)                 7.50618    0.58439  93.44613  12.844  < 2e-16 ***
Pattern2                    0.03624    0.33169 113.98836   0.109    0.913
Pattern3                   -0.30150    0.33491 114.38222  -0.900    0.370
Position2                  -0.10031    0.33691 114.43496  -0.298    0.766
Position3                  -0.30517    0.33270 114.26501  -0.917    0.361
Breathing_rate4501500_ni    0.32085    0.06460 128.79268   4.967 2.12e-06 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation of Fixed Effects:
            (Intr) Pttrn2 Pttrn3 Postn2 Postn3
Pattern2    -0.312
Pattern3    -0.321  0.491
Position2   -0.236  0.022 -0.019
Position3   -0.225 -0.014 -0.044  0.504
Br_4501500_ -0.728  0.041  0.074 -0.068 -0.072
```

FIGURE 77: R Output: LF power within interventions

10.4.1 Interviews

Participant 1:
All placements were all comfortable. I would never buy a haptic feedback product, except a game controller. In(Inhale) and Out (Exhale) was most intuitive because the action fits the name.

It was not very clear when the switch was from in to out. Lower abdomen makes sense because you need to breathe through the belly. In my body the lower abdomen is the place where the motors consistently made the most contact. Contact of the motors was most uneven, so I couldn't feel the vibrations evenly spread which lead to a degradation of my comfort.

Participant 2:
I would lean towards not buying the product on the market because I am not aware of the health benefits breathing has. Intensity was most intuitive because I did not need to constantly check which direction the motors were going and if it reached its maxed. And its intuitive because I have 6 actuators that increase in intensity rather than just 1.

I constantly had to remind myself that when I breathe in I need to breathe out. It's just confusing. Its counter intuitive if I say so myself.Things in front of me are generally more obvious. I can also easily touch my lower abdomen with my hands to feel the motors if I need to. It's strange for me having a belt that is too high. I also enjoy the feeling of having a belt that tightens my stomach to make me look sexy. I don't enjoy a device behind me doing things. I feel it better on my stomach than my back also.

Participant 3:
I'm not sure if I would use it because I don't feel like I need something to help me. Maybe if I had a problem with asthma it would be nice. I wanted to take deeper inhales, so if I could

determine the frequency it would help me want to buy it.Intensity was the best. I have the same feature on my iwatch. Its about stress relief and breathing exercises. This was the most easy one to follow. It helps me calm down, I use it when I'm stressed. I could feel it best on my back. And therefore it was the most comfortable. The wrist is more comfortable on the wrist than on my body. Because I;m more comfortable wearing my watch. Diaphragm was least comfortable because it felt weird to put something there. I didn't feel like it obstructed my breathing. I never put things there so it feels quite weird. In general, the patterns helped guide my breathing.

Participant 4:
Because people that have problem with breath and no symmetric breathing patterns could benefit from this. Pattern 3 was most intuitive. If you visualise it (chest breathing makes it easier), that's why it makes sense. Intensity was the least intuitive. Didn't know which exact time to breathe in and breathe out. It did not block the diaphragm. I think on the lower abdomen we have the most receptors and I could feel it better. The lower back I could not feel and diaphragm obstructed my breathing and was not that comfortable.

Participant 5:
Depends on the stage, if I have breathing problems I would use it. But I am healthy so I don't think I would need it. IF I have anxiety I would also probably use it because it would help to be in the moment but it needs to be marketed well to be used in that scenario. I had anxiety and I really noticed that that caused me to have problems with breathing as well which is why I think that would be the target group. I would want some visual feedback to know how my breathing changed if I were to purchase the product. Some numbers to see. Something tangible. Like a connected app, anything on a screen. The intensity pattern was most intuitive. When the vibration moved it was hard to follow the pattern. Meanwhile when the vibration was in one place you only had to follow the intensity. It was most clear.

Its more intuitive if its in inhale and out exhale. I don't really feel the difference in the patterns but its more of a thought process that makes it more intuitive.Lower abdomen was the most comfortable. The back was the least comfortable. It is more intuitive to feel it from the front. I couldn't feel it that well on my back either. When I feel it in the back and try to connect it in my brain with my breathing process, it is harder. Your belly is more common to be touched / involved in processes rather than your back, so it feels unusual to me. I am not more conscious of my posture with the belt.

Participant 6:
I'm already doing meditation and breathing exercises and I don't think this has something to add. To do normal breathing in and out I would not need this. Maybe to breathe in, hold, breathe out, it could help me but for now I do not need. I prefer to breathe naturally without impulses or external guides. The cables make is difficult to wear. The belt is very small, I would prefer something that can cover a larger area. I want something in a fixed position so I do not need to adjust.

I feel like the belt would fall, so I would want something sturdier, a larger belt that you would not need to adjust. (example watch)In inhale and out exhale, chest breathing visualisation is why that makes most sense. Out inhale and in exhale was counter intuitive in my way of understanding breathing. The intensity pattern made sense to me. The diaphragm was most comfortable because it was closer to the breathing organs. I could not follow what was going on on the back. I could not feel it so well what was happening, it was going against my brain. Because how is my back connected to breathing. I was afraid it would fall so I was constantly

sitting straight.

Participant 7:
I think it would be very useful if you have stress issues or breathing problems but I don't experience that at the moment. If the core reason to use this is breahting exercises I would not use it because I don't do this. Maybe if you want to practice a music instrument or scuba diving I think it would be useful. If I would see a use for me to use this, I would use it but I don't see a use. If you could add music that works to the same breathing rhythm I think that would be cool and be a positive step in my purchasing decision. It depended on the placement for me which pattern made more sense.// Back: Out Inhale, In Exhale
Front: In Inhale Out Exhale

It felt like these were the muscles that were being activated by breahting. Back posture differs, more focussed on how it feels.

Intensity was least intuitive because there was no clear reversing point. Bit of grey area what happens there. Back was most comfortable because it felt like it made sense. It felt like it was activating the muscles. I could feel the motors best on my back too. Lower abdomen was least comfortable because it stressed me out because it felt like it was something vibrating on my belly and that's strange and wasn't supporting any breathing pattern.
Participant 8:
I see the potential, It can definitely help me. It needs more polish. The system should work seamlessly. I would expect this to work wirelessly and it would have to help me place it properly and help me get a reading. It would have to be very robust (sensor placement). It would help me in calming down. I think it's a very interesting experiment on myself. If I were training for the bata, I would want to see my HRV improve, as a sports tool. Preferably web application, I don't want an app.

In(Exhale), Out(Inhale), because you visualise with breathing with my belly button that expands. And intensity is a close second because it gives me a tad harder when you should be at max with breathing and when my lungs are empty. Least intuitive because I visualise it with a hoop around my waist and its counter intuitive. Lower abdomen: feels most as if the band isn't there and it gives me the strongest sensation and feedback. Diaphragm least comfortable because I feel slightly constrained whilst breathing.
Interesting project.

Participant 9:
I'm already a pretty anxious person so having this thing that forces me to breathe and genuinely induces calm makes me want to spend money on it. During anxious times it can be difficult to find a breathing pattern yourself so I think I would have a need for it.

Get rid of the wires. If there were a wearable heart rate monitor that wasn't on my finger I would want it, so I could multi task like doing dishes. Pattern 3: As my diaphragm was expanding it was moving out and felt intuitive. Intensity was least intuitive because I was struggling to find the max point because I don't know when its gotten to the max point and the min point.

Back: I felt the vibrations the clearest on my back and it also helped me be conscious of my posture. I was sitting straight the entire time.Lower abdomen was really ticklish and

diaphragm constrained me so I felt like I was fighting against the belt. Lower abdomen: Once the ticklishness was gone, it felt fine. It was just the initial thing and took some time getting used to. Theres a lot of movement happening in the front, and I'm rarely having things in my back which feels more like a foreign on back. Which made me more conscious of it.

Participant 10:
I think if I would train my breathing, I would go with some audio based thing because it seemed to work quite well in the calibration. I have some interest in training my breathing to use more lung capacity for diving as such and cold water swimming.

If it would combine vibration with audio it could be nicer. Intensity was the most intuitive. It was somewhat difficult to feel the direction on your skin. Intensity helped. Pattern 3 was the least intuitive because its hard to feel the direction and it makes more sense to think inwards in and outwards out.

Diaphragm and lower back were pretty much the same. Muscles are more tense there and vibrations feel quite comfortable, massaging feeling. Having it in front made me more conscious of my posture because theres more going on in the front to make me aware of my breathing and posture. Lower abdomen because I could feel it less. I feel like I had less sensation, even with the intensity adjustment.

Because right now I do not see a use for it for myself. If the intention was clear, I would consider. If it were used for a specific medical issue, like if someone hyperventilates a lot or has panic attacks it could teach them how to breathe and if it worked, I would maybe be interested in it. For the patterns, I think it would be nicer to be combined with visual feedback. I think the haptics are interesting and the patterns are smooth and they highlight parts that are used to breathe, but I would want visual feedback with LEDs, or arrows, or anything else on a screen to indicate direction but its hard to give feedback because most people are not aware of how our bodies move when they breathe and the patterns are good to make people aware of how they breathe. Pattern 2 was most intuitive, because when I think of breathing in, vibrations go towards the belly button and same for out.Pattern 3 was the worst because counter intuitive. Lower Abdomen because I felt it was more concentrated around where the airflow is. Diaphragm felt least intuitive and uncomfortable. Vibrations made me both more aware of my posture and how my body was moving during breathing.

Participant 11:
I don't really have breathing problems. I would use it if I had breathing problems but I don't. It would need to contain less wires. They are very impractical. If the device were more compact that you could put it on and switch it on on the belt. It would be good. I don't want the motors to directly touch my skin, there should be a layer in between. It would feel nicer if there was a thin textile layer between the motors and skin but everything should be more embedded.

Pattern 2 was most intuitive and follows how you breathe. It feels intuitive to count so I like that the motors switch on sequentially. And in in and out out is just easier to remember. I could not tell the intensity apart and there was no break in between so I could not correctly determine the switch from the intensity is getting lower to it is going higher.

Diaphragm was best because it was easy to install and its where breathing happens. Its where your lungs are. I understand the lower abdomen placement because you can be a stomach

breather but the diaphragm is important because you definitely breathe in through your lungs. Lower abdomen feels very intrusive to have it directly over my panty line. If you're a belly breather it does make sense but I prefer the ribs because that is where I breathe. I'm used to having my bra close to my diaphragm too which is maybe why it feels more normal. The lower back felt comfortable from the placement but I do not think that that's where it makes any sense for breathing because I do not breathe there.

Participant 12:
I don't think so because I don't have trouble breathing so I would not need the intervention. Maybe if I were a granddad or old person or a COVID patient. If it were a nice looking belt, then maybe. Maybe for some people it would be nice to sleep but I don't think I would buy it. I've never had a vibrating belt so I don't know. If it would make me warm in the Netherlands I would but it. Intensity was the best because when you go to trainings or PE in school or stretch it was always the visual help of breathing in and breathing out and I think this connects the visual with the haptic. Pattern 3 was counter intuitive. I expected the opposite. Tummy goes out but vibrations go to the back so it doesn't make sense The diaphragm helped me most. I was more conscious of my lung movements. I can feel my lungs more with feedback there. The tummy wasn't comfortable because the belt became tigheter when I breathed in. Most comfortable was the lower back for these reasons.

Participant 13:
I would use only one or two patterns of the different patterns that I tried. I didn't find all to be very comfortable. I can choose not to use the settings I don't like. It could be more if I knew it was effective. Instead of a belt, the vibrators should probably attach to the fabric I'm wearing itself. Because then it consistently sticks to the body than moving when Im breathing in and out. Make more robust.

Lower abdomen intensity was most intuitive. On the back inward and outward was least intuitive. Its harder to feel on the back and I have to do more work to guess which time it is because I cannot feel it very well. I need to think at feel those gaps and it makes it tiring.