USING MOBILE TECHNOLOGY TO IMPROVE SELF-
REGULATION DURING EXERCISE

Alex Shaykevich

This thesis is presented for the degree of Doctor of Philosophy of the University of
Western Australia

School of Sports Science, Exercise and Health
School of Computer Science and Software Engineering

The University of Western Australia

December 2014
ACKNOWLEDGEMENTS

I would like to offer my sincere appreciation to my supervisors, James Dimmock, Bob Grove, Ben Jackson, and Mohammed Bennamoun for their support, interest, and encouragement of my work. As a newcomer to the field, this research would not have been possible without their insight and technical guidance. I would also like to thank the Australian Postgraduate Award for funding this research.

I’d like to thank Dr. Michael Rosenberg (UWA) and Dr. Christo Pantev (Uni. Muenster) for broadening my horizons by allowing me to be involved in work beyond the scope of my own research.

I’d like to extend my sincere appreciation to Dr. Grant Landers, Sharon Gam, and Dr. Francois Cottin for their technical assistance in recruitment, data collection and analysis. I also owe a special thanks to the incredible administrative and technical support staff at SSEH without whom the day-to-day realities of research would not be possible.

I will always be grateful to my parents, Lana and Yakov, for their unwavering love and support.

Finally, to the many friends, among them Thea, Luke, Dan, and Steve who’ve endured my endless ramblings about technology and research, I am very grateful for your ears and your patience.
EXPLANATORY NOTE

Guidelines at the University of Western Australia provide an option for candidates for the Doctor of Philosophy degree to compile their thesis as a series of manuscripts. These may be published journal articles, manuscripts that have been submitted for review but not yet accepted, manuscripts that could be submitted, or any combination of the preceding. The present thesis has been structured in such a way. In keeping with current scientific writing guidelines, the included manuscripts make use of the “active” voice incorporating the narrative use of “we” throughout. However, the present thesis represents the exclusive, independent work of Alex Shaykevich unless otherwise noted in the accompanying author’s declaration. The co-authors cited below provided editorial comment and revisions after an initial, complete draft had been prepared. With the guidance of these supervisors, the candidate performed all experimental design, data collection, analysis, and manuscript preparation. Metabolic testing described in the Chapter 5 case study was performed by Sharon Gam, and her contribution is recognized in the acknowledgements within the chapter. Work accepted for conference and journal publication is cited at the conclusion of this note.

The body of this thesis contains six chapters consisting of an introduction, four manuscripts, and a general discussion reviewing the work performed and offering future directions for research. Short introductions prior to each manuscript are meant to bridge the work thematically across chapters. Each of the six chapters contains its own reference list organized according to the modified National Library of Medicine (NLM) citation style as specified by *Medicine and Science in Sports & Exercise*. Figure, listing, and table legends pre-append the chapter number for unique identification within the thesis (e.g., Table 1.1, Figure 5.1).
Publication (Chapter 4)


Conference Poster (Chapter 5, Appendix E.4)

ABSTRACT

An extensive collection of mobile software was developed and used in multiple experiments exploring self-regulation during exercise leading to a number of key findings. The present thesis represents a multidisciplinary approach including elements of software engineering, exercise physiology, computational biology, and biofeedback. In all, the work presented in this thesis includes:

- Three complete mobile software applications.
- Two human experiments including a 5-week intervention.
- One comprehensive software library for the study of heart rate variability (HRV).
- One case study involving human exercise and HRV.
- One validation study focused on HRV analysis.

A novel form of continuous acoustic feedback, developed as part of an ad hoc mobile software application, outperformed the current “gold standard” as implemented in consumer heart rate monitors. Participants were exposed, in a repeated measures fashion, to one of 2 different feedback conditions and a silent control during 20 minutes of moderate intensity exercise on an indoor stationary bicycle. Feedback conditions included either a boundary-style feedback emulating current heart rate monitors consisting of a sequence of auditory “beeps” heard only when heart rate fell outside the target training zone, or a novel form of continuous feedback developed specifically as part of this study. Time in Zone (TIZ), defined as the ratio of the time spent within the target training zone divided by the overall time of exercise, rating of perceived exertion (RPE), and subjective measures of association, dissociation, and distress were compared
across feedback and control conditions using one-way, repeated measures ANOVA. TIZ increased significantly in both the continuous ($M \pm SD$: .99 ± 0.01) and boundary (.94 ± 0.05) conditions over control (.52 ± 0.40) and was significantly greater for continuous versus boundary, all $p_s <= .01$. RPE did not change significantly under different feedback conditions. Dissociation was significantly reduced under continuous feedback compared to both control, $p < .01$, and boundary, $p < .05$. No significant differences in association or distress across conditions were present, though a moderate effect size, $Cohen’s d = .55$, for association was observed between continuous and boundary conditions.

The ability to exercise autonomously at a moderate to vigorous intensity can be entrained through repeated exposure to auditory feedback. Healthy adults performed 10 indoor exercise sessions on cycle ergometers over 5 weeks following a twice-weekly schedule. During these sessions, participants received auditory feedback (FB) designed to maintain heart rate within a personalized, moderate-intensity training zone between 70 and 80% of maximum heart rate. All feedback was delivered via a custom, mobile software application. Participants underwent an initial assessment (PREFB) to measure their ability to maintain exercise intensity defined by the training zone without use of feedback. After completing the feedback training, participants performed three additional assessments identical to PREFB at 1 week (POST1), 2 weeks (POST2), and 4 weeks (POST3) after their last feedback session. TIZ, RPE, instrumental attitudes, and affective attitudes were then evaluated to assess results using two-way, mixed-model ANOVA with session and gender as factors. Training with feedback significantly improved TIZ ($p < .01$) compared to PREFB. An absence of significant differences in TIZ between FB, POST1, POST2, and POST3 ($p >= .35$) indicated that these
improvements were maintained after feedback was removed. No significant differences in RPE, \( p \geq .4 \), or attitude measures, \( p \geq .3 \), were observed.

Real-time analysis of HRV parameters during exercise was realized as both a software library (HRVKit) and a standalone mobile application (HRVLab). Comparing results from HRVKit and a “gold standard” HRV analysis application revealed overall high levels of agreement with intra-class correlations (ICCs) \( \geq .81 \). A case study using HRVLab for real-time analysis during a graded exercise test was performed, and results are consistent with existing literature and suggest anaerobic threshold may be determined using this non-invasive technology.
# Table of Contents

Acknowledgements .................................................................................................................. 2  
Explanatory Note .................................................................................................................... 3  
Abstract .................................................................................................................................. 5  
Chapter 1 - Introduction ............................................................................................................ 10  
  Overview ............................................................................................................................... 10  
  Exercise Recommendations, Health Outcomes, and Adherence ........................................ 10  
  Afferent Cues and Effort Perception ....................................................................................... 12  
  Augmented Feedback ........................................................................................................... 13  
  Auditory Feedback Instrumentation during Aerobic Exercise ............................................. 16  
  Music in the Exercise Domain .............................................................................................. 19  
  Self-Regulation Entrainment ............................................................................................... 22  
  Heart Rate Variability and Physiological Threshold Detection .......................................... 23  
  Emerging Research Questions and Methods ....................................................................... 25  
  References ............................................................................................................................ 26  
Chapter 2 .................................................................................................................................. 36  
Tempony: A Mobile Software Instrument for Exercise Feedback Research .......................... 37  
  Abstract ............................................................................................................................... 37  
  Keywords ............................................................................................................................. 37  
  Introduction ......................................................................................................................... 37  
  Methods ............................................................................................................................... 40  
    Audio Playback .................................................................................................................. 41  
    Mobile Software Application ......................................................................................... 45  
  Conclusion ............................................................................................................................. 51  
  References ............................................................................................................................ 52  
Chapter 3 .................................................................................................................................. 55  
Comparing Different Forms of Acoustic Biofeedback during Moderate Intensity Exercise .......................................................................................................................... 56  
  Abstract ............................................................................................................................... 56  
  Keywords ............................................................................................................................. 57  
  Introduction ......................................................................................................................... 57  
  Methods ............................................................................................................................... 61  
  Results ................................................................................................................................ 66  
  Discussion ............................................................................................................................ 67  
  References ............................................................................................................................ 70  
Chapter 4 .................................................................................................................................. 74  
Auditory Feedback Improves Heart Rate Moderation during Moderate Intensity Exercise .......................................................................................................................... 75  
  Abstract ............................................................................................................................... 75  
  Keywords ............................................................................................................................. 76  
  Introduction ......................................................................................................................... 76  
  Methods ............................................................................................................................... 78  
  Results ................................................................................................................................ 82  
  Discussion ............................................................................................................................ 84  
  Acknowledgements ............................................................................................................ 88  
  References ............................................................................................................................ 88  
Chapter 5 .................................................................................................................................. 91
Overview

Exercise is vital for human health, yet sedentary lifestyles persist. Compounding the issue, even when the general population exercises, many individuals cannot gauge intensity adequately enough to fully reap the potential benefits. The results can range from exercising without sufficient intensity to promote cardiovascular health to exercising too vigorously such that the consistency of physical activity is compromised.

Augmented feedback, which is applicable to this problem, can be used to promote skill acquisition where self-regulation based on human senses alone (i.e., inherent feedback) may be insufficient to ensure adequate adherence to individually prescribed moderate intensity efforts. Moreover, the proliferation of mobile technology since the advent of the iPhone in 2007 has created a unique platform for developing augmented feedback instrumentation particularly suited for exercise. The present thesis describes a collection of such systems, their validation, and the experimental results of their use.

Exercise Recommendations, Health Outcomes, and Adherence

The 2011 American College of Sports Medicine (ACSM) statement on public health and exercise prescription recommends five, 30-minute moderate intensity exercise sessions per week totaling 150 minutes (42). The ACSM guidelines build on a range of studies supporting the basic conclusion that exercise prevents and, in some cases, treats disease. A partial list of dose-responsive disease outcomes ameliorated through exercise includes colon and breast cancer, type 2 diabetes, cardiovascular disease, hypertension and stroke (60). Further evidence related to cancer (108), cognitive function (113,122), and women’s health (72,73) continues to emerge.
Both subjective and objective classifications exist for the terms “moderate” and “vigorous” in the context of exercise intensity. Haskell et al. (50) suggest that moderate intensity exercise is “generally equivalent to a brisk walk and noticeably accelerates the heart rate” (p. 1423), while vigorous intensity exercise “causes rapid breathing and a substantial increase in heart rate” (p. 1423). Garber et al. (42) include several objective classifications for exercise intensity including estimates based on a percentage of maximum heart rate (HRmax), such that moderate intensity may be considered from 64-76% of HRmax, and vigorous intensity from 77-95% of HRmax. Despite these target recommendations, research has shown the general population may struggle to maintain bouts of moderate intensity exercise owing to difficulties in correctly self-identifying exertion. That is, even at intensities well below those that would limit one’s ability to perform a task, adherence is compromised by an inability to correctly gauge effort. Ekkekakis, Lind, and Joens-Matre (34) noted that individual self-selected exercise intensities can vary greatly, while Braham, Rosenberg, and Begley (14) observed that intensity increased significantly when specific instructions to exercise moderately were introduced. Additional research with adolescents (47) implies that this population may significantly underestimate intensity at moderate and vigorous activity levels. Moreover, exercise intensity can potentially play an important role in exercise adherence. Williams (115) and Ekkekakis and Hall (33) note a marked decrease in affect with increasing intensity, particular above the lactate threshold, and suggest pacing strategies to help minimize these negative consequences. Thus, the evidence suggests the need for real-time, objective biofeedback suitable for “everyday” (i.e., ecologically valid) settings.
Afferent Cues and Effort Perception

Human senses provide a continual flow of information during physical activity. Alternatively referred to as inherent or afferent feedback, these signals allow an individual to gauge intensity and can include both cardiopulmonary (e.g., heart rate, minute ventilation, respiratory rate) and peripheral (e.g., skin temperature, sweat rate, mechanical strain) sensations (49). No single afferent signal appears to dominate effort perception (49), however, leading researchers to propose regression models of fatigue incorporating multiple sensory cues (81,104). Whether this is a wholly conscious process or not remains unclear. Edwards, Melcher, Hesser, Wigertz, and Ekelund (32) have proposed that conscious awareness is required to translate sensory information into effort perception, while Mihevic (77) has proposed both conscious and unconscious integration of afferent cues.

Ratings of perceived exertion scales (RPE) have been used to quantify effort perception since Borg’s initial observation of high correlation between RPE and heart rate, ultimately leading to the development of Borg’s widely adopted 15-point scale (12). Borg reported correlations from $r = .80$ to $r = .90$ between heart rate and RPE scores, and suggested that heart rate should be approximately 10 times the RPE score at moderate to high intensities for healthy, middle-aged males. Other afferent cues have also been shown to correlate well with RPE scales. Robertson (89) has reported correlations from $r = .61$ to $r = .94$ between RPE scores and respiratory rate, while Edwards, Melcher, Hesser, Wigertz, and Ekelund (32) reported correlation coefficients of $r = .77$ and $r = .63$ between RPE and blood lactate for continuous and intermittent exercise bouts, respectively.

RPE scales, however, cannot be considered a substitute for objective measurement in all cases. Lamb, Eston, and Corn (64) performed a reliability analysis on RPE ratings
using the 95% limits of agreement method and reported that bias increased with work rate. At the highest of 4 exercise intensities, the researchers reported a 3-unit difference in RPE scores and Pearson correlation declining from .81 to .60 as intensity increased. Likewise, an inverse relationship between cadence and RPE has been reported with lower cadence eliciting higher RPE at similar VO₂ levels (86). Similarly, Pandolf, Kamon, and Noble (85) reported higher RPE scores at the same heart rates using eccentric versus concentric loading. Environmental factors can impact the heart rate/RPE relationship as well with temperature playing a dominant role. Two studies (53,84) have described disproportional increases in heart rate and RPE with increasing temperature. Recent work by Parry, Chinnasamy, and Micklewright (87) has demonstrated “optic flow” impacts RPE as well. At the same cadence and heart rate, the perception of moving through space at a slower pace elicits lower RPE scores. In addition, psychological orientation may play a considerable role in effort perception. Banting, Dimmock, and Grove (8) reported participants exposed to autonomous priming exercised at a higher intensity while reporting lower RPE compared to a group primed with controlled motivation. Though RPE scales are widely used and track well with physiological correlates of exertion, objective measures such as heart rate may more accurately assess cardiovascular load.

Augmented Feedback

Although effort can be successfully regulated using internal feedback, a complementary system of external mechanisms can also be utilized. As opposed to inherent feedback from afferent cues, information related to physical performance delivered through a means other than one’s own senses is termed augmented feedback. Although augmented feedback mechanisms have been primarily studied in the context of motor skill acquisition, insight may be gleaned from this work informing the
application of feedback to the pursuit of improving self-regulation during exercise. Broadly speaking, exercise-related augmented feedback can take one of two forms: knowledge of results (KR) and knowledge of performance (KP). KR provides feedback relative to a specific goal (e.g., running speed, shooting accuracy, cycling velocity) while KP addresses the kinematic details of performance (e.g., elbow flexion, head position, knee angle). Although KR and KP schemes present different forms of information to the recipient, researchers have suggested that the underlying mechanisms by which feedback is ultimately integrated are similar (44,95). Extrinsic cues can be delivered through various modalities including auditory, visual, and haptic, providing the receiver with critical information about actual versus desired performance. In the context of steady state, aerobic exercise, augmented feedback can serve multiple purposes. First, it can be used to directly guide behavior by providing an objective reference toward which task performance is adjusted (21,36,88). Next, it can serve to entrain behavior through the integration of extrinsic and intrinsic cues such that target adherence is improved even in the absence of external feedback (30,37,74,101). Lastly, augmented feedback can influence psychological parameters such as attentional focus and task-related interest (1,3,69,98,109), which can ultimately impact performance as well as adherence.

The timing of feedback appears critical for optimal results, but there are conflicting findings on this issue. Early research suggested a positive correlation between feedback frequency and performance (11,70). However, more recent studies contradict these earlier findings, indicating that reduced relative frequency improves results (91,102, 112,116,118,119). Salmoni, Schmidt, and Walter (91) have proposed the “guidance hypothesis” to explain the potentially maladaptive influence of high KR frequency during the learning phase. This hypothesis proposes that frequent feedback during task
performance can improve results; however, it may also block internal learning mechanisms necessary to carry out the same activity in the absence of feedback. This may be partially due to a reliance or even dependence on external feedback at the expense of developing sensitivity to internal cues (91,96,125) and an overstimulation of corrective activities (96). Yet, empirical evidence remains equivocal on the matter. In a recent study, Lin and Shea (63) found no improvement with reduced feedback frequency, while Wulf, Shea, and Matchiner (120) reported improved results with more frequent feedback. Wulf et al. also noted that task complexity may play a crucial role in determining optimal feedback rates, and other work appears to support the premise that more difficult tasks may require more frequent feedback (48,93,121,124).

Numerous timing strategies have been developed, in part, to mitigate the potentially negative effects of frequent augmented feedback. Feedback frequency can be reduced directly through withholding (112,116) or averaging (88,117,124,125) results. So-called fading techniques deliver high relative rates of feedback in the beginning of a task but then taper off (116,119,120). Bandwidth feedback takes an adaptive approach by applying stimuli only when task performance falls outside of a “band” of desired results (7,46,65,66,97). Thus, feedback frequency changes in response to competence, diminishing as proficiency increases. Concurrent and continuous models deliver feedback in real time during activity, typically through visual means. This technique has been shown to improve specific performance in continuous aerobic activities such as running (36), cycling (15,26,76,92), and swimming (21). As is the case with all feedback modalities, feedback frequency can impact retention. Swinnen, Schmidt, Nicholson, and Shapiro (105) suggest an as-yet unquantified minimum time interval between action and KR is necessary to fully integrate intrinsic and extrinsic cues. Likewise, Schmidt and Wulf (94) reported that retention was negatively affected by

15
continuous feedback. However, it is important to note that applying motor learning paradigms to cardiovascularly-limited activities with relatively simple locomotor requirements may not be entirely appropriate. Likewise, a distinction must be drawn between study designs aiming to develop a particular skill, in which the guidance hypothesis is relevant, and those seeking to improve task performance directly through the use of augmented feedback regardless of entrainment effects.

**Auditory Feedback Instrumentation During Aerobic Exercise**

The consumer heart rate monitor (HRM) is likely the most common piece of augmented feedback equipment used during exercise. In the 30+ years since the introduction of the Polar Sport Tester PE 2000, HRMs have become inexpensive, ubiquitous devices for the observation of heart rate during physical activity. The typical pairing of an HRM chest strap with a receiver watch creates a lightweight augmented feedback device often using auditory alarms to signify lack of adherence to a pre-defined target training zone. Validation against echocardiogram (ECG) has established that such devices offer reliable beat-to-beat statistics as well as mean values (41). While undeniably a type of mobile computer, an HRM nonetheless suffers from a variety of limitations. Auditory alarms are pre-programmed and often limited in informational content. In fact, the delivery of acoustic cues from the watch to the user is often inhibited by environmental factors, such as ambient noise, restricting the ability of the recipient to hear them. While new consumer products continue to evolve, flexible instruments suitable for research are considerably less prolific.

Of course, investigators have demonstrated a desire to exploit emerging technology in the development of new experimental tools. Eriksson, Halvorsen, and Gullstrand (36) developed a system capable of delivering both auditory and visual feedback during treadmill running in a successful experiment to improve running economy. Participants
received feedback on stride rate, vertical displacement, and mechanical power (an ad
hoc measure derived from the two others) and were directed to make the necessary
changes to reduce power at a fixed treadmill speed though no specific instructions about
achieving this goal were given. A successful reduction in power while maintaining the
same running speed was interpreted as an improvement in overall running economy.
Nearly all participants were able to spontaneously adjust their running technique,
mostly through increasing stride rate and reducing vertical displacement. In this
instance, auditory feedback proved more effective than visual feedback in reducing
power. The authors speculated that reduced frequency from audio feedback versus
continuous visual stimuli might account for this finding. This explanation would be
consistent with previously mentioned studies showing the potentially detrimental effects
of high KR rates. Wijnalda, Pauws, Vignoli, and Stuckenschmidt created the IM4Sports
system (114), a mobile hardware/software prototype integrating a portable mp3 player.
The goal of this project was to create a personal music player capable of varying
musical tempo, a technique known as tempo shifting, in real time to support motivation.
In the words of the authors, “Depending on the required motivation, the system adapts
the music playback to the user’s performance or training goal” (p. 29). The particular
adaptation strategies included pace-fixed, pace-matching, and pace-influencing modes
in which musical tempo would remain constant, match the user’s cadence, or change
towards a target cadence, respectively. Results appeared inconclusive, as the authors
stated that “synchronization was hard to achieve because using a treadmill produced
undesirable effects; abrupt speed changes made runners vary their stride frequency and
stride length in erratic ways” (p. 31). Unfortunately, no further work appears to have
been done on the IM4Sports system. D-Jogger (78) was a PC-based audio application
with similar tempo shifting capabilities as IM4Sports. The authors used this system to
study the entrainment of gait synchronization with acoustic beat detection during treadmill walking. The results of the study showed a 56.79% success rate in spontaneous step/beat synchronization among the participants. Another PC-based system, moBeat (109), used computer generated (MIDI) music to assess the effects of music on intrinsic motivation, attentional focus, perceived exertion, and adherence to prescribed heart rate targets during an indoor cycling task. Music tempo was synchronized to cadence while “musical richness” (p. 138), expressed in three layers of auditory information (1 = basic rhythm, 2 = additional percussion sounds, 3 = base and melodic synthesizer notes) was used to guide exercise intensity. Conventional watch-based HRMs were used as non-musical control conditions to provide heart rate feedback. The authors reported significant improvements using the fun/enjoyment, perceived competence, and value/usefulness subscales of the Intrinsic Motivation Inventory (IMI) (75), as well as significant reductions in dissociation and distress using the musical condition. No significant differences were reported in perceived exertion or adherence to exercise intensity compared to traditional HRMs. Despite successful prototypes and research findings obtained directly through the use of these novel devices, no further work appears to have been done on these systems or, in fact, even similar ones.

The dearth of subsequent instruments is particularly surprising in light of the rapid advancement in mobile technology since the introduction of the Apple iPhone in 2007, the first so-called “smart phone”. A review of over 70 journal articles citing the previous systems as well as keyword searches for “mobile AND exercise” fails to find even a single new research instrument leveraging modern mobile computing in the study of aerobic exercise. Conversely, public health investigators have steadily incorporated mobile technology into new research protocols. Killingsworth and Gilbert
(61), for example, leveraged a mobile Web application to examine mood and concentration in over 2200 subjects, and O’Malley, Dowdal, Perry, and Curran (83) created and tested a mobile software application for adolescent obesity management. Furthermore, Duncan, Vandelanotte, and Kolt (31) developed a Web- and mobile-enabled application and reported improved physical activity and dietary behaviors in middle-aged males over the course of a 9-month intervention. Even when researchers aren’t directly involved in software development, they maintain a keen interest in the state of the technology. Arnhold, Quade, and Kirch (5) analyzed 656 mobile applications for diabetes care and concluded “the usability of diabetes apps for patients aged 50 or older was moderate to good” (p. 11). Free et al. (38) assessed the effectiveness of mobile-based health interventions and reported text messaging improved adherence to smoking cessation and antiretroviral trials. From these and other recent publications, it is clear that mobile technology is rapidly becoming recognized as a new and important research tool.

Music in the Exercise Domain

It is little wonder that music was the primary focus of nearly all the previously mentioned exercise-related software projects. In their 2012 review of music in the exercise domain, Karageorghis and Priest (57) described numerous effective applications of music prior to, during, and after physical activity. While the present thesis does not include direct experimental work incorporating music, the software development effort described within is informed by current research and represents an extensive technological capability to manipulate music in real time during task performance. Therefore, a brief discussion of the relevant research on music in the exercise domain is warranted.
Physical activity concurrent with music can be broadly termed as either synchronous or asynchronous. Karageorghis and Priest (58) define the former this way, “The synchronous application of music entails an exerciser’s conscious coordination between their movements and the tempo or rhythmical qualities of music” (p. 67). Music-movement synchrony produces an ergogenic effect and has been found to significantly reduce oxygen consumption in both cycling (6) and running (107) tasks. It has also been shown to increase running speed (100) and improve time to volitional exhaustion (4,55,107) over no-music or asynchronous music controls. Results are equivocal, however. A recent study by Lim, Karageorghis, Romer, and Bishop (68) reported less limb discomfort with synchronous versus asynchronous music, but no reduction in metabolic cost, contrary to previous results (6,107). Such contradictory findings may be at least partially explained by relatively poor actual synchronization ability among untrained individuals, only 56.79% as reported by Moens et al. (78) in their work with D-Jogger. The actual beat-by-beat ability of people to accurately synchronize movement with music has not been fully explored and may represent an important confound worth researching further.

In contrast, asynchronous music lacks “conscious coordination” of movement to musical rhythm, yet still has been shown to have beneficial qualities. Numerous studies have noted significantly reduced RPE with music versus no music controls (13,79,123). There is some disagreement, however, regarding the exercise intensities at which music attenuates RPE. Boutcher and Trenske (13) observed significant effects at moderate, but not low intensities, while Yamashita, Iwai, Akimoto, Sugawara, and Kono (123) reported the opposite relationship of RPE to work rate. Karageorghis et al. (54) have suggested the existence of a specific relationship between exercise intensity and preferred musical tempi that may explain such inconsistent findings. Namely, music
chosen by researchers or participants may lack the tempo characteristics necessary to elicit optimal results given selected work rates. In light of this, instruments capable of adjusting musical tempo such as D-Jogger, IM4Sports, and moBeat are highly relevant to this area of research. In fact, Karageorghis and Priest (58) specifically referred to moBeat as being “at the vanguard of technological development in this field” (p. 68). These authors also noted the inability of moBeat to play user-selected music, and that this instrument’s reliance on MIDI sequencing was a serious shortcoming. The perceived motivational quality of music, a highly subjective notion, is significant as well. Karageorghis and Priest (57) report on three studies comparing the effects of synchronous motivational to synchronous oudeterous (i.e., neutral) music (55,100,107), noting consistently superior ergogenic outcomes for the motivational music conditions. Motivational music has also been shown to have a greater effect on endurance when compared to acoustic stimuli composed only of rhythm (25). In order to address individual musical preferences, researchers have developed the Brunel Music Rating Inventory (56).

Although not mentioned explicitly in the original studies, the direct manipulation of musical qualities such as richness or tempo through exercise behavior represents the notion of musical agency. In this paradigm, an individual is able to control aspects of the acoustic signal, acting somewhat like a musician, though of course in a far more limited capacity. Examples of this include IM4Sports’ ability to match musical tempo to cadence and moBeat’s manipulation of musical richness in response to exercise intensity. While specific research on musical agency during exercise is limited, owing perhaps to the technical hurdles involved, studies have already shown significant results in reducing perceived exertion (39) and enhancing mood (40).
Self-Regulation Entrainment

The ability to accurately gauge and regulate exercise intensity can be improved with specific training. In particular, numerous studies have focused on the use of RPE scales to achieve this result (30,37,74,101). While specific protocols vary, RPE entrainment methods follow a common approach. Participants undergo training in what is known as the estimation trial, during which they note RPE at specific intensities. This task is typically a graded exercise test accommodating the association of RPE with different work rates. In the subsequent production trial, participants attempt to reproduce work rates corresponding to the previously reported RPE scores. This technique has been used successfully to reproduce intensity in short duration exercise bouts lasting less than or equal to 5 minutes with intervals between estimation and production trials lasting from 2 to 14 days (30,37,74). Dunbar et al. (30) reported RPE-entrained reproduction was generally accurate at exercise intensities between 50 and 70% of VO₂ max. The approach is not without certain limitations, however. In contrast to the previously mentioned study, Smutok, Skrinar, and Pandolf (101) reported inaccurate exercise intensity reproduction at work rates below 80% of maximum heart rate. The authors specifically mentioned that this technique might be unsuitable if lower/moderate intensities are sought. In addition, both Noble (82) and Byrne and Eston (17) have counseled caution when comparing estimation and production trials, especially when graded exercise tasks are used during estimation, as the two conditions may represent fundamentally different work modes. Lastly, Dishman (29) noted twenty years ago that more work on long term entrainment was required, though little appears to have been done in the intervening years.

Surprisingly, the use of augmented feedback in the entrainment of self-regulation during aerobic exercise has been limited. Only a single study appears to have attempted
this approach. Conley, Gastin, Brown, and Shaw (22) outfitted a group of children (mean age = 12.4 years) with HRMs and receiver watches during six, approximately 55-minute physical exercise (PE) sessions over the course of a 7-week intervention. Exercise modalities varied in a circuit and included “running, jumping, hopping, stepping” (p. 154). The HRMs used by participants in the feedback group were programmed to sound an alarm when heart rate exceeded 140 bpm. A teacher stopped the lesson at 5-minute intervals and asked the children to consider how hard they had been exercising. Upon completion of each session, the children were given information on actual versus self-estimated time spent exercising above 140 bpm. A control group received no feedback of any kind though their heart rates were also monitored by HRMs with taped-over displays. The researchers found no improvement in the children’s ability to estimate time spent exercising above 140 bpm when comparing pre- and post-intervention results spaced 1-week before and after the feedback sessions, respectively. Several factors may explain these results. As noted by the researchers, children may not have sufficient cognitive abilities to correctly estimate both exercise intensity and time simultaneously. More importantly, the authors noted that “no formal effort perceptual scaling metric was used however to encourage children to internalize the sensations of different physical activity intensities” (p. 155). This would suggest that a specific attentional focus strategy noting the presence and intensity of afferent cues concurrent with biofeedback might be necessary for correct entrainment. Lastly, the varied nature of the physical activity, as opposed to single-mode, steady state exercise (e.g., running or cycling) may have hindered effort-perception integration.

Heart Rate Variability and Physiological Threshold Detection

Analysis of the inter-beat intervals (IBI) of the cardiac signal is used in the study of the autonomic nervous system (ANS) and sympathovagal balance of its two branches,
sympathetic and parasympathetic regulation. Commonly known as heart rate variability (HRV) analysis, it is a widely reported technique that has been applied in a variety of disciplines including human health (9,18,62), psychophysiology (20,27,106), and exercise (10,16,23,28,43,52,59,103). Camm, Malik, Bigger, and Breithardt (19) provide an extensive overview of indices used in HRV analysis. These include both time-domain measures (STNN, RMSSD, PNN50) as well as frequency-domain statistics derived from the power spectral decomposition (PSD) of the IBI sequence. Low frequency (LF), often defined between .04 and .15 Hz, and high frequency (HF), between .15 and .4 Hz, spectral bands of the PSD are mediated by cardiac autonomic outflows and parasympathetic regulation (2,45,71), respectively.

HRV should be of particular interest to researchers interested in moderating exercise intensity, as the change in sympathovagal balance accompanying increased effort can be monitored using HRV analysis (23,24,43). In studies by Cottin et al. (23) and Cottin, Medigue, Lopes, and Petit (24), participants performed an incremental exercise task while both IBI and ventilation data were simultaneously collected. Comparison of the results demonstrated spectral HRV analysis could be used to accurately identify the two ventilatory thresholds. The first ventilatory threshold (VT1), also referred to as the anaerobic threshold (AT), represents a critical physiological transition from moderate to vigorous intensity effort (110,111). Likewise, the second ventilatory threshold (VT2), also known as the respiratory compensation point (RCP), denotes a second transition at which a given level of effort becomes unsustainable due to rising CO2 production accompanied by heavy breathing (hyperpnea) (110,111). More recent studies have continued this approach in different populations (67), using different HRV indices (59) and to additionally identify lactate threshold (LT) (43,59,99). As previously mentioned, correct identification of training zones is important for health
outcomes since moderate levels of effort are generally prescribed (50), and exercise intensity has psychological implications that may impact adherence (33,35). HRV-based techniques may one day allow a non-invasive, inexpensive alternative to current “gold standard” testing relying on gas and blood analysis.

The tools available to researchers interested in HRV analysis consist of PC-based applications such as Kubios (80) and aHRV (Nevrokard, Slovenia), software libraries such as RHRV (90), or ad-hoc computer codes. The principle disadvantage of these tools is that, typically, only post-hoc analysis is supported since IBIs must be first collected before analysis can take place. At present, there are no software libraries suitable for real-time HRV analysis using mobile technology mentioned in the scientific literature. A recent publication by Heathers (51) does describe a mobile software application and commercial heart rate monitor based on photoplethysmography (iThlete Finger Sensor: HRV Fit Pty Ltd, Hampshire, UK). However, this system is unlikely to be suitable for realistic exercise as the finger sensor is subject to motion artifacts. As the author notes when describing the experimental procedure, “the angle of the upper arm was maintained static and at rest, as changes in arm height and elbow angle have been observed to modify the pulse transit time” (p. 299). Nonetheless, this work highlights the potential for combining off-the-shelf technology with mobile software to create inexpensive, ecologically valid instruments for real-time HRV analysis.

**Emerging Research Questions and Methods**

While the need for exercise at moderate and higher intensities is unequivocal, mechanisms to support in-task adherence are limited. The need, however, is quite pressing as literature has clearly demonstrated intensity varies considerably during unsupervised exercise and is affected by external factors as well as psychophysiological cues. Objective feedback in the form of heart rate monitors has existed in the consumer
market for decades, yet techniques leveraging these and similar tools have advanced little. The advent of mobile technology able to interface with biometric sensors and deliver feedback in real time represents a novel opportunity for research. The fact that, thus far, it has not been capitalized upon in the study of steady-state aerobic exercise represents a missed opportunity to progress our understanding in multiple areas of interest including feedback, psychophysiology, skill acquisition, human/computer interaction, and software engineering. Moreover, by applying good software practice to build novel, multi-purpose instrumentation, a large community of researchers can be supported.

REFERENCES


9. Bau PFD, Moraes RS, Bau CHD, Ferlin EL, Rosito GA, Fuchs FD. Acute


36. Eriksson M, Halvorsen KA, Gullstrand L. Immediate Effect of Visual and


49. Hampson DB, Gibson ASC, Lambert MI, Noakes TD. The Influence of Sensory Cues on the Perception of Exertion During Exercise and Central


122. Yaffe K, Barnes D, Nevitt M, Lui L-Y, Covinsky K. A Prospective Study of


CHAPTER 2

The recent proliferation of mobile computing has created an unprecedented opportunity to create instrumentation for the study of augmented feedback in aerobic exercise. While commercially available mobile hardware is ubiquitous and remarkably powerful, anyone wishing to develop software suitable for research must overcome numerous challenges. Though low level software interfaces are available, virtually nothing exists in the way of more sophisticated libraries that can be assembled into domain-driven applications. The following chapter describes an extensive, reusable collection of software components and a complete mobile application integrating them into an instrument suitable for research. The design encapsulates biometric input from numerous sensors (e.g., heart rate, cadence, power), a flexible auditory feedback engine, and an extensive capability to work with personal music. This work forms the foundation of a powerful toolkit used throughout several of the proceeding studies.
ABSTRACT

The present work describes a collection of reusable software components and a mobile software application named Tempony that can be used as a flexible instrument for exercise feedback research. The application runs on the family of Apple iOS devices and integrates multiple 3rd party biometric sensors supporting the Ant+ and Bluetooth 4.0 protocols. Tempony allows researchers to use a single device capable of receiving biometric inputs, providing acoustic stimuli in real-time, and recording performance results in a portable, ecologically valid form using off-the-shelf, readily available components.

KEYWORDS

iOS, heart rate, music, application, cadence, biometrics

INTRODUCTION

The continual flow of information acquired by human senses during physical activity is referred to as inherent feedback (30). In contrast, augmented feedback is provided externally, by way of coach, computer, or instrument. Ultimately, feedback provides its receiver with a knowledge of result (KR), considered an essential element in motor learning and skill acquisition (23). The release of the Polar Sport Tester PE 2000 in 1982, a wireless, portable heart rate monitor, introduced instrumental augmented feedback to a wide audience of recreational and competitive athletes. In the decades since, Polar, Garmin, Suunto, and many other commercial vendors have continued to refine this design to the point that the consumer heart rate monitor is now ubiquitous.
Though undeniably a kind of mobile computer, a heart rate monitor provides only limited forms of feedback, typically through a visual display and auditory alarms.

Although exercise sensors such as heart rate monitors and foot pedometers have become commonplace in research settings, few projects have attempted to integrate them into more complex, dynamic instruments. In an exception to this, Phillips Research created the IM4Sports system (35) incorporating a proprietary, portable mp3 player and heart rate sensor to examine the influence of adaptive music selection on exercise. Furthermore, D-Jogger (26) and moBeat (33) were PC-based prototypes developed to explore, among other things, the effects of music on endurance exercise. These systems gave their designers the ability to construct protocols otherwise impractical or even impossible using existing equipment. They were not, however, without their limitations. Whereas moBeat was capable of altering tempo in response to exercise intensity, it relied on synthesized MIDI music rather than conventional audio recordings, thus reducing its utility with popular and familiar forms of music. D-Jogger and moBeat further suffered from a lack of portability, since a PC was required to run both systems. Though portable, IM4Sports was a one-off prototype and no further work appears to have been done on it. The capability of such systems, as well as their shortcomings, are instructive as we look toward even more powerful tools.

So-called “smart phones” have proliferated since the introduction of the Apple iPhone (Apple Inc., Cupertino, CA) in 2007. Beyond what the name might suggest, these devices are in fact powerful, programmable mobile computers with a variety of on-board sensors, increasingly fast microprocessors, and often continuous Internet connectivity. For many users, their mobile phones also store vast amounts of personal music and act as a principal gateway to social media. Obviously developed with portability in mind, modern mobiles are built robustly and offer reasonably long battery
life. In addition, an ever-growing array of wireless peripherals is becoming available, many specifically designed for exercise. Heart rate monitors, bicycle power meters, and even glucose monitors can now communicate directly with mobiles using common, industry-standard protocols. Economies of scale and continuous improvement have created a marketplace of affordable, ubiquitous commercial hardware that can be leveraged by investigators willing to use them as a platform for novel instrumentation. Recent work in public health has directly integrated mobile computing into research, dramatically improving sample sizes over traditional methods and implementing novel protocols thus creating new opportunities for investigation. Killingsworth and Gilbert (20) examined concentration and attitude in over 2200 subjects using a mobile Web application, and Shiyko, Lanza, Tan, Li, and Shiffman (31) demonstrated success at implementing a smoking cessation intervention using similar mobile technology. As public health researchers have steadily embraced this new technology (4,7,8,10,24), surprisingly little use of it has been made in the field of exercise research. A review of 71 journal articles citing the previously mentioned software systems as well as a keyword search for “mobile AND exercise” fails to show a single new instrument leveraging modern mobile computing during aerobic exercise. Like the applications that have come before, the focus of the present work is primarily on auditory stimulus. Although mobiles possess sophisticated touch screens suitable for such highly interactive activities such as gaming, visual disruption during exercise may, at the very least, be distracting and, at worst, dangerous, especially in ecologically valid settings. However, visual acuity does not appear to degrade with the addition of limited auditory information (34) leaving us to consider primarily acoustic mechanisms.

Any review of the effects of auditory stimulation during exercise would be incomplete without a discussion of music. The influence of music on exercise has been
studied in a variety of aerobic disciplines including walking, running, cycling, swimming, and rowing (2,14,15,22,27,32) and has been the subject of several reviews (19,16,17). Listening to music during exercise can reduce feelings of fatigue (6), provide a general sense of motivation (18), and improve mood (22). The interplay of rhythm perception and bodily movements results in a phenomenon known as auditory-motor coupling (21,25). Movement synchronized with music in such a way has been shown to reduce oxygen consumption (3,32), improve time to volitional exhaustion (32), reduce limb discomfort (22), and improve running economy (5). Recent studies have expanded the traditional uses of music by introducing the concept of agency into the experience (11,12) whereby a user’s behavior generates aspects of the music they hear. Musical stimulus has even shown promise as a complementary therapy in the rehabilitation of stroke (1,28,29) and Parkinson’s disease (9,13). Subsequently, the aim of this work was to integrate newly available mobile technologies into a comprehensive instrument suitable for research.

METHODS

The software described in the present study is written in the Objective-C language and targets the iOS family of Apple mobile devices (e.g., iPhone, iPad, and iPod Touch). The choice of platform was driven by several considerations. At the time of the initial work, iOS was unique among mobile operating systems in supporting biometric sensors through the use of an inexpensive 3rd party hardware accessory, the Wahoo Key (Wahoo Inc., Atlanta, GE). The Wahoo Key, along with an accompanying application programming interface (API), freely available from Wahoo, allows iOS devices to receive signals from a variety of Ant+ compatible peripherals. Ant+ is an industry standard wireless communication protocol used by many device manufacturers, particularly in the exercise and health domains. Products ranging from heart rate
monitors to bicycle power meters broadcast telemetry over Ant+. Additionally, iOS exposes a flexible, low latency audio API closely integrated with the underlying hardware upon which novel audio applications can be developed. The iOS platform also enables direct access to a user’s personal music collection with a further ability to receive decompressed, pulse code-modulation (PCM) audio samples from the dedicated on-board hardware, thus creating an opportunity to directly manipulate music in real-time. The present work will first describe an extensible audio architecture built specifically for this study. This will be followed by the presentation of a complete mobile application integrating the audio library with various other components producing a general instrument suitable for research.

**Audio Playback**

**Audio Engine.** The iOS family of devices includes audio playback and recording hardware supporting 16-bit, stereo output at a sample rate of 44.1 kHz, an industry standard representing CD quality. These numbers refer to what is known as *uncompressed* audio as opposed to compressed formats such as mp3 in which acoustic information has been sacrificed in order to reduce file size. iOS exposes a set of software libraries, CoreAudio, which provide low-latency access to the underlying audio hardware. Using CoreAudio, a sample-level playback engine, AudioEngine, and classes for decoding compressed audio stored on the device have been created. The AudioEngine is a mixer that takes multiple audio streams and combines them into a single output, a process often referred to as “muxing” in the terminology of audio engineering. The lowest unit of input/output within the architecture is a single byte. In the context of the 16-bit audio environment supported by iOS, this simply means that a single frame of audio in a single channel consists of 2 bytes. Therefore, a stereo signal contains 4 bytes per frame, 2 for the left channel and 2 for the right. Here, audio is
represented as a repeating sequence of left/right/left/right samples, referred to as an *interleaved* format. At 44.1 kHz, there are 44,100 frames per second, *per channel*, or 176,400 total bytes per second in a stereo signal. The *AudioEngine* reads these bytes continuously from a collection of *AudioSource* objects, mixes them, and finally renders the result to the audio hardware. It should be noted that source audio must be uncompressed; therefore, the framework that has been developed includes components to address the extraction of raw audio from compressed formats. If there is insufficient source audio for the *AudioEngine* to process, it simply passes through silence by rendering an appropriate quantity of zero-valued bytes. The architecture of this audio playback system is illustrated in Figure 2.1.

**Audio Stream Architecture.** *AudioSource* represents an interface, a kind of contract between software components. Specific implementations of *AudioSource* are actually responsible for implementing the logic the interface guarantees. In general, such designs support the principle of encapsulation, simplifying and supporting the interoperability of software components. The primary responsibility of an *AudioSource* is to provide uncompressed audio bytes to the *AudioEngine*. The specific way in which it may do this is only relevant to its internal functioning and not to external components. Within the current design, there are three distinct types of *AudioSources*, two for audio assets and one for metronomes. The first asset source is *ExtAudioFileReader* and may be used when music or audio can be located on the device as a physical file. This is true in the case when some piece of audio is bundled directly into an application or uploaded, via iTunes, into its workspace. *ExtAudioFileReader* may be used to read source audio from either compressed (mp3 or m4a) or uncompressed (WAV) audio files at a specified sample rate and can convert mono to stereo, or vice versa, in real-time. Audio files stored on the device and synced via iTunes require a different approach. The
iOS family of devices shares a history with Apple’s pre-iOS iPod music players. As such, they use a proprietary multi-media database that does not offer file-level access.

*Figure 2.1. Class diagram depicting Tempony AudioEngine architecture.*
Fortunately, the CoreAudio framework does provide a way to access and decode these audio assets leading to the implementation of AVAudioSource. This component reads audio directly from iTunes music assets stored on the device. As with ExtAudioFileReader, AVAudioSource shares the AudioSource interface and can deliver uncompressed audio bytes with a specified sample rate and channel number.

Whereas the previously described AudioSource directly correspond to specific, discrete audio files, a more flexible class of metronomes has also been developed. Rather than streaming data from a single audio file, metronomes construct a source of bytes in real time by continuously sequencing the contents of a short audio sample representing a “beep” or a “snap” with an appropriate quantity of silence. The end result is a continuous metronome whose tempo, or beats per minute (bpm), can be controlled in real time. In this way, a metronome is effectively endless, though it can be paused or muted to remove it from the final audio mix. The flexibility of this design has allowed for the creation of metronomes with varying tones and tempos depending on performance relative to biometric targets. For example, a heart rate metronome can change tone signaling whether a user is above or below a target training zone making it easier to differentiate between the need to increase or decrease intensity. On the other hand, a metronome providing feedback for cadence is designed in such a way as to mimic a particular target tempo that may be individually prescribed. Thus, a single AudioSource designed in this fashion can serve multiple users. Metronomes for heart rate (HRAudioSource), cadence (SnapAudioSource), and power (PowerAudioSource) have been developed in this fashion (see Figure 2.1). Of course as previously mentioned, some, or all, AudioSource may be silenced using their respective volume settings as appropriate for a given feedback condition.
**Tempo Shifting.** The ability to manipulate musical tempo (i.e., tempo shifting) was a key design goal of the software. Tempo shifting, as opposed to simply controlling the playback rate, results in audio without any accompanying artifacts (i.e., the “chipmunk” effect). Though different tempo shifting methods exist, the open source audio processing library *SoundTouch* (Oli Parvainen, Finland) was chosen and integrated directly into the *AudioEngine*. *SoundTouch* is computationally efficient and designed for real-time applications as all processing is done in the time domain and independent tempo and pitch adjustment is supported. If tempo or pitch settings on *AudioEngine* warrant it, decompressed audio samples from a music source are passed through a *SoundTouch* processor prior to mixing with other streams. The resulting audio buffer may contain more (in the case of slowing tempo) or fewer (in the case of increasing tempo), bytes than the original buffer. Subsequently, a lightweight first-in-first-out (FIFO) buffer is used to store and read music data.

**Mobile Software Application**

Tempony is an iOS mobile application integrating the previously described audio components with a variety of additional features. The following describes aspects of the software including sensor support, the graphical user interface, feedback, scripting, storage and retrieval of exercise sessions. Several screens from the application, including the initial “home” screen, are reproduced in Figure 2.2.
Biometric Input. Current iOS devices natively support Bluetooth 4.0 (BTLE) while older devices can communicate with Ant+ peripherals through the addition of a Wahoo Key. At present, Tempony provides support for four sensors that are particularly relevant for cyclical aerobic exercise research. These are heart rate monitors, bicycle cadence sensors, foot pedometers, and bicycle power meters. Certain sensors like bicycle/speed units or crank-based power meters provide more than one biometric measure within the same data structure, so Tempony inspects the incoming signals to extract as much meaningful information as possible. As data are received, a state object is updated, and the signal is globally rebroadcast such that other software components are notified of the change. This architecture can be considered a software bus for biometric data (see Figure 2.3). Presently, the Wahoo software library limits the number of simultaneous sensor signals that can be received to three, and Tempony has been successfully run simultaneously receiving heart rate, bicycle power, and bicycle cadence. Since running and bicycling metrics are mutually exclusive, the current implementation is sufficient to capture relevant signals for each discipline. New sensors will be integrated as they become available.
Figure 2.3. Illustration of the biometric message bus integrating heart rate (A), foot cadence (B), bicycle cadence (C), and bicycle power (D). Exercise data are broadcast to the bus which then passes them on to subscribing components such as the user interface, database, and software components managing feedback.

Data Storage & Retrieval. Tempony uses an internal data store to record exercise session information. Depending on sensor availability, Tempony can store heart rate, foot/bike cadence, bike power, and GPS coordinates at one-second intervals for the duration of a recording session. An object model encapsulates all data related to an exercise session. This entity is then persisted to an embedded relational database management system (RDBMS) using a data access object (DAO). SQLite is currently used as the RDBMS. The use of a dedicated RDBMS instead of an object-relation mapping (ORM) tool provides a degree of flexibility in post-processing the captured
data. For example, it would be possible to aggregate multiple recorded sessions from different devices by directly accessing the relevant embedded databases. The fact that an entire SQLite database is represented by a single file makes this all the easier. Workouts can be recalled directly within the application and scatter plots of heart rate over time may be viewed (see Figure 2.4). In addition, individual recordings may be exported to a comma-separated values (CSV) file compatible with Microsoft Excel, and early support for uploading data to social media has been implemented.

**Figure 2.4.** Tempony workout recall and plotting screens. **Figure 2.4A.** Listing of all recordings. **Figure 2.4B.** Heart rate plot over time. **Figure 2.4C.** Summary statistics overlay.

**Sequential Training Design.** Modern endurance training often involves performing at multiple training intensities within the same exercise session. For example, a 10-minute warm-up followed by 30 minutes at a particular intensity, and finally concluding with a 5-minute cool down. In seeking to accommodate such structured training, Tempony implements a type of “workout builder” consisting of a model and timing framework. The model is described by individual objects
implementing a FeedbackVolumeProvider interface providing duration, upper/lower value limits, and mechanisms for dictating feedback parameters. These FeedbackVolumeProviders are, in turn, added to a Workout. A class diagram for this architecture is available in Appendix 2.C. This paradigm can be used to build a sequential workout with multiple training parameters.

Figure 2.5. Creating sequential workouts in Tempony. Figure 2.5A. Adding a heart rate, bike cadence, bike power, or foot cadence based Workout. Figure 2.5B. A series of sequences are added to each workout consisting of a duration and feedback boundaries. Figure 2.5C. Feedback boundaries and durations are defined for each Sequence.

Tempony allows one to build such workouts providing feedback relative to heart rate, cycling cadence, running cadence, or cycling power. Workouts are persisted within the application and are editable. Once a Workout is selected, it is passed to a WorkoutTimer that mediates the activation of the FeedbackVolumeProvider objects and broadcasts event notifications upon the start and end of the Workout as well as the transitions between feedback sequences. A centralized FeedbackController mediates between the feedback parameters, the AudioEngine, and various AudioSources, performing functions such as starting and stopping metronomes, adjusting tempo, and controlling feedback volume. This is accompanied by a comprehensive user interface for the creation, editing, and selection of Workouts (see Figure 2.5). In practice, a user
creates a *Workout*, or selects a pre-existing one, and starts it. Once underway, the relevant biometric signals are passed down to the current *FeedbackVolumeProvider* which returns the appropriate parameters. Then, the *FeedbackController* uses this information to drive auditory feedback, though this may sometimes mean no feedback at all. Specific details about the implementation of *FeedbackVolumeProviders* are provided in the following section.

**Configurable Feedback.** It would be impossible to predict all the ways in which feedback might be administered during exercise, and extremely inefficient to alter, recompile, and redeploy the application every time a change is needed. Tempony, therefore, provides a way to externalize real-time control of various aspects of the feedback delivered by the application using a runtime JavaScript interpreter. JavaScript is a lightweight programming language ubiquitous in online development and is used within nearly all Web browsers including the one built into iOS, Safari. Tempony is able to process logic defined in JavaScript and retrieve the results. The advantage of this solution is that these JavaScript code blocks, known as “functions”, exist outside of the principal Tempony application where they are freely editable. As previously described, a series of internal components mediates communication between Tempony and these functions at runtime, passing biometric and state information to them, retrieving values for feedback, and then applying these to the various feedback channels within the application (see Appendix 2.B). The previously described *FeedbackController* manages this overall process. Listing 2.1 gives an example of a JavaScript implementation controlling the volume of *HRAudioSource*, the metronome providing heart rate feedback. Note the function takes into account whether music is currently playing and ramps volume accordingly. Currently, the auditory feedback channels that fall under this purview are the *HRAudioSource, SnapAudioSource, PowerAudioSource*, and the
several components managing music. A complete reference implementation for all currently supported functions is provided in Appendix 2.C.

```javascript
/** Heart rate metronome volume calculation.
 * @param hr Current heart rate
 * @param playing Is music currently playing?
 * @param upper The upper heart rate limit of the current feedback zone.
 * @param lower The lower heart rate limit of the current feedback zone.
 * @param percent From 0 -> .5. Defines how far from the center feedback
 * should begin creating a no feedback central band (e.g., .45 means no
 * feedback in the middle 10% of the band)
 * @return A value between 0 and 1, <=0 will pause the metronome, 1
 * indicates play full volume
 */
function volumeForHR(hr, playing, upper, lower, percent) {
    var diff = Math.abs(upper - lower);
    var per = percent * diff;

    // these are the inside edges
    var upper0 = upper - per;
    var lower0 = lower + per;

    // three conditions to get through right away
    if(val >= lower0 && val <= upper0) {
        // this is the central band
        return 0;
    } else if(val >= upper) {
        // above the upper bound
        return 1.;
    } else if(val <= lower) {
        // below the lower bound
        return 1;
    }

    var t = 0.;
    if(val > upper0 && val < upper) {
        // how var in are we
        t = (val - upper0)/(upper - upper0);
    } else if(val > lower && val < lower0) {
        t = (lower0 - val)/(lower0 - lower);
    }

    var send = playing ? Math.sqrt(t) : (t*t);
    return send;
}
```

Listing 2.1. Sample JavaScript Functions for Real-Time Control of HR Metronome

CONCLUSION

The present study describes a collection of software representing a significant advancement in acoustic feedback and stimulation during exercise. This software both addresses the shortcomings of previously reported systems and offers novel functionality. Specifically, a mobile architecture ensures the ability to use these tools in ecologically valid environments untethered to the constraints of the exercise laboratory.

A variety of wireless biometric sensors have been integrated using a scalable design that
will include more as they become available. The use of existing consumer-off-the-shelf components yields an inexpensive, ubiquitous platform that can scale easily with researcher requirements. To the author's knowledge, this is the first such instrument directly leveraging consumer mobile devices and sport-specific peripherals. We have implemented a flexible audio playback architecture encompassing both dynamically generated and pre-recorded acoustic signals including an extensive ability to independently adjust musical tempo and pitch in real time. Biometric data and acoustic feedback are tied together via an extensible, real-time framework capable of accommodating nearly infinite protocols for novel investigation. Lastly, all functionality has been encapsulated within a single mobile software application including the ability to parameterize feedback sessions, access user-selected music, and store and retrieve exercise session data.

REFERENCES


7. Buhi ER, Trudnak TE, Martinasek MP, Oberne AB, Fuhrmann HJ, McDermott RJ. Mobile Phone-Based Behavioural Interventions for Health: a Systematic


22. Lim HA, Karageorghis CI, ROMER LM, Bishop DT. Psychophysiological


CHAPTER 3

After successfully creating a software instrument for biofeedback research in Study 1 of this thesis, attention turned to using it for experimentation. The present study focused on developing and testing a novel form of auditory, heart rate-based feedback to improve self-regulation during exercise. This was compared to the current gold standard (i.e., high/low alarms) as widely implemented in consumer heart rate monitors. While research in motor skill acquisition has extensively studied different methods of feedback, relatively little work has focused specifically on approaches to heart rate-based feedback during exercise. Implementation of different forms of auditory feedback was greatly simplified through the use of the previously developed software. Moreover, much of the experimental protocol was directly implemented within the software as well.
ABSTRACT

**Purpose.** The purpose of this study was to compare the effectiveness of two forms of heart rate-based auditory feedback in regulating effort during moderate intensity exercise. **Methods.** Fifteen participants were exposed, in a repeated measures fashion, to one of 2 different feedback conditions and a silent control during 20 minutes of moderate intensity exercise on an indoor stationary bicycle. Feedback conditions included either a boundary-style feedback emulating current heart rate monitors consisting of a sequence of auditory “beeps” heard only when heart rate fell outside the target training zone, or a novel form of continuous feedback developed specifically as part of this study. Time in Zone (TIZ), defined as the ratio of the time spent within the target training zone divided by the overall time of exercise, rating of perceived exertion (RPE), and subjective measures of association, dissociation, and distress were compared across feedback and control conditions using one-way, repeated measures ANOVA. **Results.** TIZ increased significantly in both the continuous ($M \pm SD: .99 \pm 0.01$) and boundary ($94 \pm 0.05$) conditions over control ($52 \pm 0.40$) and was significantly greater for continuous versus boundary, all $ps <= .01$. RPE did not change significantly under different feedback conditions. Dissociation was significantly reduced under continuous feedback compared to both control, $p < .01$, and boundary, $p < .05$. No significant differences in association or distress across conditions were present, though a moderate effect size, *Cohen’s d* = .55, for association was observed between continuous and boundary conditions. **Conclusion.** Using a novel form of continuous auditory feedback results in improved TIZ as well as a reduction in dissociation when compared with
traditional boundary-style feedback and may be useful when strict adherence to exercise intensity is required.

KEYWORDS

iOS, mobile, heart rate, self-regulation

INTRODUCTION

The sedentary lifestyle common in much of the Western world leads to a variety of health problems and has been linked to obesity, type 2 diabetes, cardiovascular disease, and cancer (28), among other deleterious conditions. These issues can be ameliorated, however, through physical activity (24). Outcomes ranging from fat loss (36) to improved cardiovascular fitness (7) can be accomplished through training at specific exercise intensities. Though researchers tend to prescribe these intensities in terms of oxygen consumption (%VO₂ Max), they can generally be translated into heart rate targets (20,42) that are easier to follow. Despite these documented health benefits, a large percentage of the population fails to exercise sufficiently. In the US, nearly 50% of adults fail to meet target guidelines for aerobic physical activity (25).

Compounding this lack of exercise, even when aerobic activity is performed, many individuals struggle to maintain sufficient intensity to fully reap the benefits of exercise. Ekkekakis, Lind, and Joens-Matre (15) reported, for example, that individual self-selected exercise intensities can vary widely, and Grimwade, Angus, and Beneke (23) have suggested that individuals significantly underestimate effort when moderate to vigorous intensities are prescribed. External factors can further confuse effort perception. Ironically, specific verbal instructions to exercise at a moderate intensity have been shown to introduce significant variability in self-selected exercise intensity (3). Temperature can influence both perceived exertion and heart rate during exercise.
as can spatiotemporal effects such as the rate at which scenery passes by during activity outdoors (i.e., optic flow) (35). Psychological effects may also influence effort regulation. For instance, autonomous priming prior to exercise has been shown to elicit higher intensity yet lower RPE compared to a controlled motivation prime (2). Exercise intensities exceeding the anaerobic threshold lead to a sharp rise in feelings of displeasure and may further compromise adherence (14). Clearly, subjective self-regulation relying only on internal sensory cues has limitations.

Fortunately, objective classification of exercise effort is possible using inexpensive commercial instrumentation. The consumer heart rate monitor (HRM) is perhaps the most widely used piece of equipment providing feedback during exercise. HRMs have been broadly available since the introduction of the Polar Sport Tester PE 2000 in 1982 and have become ubiquitous, inexpensive tools with demonstrated accuracy (19). HRMs and similar instruments provide their users with external, or augmented, feedback as opposed to inherent feedback delivered through human senses alone. Ultimately, all feedback provides its receiver with a knowledge of result, and such knowledge is an essential element in learning supporting the necessary changes needed to improve results (30). Although many features of HRMs have evolved over the past 30 years, the nature of the feedback they provide has changed little. A visual display and auditory “high” and “low” alarms provide feedback relative to a defined target training zone. The auditory aspect of this type of feedback can be considered a form of bandwidth feedback, wherein feedback is only received when performance, in this case heart rate, deviates outside a central “band”. Bandwidth feedback has been broadly studied in the context of motor learning (22,29,41) and is one of the mechanisms proposed for overcoming a peculiar paradox of feedback. Namely, that while some external feedback is often necessary for sufficient knowledge of result, too much
feedback often degrades performance (39,40). Although a conclusive explanation for this finding has not yet been determined, researchers have proposed that frequent feedback can interfere with internal error-detection mechanisms (37,46) while introducing maladaptive behavior (40) during the acquisition phase of learning. The occurrence of such negative consequences, however, has been largely observed in motor learning tasks. When applied to cyclical aerobic activities (e.g., running, cycling, swimming), higher frequency concurrent feedback mechanisms appear to enhance performance. In contrast to the bandwidth approach, such models provide feedback in real time during exercise and have been shown to improve specific performance in a variety of aerobic disciplines such as running (16), cycling (6,11,32,38), and swimming (9). External factors, feedback or stimuli, can not only influence performance directly, but may also affect attentional focus during activity (43). Dissociation, or shifting attention away from bodily sensations and task-specific details, is a common strategy employed during exercise and is often favored by less experienced athletes (4). In contrast, association denotes an inward focus on physical cues (e.g., breathing, skin temperature, peripheral strain) and is often favored by more practiced athletes (4). Previous findings (43) suggest that external feedback can significantly reduce dissociation during aerobic exercise tasks.

While an extensive body of literature exists documenting the effects of augmented feedback in motor learning, surprisingly little work has been done in the context of regulating exercise intensity. The basic metaphor of high/low auditory alarms introduced in early HRMs continues to this day. Several projects, however, have created new interactive instruments for use during exercise (33,43,44). D-Jogger (33) and moBeat (43) were PC-based software applications using musical feedback to guide training intensity, while the IM4Sports system was built around a one-off mobile
prototype (44). No further work appears to have been done on these instruments, however, and there is little literature describing new systems targeting aerobic exercise and acoustic stimuli. The underlying technical difficulties associated with building ad-hoc instrumentation capable of receiving heart rate data and responding with feedback in real time may, at least in part, explain the dearth of research in this area.

Fortunately, the proliferation of mobile computing in recent years offers new opportunities to further develop feedback instrumentation leveraging off-the-shelf consumer technology. Today’s mobiles represent increasingly powerful, programmable computers capable of receiving biometric input from a variety of consumer-level sensors common in exercise. These include heart rate monitors, power meters, and foot pedometers, among others. For the researcher, this represents a flexible platform on which original forms of feedback can be created and perhaps eventually translated to the consumer market. The present study will describe a novel form of heart rate-based auditory feedback using aspects of both bandwidth and continuous approaches and implemented as part of an ad-hoc mobile software application. We compare this with a more traditional form of feedback representing the current “gold standard” as found in commercial HRMs which we will refer to as boundary feedback. We will contrast the effectiveness of the two during a moderate intensity exercise task focusing on time in zone (TIZ), defined as the ratio of the time spent within a target training zone divided by the overall time of exercise, as an objective measure of performance. We hypothesized that a continuous form of feedback would significantly improve TIZ compared to boundary feedback owing to participants repeatedly relying on the latter to gauge the limits of their individually prescribed zone. In addition, we predicted that both kinds of feedback would reduce dissociation by drawing attention back to the exercise task, and that continuous feedback would produce a greater reduction in
dissociation compared to bandwidth owing to increased overall feedback frequency. Lastly, we will discuss the implications of our findings for future heart rate feedback devices.

METHODS

Subjects. Fifteen healthy adults (10 male, 5 female) aged between 21 and 76 years old participated in this study. Effective sample size was computed utilizing the technique described in Cohen (10) with $\alpha = .05$ and $\beta = .2$. Anthropometric measures are summarized in Table 3.1.

<table>
<thead>
<tr>
<th>Subjects</th>
<th>Age (years)</th>
<th>Height (cm)</th>
<th>Weight (kg)</th>
<th>LTEQ Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>N = 15</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>49.3</td>
<td>174.0</td>
<td>77.9</td>
<td>41.3</td>
</tr>
<tr>
<td>SD</td>
<td>14.1</td>
<td>6.0</td>
<td>9.9</td>
<td>26.5</td>
</tr>
<tr>
<td>Max</td>
<td>76.0</td>
<td>180.0</td>
<td>93.1</td>
<td>94.0</td>
</tr>
<tr>
<td>Min</td>
<td>21.0</td>
<td>156.5</td>
<td>60.7</td>
<td>0.0</td>
</tr>
</tbody>
</table>

LTEQ, Godin Leisure–Time Exercise Questionnaire.

Potential subjects were screened according to body mass index (BMI), and those categorized as obese (BMI > 29.9) were excluded from the study. Participants completed the Physical Activity Readiness Questionnaire (PAR-Q) (8), all answering “No” to the health-related questions, and were subsequently assumed physically fit to participate in the study. The Godin Leisure-Time Exercise Questionnaire (LTEQ) (21) was used to assess current activity levels. The LTEQ specifically addresses “planned, structured leisure activity performed outside of structured sport commitments” of at least 15 minutes and breaks the responses down by the number of “strenuous”, “mild”, and “moderate” sessions performed during the last 7 days. These responses are then
aggregated into a single value using Godin’s formula (21): \( 9 \times \text{the number of strenuous bouts} + 5 \times \text{the number of mild bouts} + 3 \times \text{the number of moderate bouts}. \) Ethics approval was received from the Human Research Ethics Office at the University of Western Australia, and all subjects provided written informed consent after receiving an explanation of the experimental procedure.

**HRmax Assessment.** All subjects completed a graded exercise test to volitional exhaustion using an indoor cycling ergometer connected to a personal computer running a proprietary software program displaying target and current wattage. Participants were outfitted with a heart rate monitor worn around the thoracic region broadcasting to an ad-hoc software program running on a mobile device (iPhone 4, Apple Inc., Cupertino, CA) and monitored by the researcher. After a 5-minute warm up, males were instructed to begin cycling at 100 W while females began at 75 W. At 1-minute intervals, target wattage increased by 25 W, and participants were instructed to match the new target using displays on a computer screen positioned in front of them. Participants continued pedaling until they were no longer able to match target wattage, at which time a maximum achieved heart rate (HRmax) was recorded for each individual. All participants were encouraged to complete the final 1-minute stage before quitting if possible.

**Software Instrument.** A mobile software instrument (Tempony) was used as part of this study to provide feedback relative to heart rate and monitor results. Tempony is an iOS application compatible with the Apple family of mobile devices (iPhone, iPad, iPod Touch) and was run on a dedicated 4\(^{th}\) generation iPod Touch running iOS version 5.01. The application has been developed as part of ongoing research into mobile instrumentation for exercise. The software is able to receive continuous heart rate data from Ant+ compatible HRMs through the use of a 30-pin hardware “dongle” (Wahoo
Key, Wahoo Inc., Atlanta, GE) and a 3rd party software library provided by the vendor (Wahoo API). Ant+ is an industry standard 2.4 GHz wireless protocol supported by a wide variety of hardware vendors catering to the health and fitness industry. All subjects were outfitted with identical hardware and software consisting of a Wahoo HRM, an iPod Touch running the Tempony software, a neoprene armband housing the device, and a pair of in-ear headphones (Sennheiser CX300II, Sennheiser, Germany).

The Tempony software was augmented to implement two feedback conditions. **Boundary condition** feedback implemented the “gold standard” found in consumer HRMs. At 15-second intervals, current heart rate was evaluated against a personal, moderate intensity training zone defined between 70 and 80% of HRmax. Exceeding the upper boundary triggered a “high” alarm consisting of 3 rapid repetitions of 3 bursts of a high-pitched note. Conversely, a “low” alarm, triggered by heart rate falling below the lower boundary, consisted of 4 slow repetitions of a low-pitched pulse. Thus, high and low alarms were distinguished by both pitch and phrasing. A **continuous feedback condition** was implemented as a dynamic metronome. Within the center of the target training zone, a further central band was defined at 10% of the overall boundary width (i.e., from 74.5-75.5% of HRmax). No feedback was administered when heart rate fell within this central band. Thus, this mechanism displays characteristics of both concurrent/continuous and bandwidth feedback. When heart rate exceeded or fell below the central band, a continuous metronome played with a tempo, or beats per minute (BPM), matched to current heart rate. This metronome was further delineated into a high and a low realization with the high metronome using a sharp EKG-like sample and the low metronome using a lower pitched sample of a human heartbeat. Additionally, the metronome’s volume was increased or attenuated in proportion to the current heart rate’s distance from the central band. At, or exceeding, the borders of the target training
zone, the metronome played at full volume. Approaching the 10% central band, volume declined as the square of the distance from the central band to the edge, thus volume increases were smaller in the beginning as heart rate first left the central no-feedback band. This mechanism is illustrated in Figure 3.1. Upon startup, the software adjusted the iPod’s hardware volume to 80% of maximum in order to normalize volume across all subjects and testing sessions. The Tempony software allows one to implement state logic in real time through a series of scripts, written in JavaScript, which are external to the central application itself but are evaluated by it. The code for determining continuous feedback volume as described is provided in Appendix 3.A. Lastly, a no-feedback control was defined during which no auditory feedback of any kind was administered. Tempony implements the creation of fixed time increments (e.g., 20 minutes) supporting each of the two feedback conditions and silent control, during which heart rate data are recorded to an internal database, evaluated within the context of the specific feedback condition, and the appropriate form of auditory feedback is delivered. This is managed at 1-second increments through an internal timer. Upon completion of the fixed time block, the software played a pre-recorded message to the participant advising them that the session was over.

**Feedback Testing.** Starting at least 1 week after the graded exercise task, each participant performed 3, 20-minute exercise sessions while exposed to one of the two feedback conditions (i.e., boundary, continuous) or a silent control using a repeated measures design. Session order was created using a balanced, Latin squares design (45) resulting in six possible sequences to which subjects were randomly assigned. All exercise was performed on an indoor stationary bicycle (Healthstream MB103, Healthstream Sdn. Bhd., Malaysia) while using the Tempony software, and individual sessions were spaced at least 1 week apart. This model of bicycle uses a relatively quiet
belt drive, and all testing was conducted in a small, climate controlled exercise laboratory isolated from ambient noise. Following the completion of each exercise session, subjects completed a brief questionnaire consisting of a 14-point rating of perceived exertion (RPE) scale (26) and the Attentional Focus Questionnaire (AFQ) (5). The AFQ is a 30-item instrument composed of 3 subscales assessing association, dissociation, and distress during physical activity using statements such as “Letting your mind wander” (dissociation), “Focusing on staying loose and relaxed” (association), and “Thinking about how much the rest of the exercise session will hurt” (distress). Response options were anchored on a 1 (“I did not do this at all”) to 7 (“I did this all the time”) scale.

Figure 3.1. Illustration of high/low metronomes and changes in volume associated with changing heart rate. X-axis: time (seconds). Y-axis: % of HRmax. Upper and lower dashed lines represent limits of a moderate target training zone (i.e., 70-80% HRmax) at which volume feedback is maximum. Middle dashed lines correspond to a 10% central band where no feedback is applied (i.e., silence).

**Attitudinal Measures.** Subjects’ instrumental and affective attitudes towards the use of mobile feedback software during exercise were measured prior to, and again after the conclusion of, all testing sessions using an instrument based on the Theory of
Planned Behavior (TPB) (1,12). This was comprised of a 6-item questionnaire using a bipolar scale ranging from 1 to 7 responding to the single question “Using mobile phone software to provide heart rate feedback during exercise would be…” The items were divided into three affective (unenjoyable-enjoyable, unpleasant-pleasant, uncomfortable-comfortable) and three instrumental (beneficial-harmful, worthless-valuable, undesirable-desirable) subscales, and mean scores were calculated separately for the two measures.

**Data Analysis.** TIZ was calculated for each session by evaluating the second-by-second heart rate recordings. The initial “warm up” data prior to the subject first reaching 70% of HRmax was removed so as to not bias the results based on how quickly participants first entered the target training zone. After reliability analysis, one item was removed from the AFQ association subscale and three removed from the dissociation subscale. Subsequently, Cronbach’s α exceeded .73 for all AFQ subscales. TIZ, RPE, and the adjusted AFQ subscales were then evaluated across feedback conditions using individual repeated measures ANOVA. Likewise, baseline and post-completion instrumental and affective attitude scores were compared using one-way, repeated measures ANOVA using time as the factor.

**RESULTS**

Performance and subjective results across feedback conditions are presented in Table 3.2. A significant difference in TIZ was observed using Greenhouse-Geisser correction, \( F(1.03,14.43) = 19.61, \ p < .01, \ \eta^2_p = .58. \) Post-hoc comparison using Bonferroni correction revealed significant differences in TIZ across all feedback conditions, all \( ps <= .01, \) with both the boundary and continuous conditions exceeding control, and continuous exceeding boundary. Pairwise comparison of effect sizes across
feedback conditions yielded all Cohen’s $d \geq 1.33$. No significant differences in RPE were detected, $F(2,28) = .75, p > .48, \eta^2_p = .05$. A significant overall difference was observed in association, $F(2,28) = 3.78, p < .04, \eta^2_p = .21$, but post-hoc comparison did not show significant differences, all $ps \geq .19$, between individual feedback conditions. However, there was a moderate effect size ($d = .55$) for the magnitude of the difference between continuous and boundary feedback. A significant difference in dissociation, $F(2,28) = 5.37, p = .01, \eta^2_p = .28$, was observed. Post-hoc comparison revealed dissociation was significantly reduced under continuous compared to both control, $p < .01$, Cohen’s $d = .75$, and boundary feedback, $p < .05$, Cohen’s $d = .62$. No significant difference in distress across conditions was observed, $F(2,28) = .92, p = .41, \eta^2_p = .06$.

Instrumental attitudes before ($\text{Mean} \pm \text{SD}: 5.73 \pm 1.12$) and after ($5.56 \pm 1.62$) the feedback trials did not change significantly, $F(1,14) = .17, p > .50, \eta^2_p = .01$. Likewise, there was no significant change in affective attitudes before ($4.62 \pm 1.38$) and after ($4.29 \pm 1.90$) the feedback trials, $F(1,14) = .44, p > .5, \eta^2_p = .03$.

**TABLE 3.2.** Performance and attentional focus results, Mean ± SD.

<table>
<thead>
<tr>
<th></th>
<th>TIZ</th>
<th>RPE</th>
<th>Association</th>
<th>Dissociation</th>
<th>Distress</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Control</strong></td>
<td>.52 ± 0.40</td>
<td>12.9 ± 1.39</td>
<td>4.23 ± 0.73</td>
<td>2.96 ± 1.04</td>
<td>2.32 ± 1.08</td>
</tr>
<tr>
<td><strong>Boundary</strong></td>
<td>.94 ± 0.05</td>
<td>12.7 ± 1.87</td>
<td>3.97 ± 0.86</td>
<td>2.82 ± 0.98</td>
<td>2.3 ± 1.15</td>
</tr>
<tr>
<td><strong>Continuous</strong></td>
<td>.99 ± 0.01</td>
<td>12.3 ± 1.18</td>
<td>4.42 ± 0.77</td>
<td>2.26 ± 0.82</td>
<td>2.05 ± 1.07</td>
</tr>
</tbody>
</table>

**DISCUSSION**

Both feedback conditions significantly outperformed control in regulating TIZ. The results support the broad conclusion that auditory heart rate feedback is a useful tool for self-regulation during moderate intensity exercise. The findings further indicate that without feedback, participants were only able to remain in their target training zone for
roughly half the duration of the exercise bout. This is consistent with previous research suggesting that individuals struggle to select and maintain moderate intensity exercise without guidance (3,15). Feedback, however, dramatically improved TIZ to 94% and 99% for boundary and continuous feedback, respectively. The absence of a significant difference among RPE scores between the three conditions suggests that exposure to feedback does not affect effort perception. Consistently high instrumental and affective attitudinal scores both before and after completion of the feedback sessions imply a positive valence for this kind of mobile technology.

The extremely effective performance of boundary feedback in regulating intensity ran counter to our initial expectations. Participants appeared to internalize the boundary feedback they received and seemed to require remarkably little stimuli to maintain target intensity. Such “perceptual anchoring” has been previously described in work addressing the entrainment of self-regulation during exercise (13). The high and low boundary condition audio samples were roughly 3 seconds long each. In certain cases, participants required as few as 4 instances of feedback, roughly 12 seconds in total, to maintain target exercise intensity over the course of 15-20 minutes of exercise (adjusted for the warm-up period). The comparatively minimal application of feedback may account for the absence of any effects on dissociation or association using the boundary feedback condition relative to control. Dissociation was reduced, however, under continuous feedback relative to both the control and boundary conditions. This is very likely explained by the relatively high frequency of feedback under the continuous condition wherein audio stimulus persisted until heart rate returned to the 10% central band. Subsequently, TIZ was also highest using continuous feedback with participants reaching nearly 100% compliance. Though a significant corresponding increase in association was not found, a moderate effect size of continuous versus boundary
feedback was nonetheless observed. These findings are in agreement with those reported by van der Vlist, Bartneck, and Maüeler (43), who also found a significant reduction in dissociation but no significant increase in association in their application of feedback during aerobic exercise. It has been suggested that attentional strategies are affected by intensity (31). The moderate intensity exercise bout performed in the present study may not have been sufficiently vigorous to facilitate associative changes regardless of the feedback mechanism used. More research is warranted focusing specifically on associative mechanisms, in particular on feedback/intensity interaction.

Anecdotally, several subjects reported enjoying the ability to directly interact with the continuous feedback as changes in intensity were quickly reflected in the audio they heard. This hints at the phenomenon of “musical agency” by which behavior directly creates or augments music in real time. Though a relatively new field, early research suggests a positive impact on mood and perceived exertion through such direct musical feedback (17,18). This has also been reflected in recent consumer exercise applications like “Zombies Run” (https://www.zombiesrungame.com), in which an auditory “make your own adventure” form of stimulation is experienced. Future research may focus on different bandwidth parameters and volume envelopes. For example, can one make the band too narrow or is it better to accommodate a degree of variability? Similar acoustic mechanisms focusing on cadence and pacing strategies rather than heart rate can be also explored using the same methodology. A mobile platform also provides the opportunity to answer these questions in ecologically valid settings rather than the confines of the exercise laboratory and may promote the ultimate translation of these findings to consumer applications. Given the prevalence of sedentary behavior in the general population and the relatively poor ability of individuals to regulate exercise intensity, both feedback methods presented in this study may be useful in supporting adherence to
physical activity targets. The relatively high, positive attitudes toward this technology suggest adoption is possible if the benefits are clearly communicated. In conclusion, both boundary and continuous heart rate-based biofeedback improve adherence to moderate training intensity with the latter achieving nearly perfect compliance.

REFERENCES


CHAPTER 4

The success of Study 2, both in terms of outcome as well as a positive experience working with software instrumentation, led to approaching an even more ambitious problem related to self-regulation. While previous research has focused on the entrainment of exercise self-regulation using subjective measures (e.g., RPE), no successful entrainment using objective biofeedback has been reported. Therefore, a 5-week intervention was performed providing participants with auditory heart rate feedback defining a personal, moderate intensity training zone in an effort to entrain the ability to self-regulate. Using previously built software components, a complete application was once again developed. As in the previous study, the application encapsulated virtually the entire testing protocol, including the collection of physiological and subjective data.

Note: The material in this chapter has been accepted for publication. See:
ABSTRACT

Purpose: To determine whether exposure to automated heart rate feedback can produce improvements in the ability to regulate heart rate during moderate intensity exercise and to evaluate the persistence of these improvements after feedback is removed. Methods: Twenty healthy adults performed 10 indoor exercise sessions on cycle ergometers over 5 weeks following a twice-weekly schedule. During these sessions, participants received auditory feedback (FB) designed to maintain heart rate within a personalized, moderate-intensity training zone between 70 and 80% of maximum heart rate. All feedback was delivered via a custom, mobile software application. Participants underwent an initial assessment (PREFB) to measure their ability to maintain exercise intensity defined by the training zone without use of feedback. After completing the feedback training, participants performed three additional assessments identical to PREFB at 1 week (POST1), 2 weeks (POST2), and 4 weeks (POST3) after their last feedback session. Time in Zone (TIZ), defined as the ratio of the time spent within the training zone divided by the overall time of exercise, rating of perceived exertion (RPE), instrumental attitudes, and affective attitudes were then evaluated to assess results using two-way, mixed-model ANOVA with session and gender as factors. Results: Training with feedback significantly improved TIZ ($p < .01$) compared to PREFB. An absence of significant differences in TIZ between FB, POST1, POST2, and POST3 ($p >= .35$) indicated that these improvements were maintained after feedback was removed. No significant differences in RPE, $p >= .4$, or attitude measures, $p >= .3$,
were observed. **Conclusion:** Auditory biofeedback is an effective mechanism for entraining heart rate regulation during moderate intensity exercise in healthy adults.

**KEYWORDS**

mobile, software, biofeedback, heart rate, exercise

**INTRODUCTION**

The need for moderate intensity exercise is recognized universally as both vital for human health (19) as well as performance in sport (6). Human heart rate changes in proportion to exertion during exercise. Although individuals can control their level of effort by altering behavior, it is often difficult to interpret the relationships between observable bodily sensations and heart rate. That is, despite a variety of cardiopulmonary (e.g., respiration rate, oxygen uptake) and peripheral (e.g., skin temperature, sweat rate, mechanical strain) sensory cues providing feedback on exertion during exercise (18), these sensations provide general rather than specific feedback on heart rate. Collectively, these “afferent” cues may create an internal model, refined and developed through prior experience, against which exertion is gauged (23).

It appears that no single cue dominates subjective effort perception across individuals (18) with recent research supporting a general model of fatigue (29) integrating multiple sources of afferent feedback. Regardless, despite the existence of multiple sensory cues available to gauge exertion, individuals experience difficulty selecting and maintaining specific exercise intensities (4,8,14).

The ability to exercise at particular intensities appears to be trainable, however, through various applications of augmented feedback. Here, cues are conveyed through an external, rather than internal, mechanism delivered by a coach, instrument, or computer. For example, it has been shown that receiving verbal instructions during
exercise can improve the selection of walking pace corresponding to moderate intensity (4) and that heart rate feedback from visual instruments (24), a form of biofeedback, can affect physiological parameters during treadmill walking. Moreover, several studies have used rating of perceived exertion (RPE) to develop an individual’s ability to reproduce a specific level of effort (13,16,22,28). This technique has been successfully used to reproduce average heart rate between entrainment and reproduction trials for short duration exercise bouts (less than or equal to 5 minutes) with times ranging between estimation and reproduction from 2 to 14 days (13,16,22). However, Smutok, Skrinar, and Pandolf (28) observed entrainment was dependent on exercise intensity noting successful reproduction of effort only at intensities above 80% HRmax.

Though the relationship between heart rate and RPE has been previously established (27), few studies have explored whether direct feedback via heart rate monitors (HRMs) can improve subsequent self-regulation of heart rate in the absence of further external feedback. One exception is a study by Conley, Gastin, Brown, and Shaw (10) in which children were equipped with HRMs providing feedback defining a moderate to vigorous level of exercise using both visual and audio cues over the course of six sessions. Upon completion of the intervention, participants failed to show improvement in estimating the time they had spent engaging in this level of activity versus a control. The researchers concluded that limitations in the children’s cognitive ability to estimate both effort and time and the absence of any mechanism encouraging the children to internalize effort perception relative to afferent cues might have contributed to this result.

Though instrumentation is commonly used to develop fitness in a variety of endurance disciplines, including cycling (5), swimming (25), and running (15), few studies aside from that undertaken by Conley et al. (10) have used HRMs to further
develop self-regulation as an intrinsic ability. Likewise, few studies have explored longer-term entrainment as suggested by Dishman (12). We have therefore chosen to explore the entrainment of self-regulation during exercise in order to address some of the limitations and suggestions of previous work. Specifically, the present study focused on a more realistic exercise experience; a steady state, moderate intensity bout with a duration more representative of a typical exercise session. We hypothesized that multiple sessions during which heart rate feedback was delivered automatically could entrain an ability to self-regulate at the same intensity. We were also curious whether gender might influence entrainment as several studies have suggested its influence on perceived exertion (20,21). We used mobile technology to build ad-hoc instrumentation allowing us to focus on exercise performance and not simply heart rate averages as typically measured by HRMs. Moreover, our instrument effectively automated our protocol, thus our observed results can be achieved without human intervention, giving us some insight into new research methods as well as possibilities for human-computer interaction during exercise. Lastly, we explored post-entrainment effects over a considerably longer period than has been previously reported and explored the potential for decay of these effects over time.

METHODS

Subjects. Twenty healthy adults (11 women and 9 men) aged 18-33 years were recruited from an undergraduate sports science course. Effective sample size was computed utilizing the technique described in Cohen (9) with α = .05 and β = .2. All subjects completed the Physical Activity Readiness Questionnaire (ParQ) (7) to assess suitability for participation in the study as well as the Godin Leisure-Time Exercise Questionnaire (LTEQ) (17) to establish baseline physical activity levels. A summary of participant characteristics can be found in Table 4.1. Ethics approval was received from
the Human Research Ethics Office at the University of Western Australia, and all subjects provided written informed consent.

**TABLE 4.1.** Subject characteristics, Mean (±SD)

<table>
<thead>
<tr>
<th>Subjects</th>
<th>Age (yr)</th>
<th>Height (cm)</th>
<th>Weight (kg)</th>
<th>LTEQ Score</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male (N = 9)</td>
<td>21.2 ± .8</td>
<td>176.6 ± 1.8</td>
<td>72.6 ± 2.8</td>
<td>39.9 ± 3.8</td>
</tr>
<tr>
<td>Female (N = 11)</td>
<td>20.5 ± 1.3</td>
<td>170.4 ± 1.9</td>
<td>59.8 ± 2.5</td>
<td>41.4 ± 2.4</td>
</tr>
</tbody>
</table>

LTEQ, Godin Leisure–Time Exercise Questionnaire.

**Mobile Software Instrument.** We developed a novel piece of software for this study (HRTrainer) that fully automated our protocol. HRTrainer is a mobile application that runs on the iOS (Apple Inc., Cupertino, CA) family of devices. It was installed on multiple 4th generation iPod Touch devices and paired with heart-rate sensing hardware from Wahoo Fitness (Wahoo Fitness Inc., Atlanta, GA). The Wahoo heart rate monitor consists of a transmitter and heart rate belt worn around the thoracic region that wirelessly broadcasts heart rate information to the HRTrainer software through a hardware dongle (Wahoo Key) inserted into the iPod. This combination of hardware allows the HRTrainer software to receive continuous heart rate input from a participant during exercise. Throughout testing, subjects were provided with identical equipment consisting of an iPod Touch running the HRTrainer software, an armband, a heart rate monitor and Wahoo Key, and headphones.

**Experimental Protocol.** Subjects performed an initial testing session to assess their ability to maintain a moderate heart rate while exercising. Subject age was entered into the HRTrainer software from which a theoretical maximum heart rate (HRmax) was calculated using the Inbar formula \[205.8 - (.685 \times \text{Age})\] (26). A formula-based approach gave us the opportunity to fully encapsulate our protocol in the application.
The software then calculated the upper and lower limits of a moderate intensity training zone from 70 to 80% of estimated HRmax. A session number and subject identifier were also entered to uniquely identify the particular testing session for later storage and retrieval using an internal database. After successfully pairing with the heart rate monitor, HRTrainer provided the subject written and audio instructions for the session they were about to complete. The software ensured that audio instructions were played at least once before proceeding, though they could be repeated if desired. In this initial assessment (PREFB), subjects were instructed to cycle on an indoor stationary ergometer (Monark 827E/828E, Monark Exercise AB, Varberg, Sweden) while HRTrainer provided feedback. Among other things, the instructions stated that subjects were free to change their cadence or the resistance of the ergometer at any time to meet their heart rate goals. The feedback consisted of 4 low-pitched beeps indicating that the subject’s heart rate was below 75% HRmax (i.e., the middle of the target training zone). An example of this feedback was built into the audio instructions subjects received. This feedback was spaced to occur no more than once every 15 seconds. Upon reaching 75% of HRmax, a pre-recorded audio instruction told the subjects to maintain the intensity they had just achieved for an additional 20 minutes. During this subsequent period, no further feedback was provided. In this way, all subjects were first guided into the center of their training zone before being assessed on their current ability to maintain heart rate at that level. Heart rate was recorded at 1-second intervals during the entire exercise session. Upon completing 20 minutes of exercise after first achieving 75% of HRmax, the software played another pre-recorded message indicating the session was over. The message also invited subjects to complete an RPE response (3) and a six-item instrument (1,11) designed to measure subjects’ instrumental and affective attitudes towards biofeedback software. These attitudes were based on the
generic statement, “Using mobile phone software to provide heart rate feedback during exercise would be…”, and response options were anchored on a bipolar 1 to 7 scale (where higher scores denoted more positive perceptions). All input was done directly within the application using graphical interfaces designed for the purpose, and the software ensured all items were completed before allowing the subjects to finish. All data were subsequently stored to an internal database, and subjects were dismissed with a final audio message thanking them for their time and reminding them not to use any other forms of heart rate-based feedback while enrolled in the study.

In the week immediately following the initial testing session, subjects began a 5-week feedback intervention (FB) following either a Mon/Wed or Wed/Fri schedule for a total of 10 sessions. The exercise modality remained unchanged using the same hardware, software, facilities, and cycling ergometers. However, during these sessions, subjects exercised for precisely 20 minutes while the software provided continuous feedback using both upper and lower limit alarms if subjects exceeded 80% HRmax or fell below 70% HRmax, respectively. Examples of the “too high” and “too low” alarms were played as part of the pre-recorded instructions subjects received at the beginning of each session, and the audio and written instructions provided to them by the application reflected this change. As in PREFB, subjects were free to change cadence or ergometer resistance to stay in their target heart rate zone using the feedback to guide them. No psychometric data were collected during these 10 sessions, and heart rate data were recorded and stored as in PREFB. Following these sessions, subjects once again repeated a protocol identical to the initial PREFB assessment at exactly 1 week (POST1), 2 weeks (POST2), and 4 weeks (POST3) after their last feedback session. As in the PREFB session, feedback was only provided up to 75% of HRmax, at which point a pre-recorded message instructed subjects to maintain intensity for an additional
20 minutes, during which no further feedback was provided. Psychometric and heart rate data were collected and stored as per PREFB.

**Data Analysis.** Time in Zone (TIZ), defined as ratio of time spent between 70 and 80% of HRmax to the overall time of exercise, was calculated for each session. We removed the initial “warm-up” period prior to calculation so as not to bias the results against subjects who took longer to raise their heart rates. For feedback sessions, this meant removing all data prior to the subject first reaching 70% HRmax, while for the assessment sessions, we removed all data prior to the subject initially reaching 75% HRmax. The TIZ values for all 10 feedback sessions were averaged after one-way repeated measures ANOVA revealed no significant differences across session (Greenhouse-Geisser, $F(3.15, 59.90) = .810, p = .499$). TIZ for PREFB, the average of 10 feedback sessions (FB), and POST1, POST2, and POST3 were subsequently compared using two-way, mixed model ANOVA with session (i.e., 5 levels; PREFB, FB, POST1, POST2, POST3) and gender as factors. RPE as well as instrumental and affective attitudes were likewise compared using two-way, mixed model ANOVA using session (PREFB, POST1, POST2, POST3) and gender as factors.

**RESULTS**

Mean TIZ data for PREFB, FB, POST1, POST2, and POST3 are presented in Figure 4.1. Two-way, mixed model ANOVA revealed a significant difference in TIZ across sessions using Greenhouse-Geisser correction, $F(2.20,39.51) = 8.98, p < .001$, $\eta^2_p = .33$. Neither the gender main effect, $F(1,18) = .481, p = .497$, $\eta^2_p = .026$, nor the interaction between gender and session, $F(2.20,39.51) = 2.43, p = .096$, $\eta^2_p = .119$, were significant. Post-hoc comparison of TIZ means with Bonferonni correction found no significant difference between FB, POST1, POST2, and POST3, all $ps > .35$. TIZ for
PREFB (.43 ± .37) was significantly lower than FB (.90 ± .13), POST1 (.79 ± .27), and POST3 (.83 ± .21), all ps < .05, all Cohen’s ds > 1. There was no significant difference for TIZ between PREFB and POST2 (.74 ± .33), p = .4, Cohen’s d = .86.

![FIGURE 4.1 - Comparison of TIZ means (TSE) between sessions PREFB, FB, POST1, POST2, and POST3. There is significant difference for TIZ between sessions marked a and b, p < 0.05. There is no significant difference between sessions marked a, p = 0.40. There is no significant difference between sessions marked c, p > 0.35.](image)

Descriptive statistics for RPE and the two attitudinal measures are presented in Table 4.2. No significant differences in RPE were observed between sessions, $F(3,54) = .210, p = .889$. In addition, no main effect of gender, $F(3,54) = .111, p = .743$, or session-by-gender interaction, $F(3,54) = .848, p = .474$, was observed. Similarly, no significant differences between sessions were detected for instrumental attitudes, $F(3,54) = .331, p = .803$, and there was no effect of gender, $F(1,18) = 1.081, p = .312$, or gender-by-session interaction, $F(3,54) = .562, p = .643$. Likewise, no difference in session was detected for affective attitudes, $F(3,54) = 1.556, p = .211$ and no gender effect, $F(1,18) = .268, p = .611$, or gender-by-session interaction was observed. $F(3,54) = 1.076, p = .367$. 


<table>
<thead>
<tr>
<th>Measure</th>
<th>PREFB</th>
<th>POST1</th>
<th>POST2</th>
<th>POST3</th>
</tr>
</thead>
<tbody>
<tr>
<td>RPE</td>
<td>13.3 ± 0.4</td>
<td>12.9 ± 0.4</td>
<td>13.2 ± 0.3</td>
<td>13.1 ± 0.3</td>
</tr>
<tr>
<td>Instrumental Attitudes</td>
<td>5.9 ± 0.2</td>
<td>6.1 ± 0.2</td>
<td>5.8 ± 0.2</td>
<td>6.1 ± 0.2</td>
</tr>
<tr>
<td>Affective Attitudes</td>
<td>5.3 ± 0.3</td>
<td>5.5 ± 0.3</td>
<td>5.4 ± 0.3</td>
<td>5.4 ± 0.3</td>
</tr>
</tbody>
</table>

**DISCUSSION**

The purpose of this study was to determine whether autonomous self-regulation of exercise intensity could be entrained using automated biofeedback. Our results suggest this is indeed possible using our approach. After completing 10 sessions of feedback training, subjects significantly improved TIZ without the further use of feedback to a point where results were statistically indistinguishable from the prior feedback sessions. This effect was demonstrated in all three post-intervention assessments without any evidence of decay at the 4-week mark following the feedback training intervention. To our knowledge, this is the first successful demonstration of such a long-term result regardless of the feedback mechanism used.

In keeping with previous findings (4,8,14), subjects experienced difficulty maintaining exercise intensity during the initial exercise session, PREFB. Despite being guided by auditory feedback into the center of the target training zone before the withdrawal of feedback, subjects only managed to remain in that zone an average of 43% of the time. However, with feedback this number more than doubled to 90%, a significant improvement with a notably large effect size. Moreover, this improvement was consistent from the onset of the 10-session intervention, showing no significant variation between all 10 feedback sessions. Such a major improvement supports the direct use of an HRM whenever regulation of exercise intensity is desired. As with the improvement during feedback, post-intervention performance improved significantly at POST1 and POST3 over PREFB. The lack of statistically significant difference between
PREFB and POST2 is suggested to be due to the elevated standard deviation of POST2 compared with POST1 and POST3. However, a large effect size was still observed. In cases where improvement occurred, a large effect was observed (Cohen’s $d > 1$). Collectively, these findings suggest that the sensation and interpretation of afferent cues used to self-regulate exercise intensity may be refined by external feedback.

**FIGURE 4.2** - HR traces for six subjects during POST1 assessment, 7 d after the end of the intervention. Y-axis: HR (bpm). X-axis: time (s). Solid lines represent individual HR. Dashed lines represent the upper, middle, and lower boundaries of an individual’s moderate-intensity training zone.

Hampsen (18) has suggested that “the feedback in a bout of exercise with a longer duration may allow the coordination of afferent and efferent commands such that an appropriate plateau in intensity is achieved”. ‘Feedback’ in this context refers to internal/afferent feedback rather than external biofeedback. We observed the heart rate traces and individually defined training zones of 6 distinct individuals from the POST1 trial, exactly 1 week after the cessation of feedback training (see Figure 4.2). Having observed a significant improvement in TIZ compared to PREFB, we too were hoping to find a consistent pattern of cardiac dynamics among our participants with potential plateaus at the middle or borders of the target training zone. However, actual performance does not appear to follow such a straightforward prediction. In all cases,
we can see heart rate drifting throughout the zone. Sometimes this drift has a specific
direction (Figure 4.2E, 4.2F), while at other times it appears roughly centered about a
particular mean (Figure 4.2B, 4.2C), though still showing large variability. In several
instances, there appears to be a very high sensitivity to the boundaries of the training
zone (Figure 4.2B, 4.2D, 4.2F), with abrupt adjustments in intensity seen as heart rate
approaches what Dunbar refers to as “perceptual anchors” (13). The effect is
particularly vivid as this change in behavior occurs within no more than 2-3 bpm of the
heart rate at which feedback was previously administered. Though we were unable to
observe this ‘anchoring’ behavior broadly, its existence may warrant further
investigation by using a narrower zone to establish a more explicit plateau.

No significant changes in RPE scores were observed during the course of the study
despite significant improvements in TIZ. Previous studies have used RPE, trained on
observed heart rate, to regulate intensity in subsequent production trials where heart rate
was not explicitly known (13,16,22). However, our results suggest RPE alone may not
be a sufficiently effective cue to ensure repeatability of effort intensity. These results
support and extend the previous work by Smutok et al. (28) that reported RPE alone
was only effective entraining higher intensity efforts above 80% HRmax. The stability
of RPE also suggests that changes in fitness or economy were not responsible for the
improvements in self-regulation we observed. Conversely, there is no indication that
improvement in self-regulation ability affects perceived exertion.

Attitudes towards heart rate biofeedback did not change with consistently high
scores on both the affective and instrumental measures observed before and after the
intervention. It would appear that despite the additional effort involved in wearing heart
rate monitors, as well as the potential cognitive load from actually receiving feedback,
participants did not find the experience cumbersome enough to impact their attitudes
towards the technology. Given how potentially effective aerobic training with biofeedback is, this is a reassuring result and one that suggests the population is quite open to the use of such technology when value is perceived.

Encouraging as these findings are, they do introduce further questions. We were unable to observe decay in the newly acquired skill and are left without much insight into how it might attenuate over time. It is also worth considering just how much feedback is enough to achieve the same results. Would an equal number of feedback sessions undertaken over a shorter period of time have the same effect? Or could we accomplish similar results with fewer sessions, perhaps as few as six? We’re also very curious to see how removing the initial feedback, guiding users into their target training zone before cessation of feedback, would impact these findings. Would trainees have any trouble finding their target heart rate zone if starting from rest with absolutely no feedback? We also have to consider different exercise lengths and how feedback duration complements post-feedback performance. For example, is training with 20-minute feedback sessions sufficient to entrain self-regulation during 60-minute exercise tasks or must entrainment and performance sessions be of equal duration? Lastly, it’s worth considering the issue of pacing during exercise bouts of known duration. The concept of “teleoanticipation” (30) suggests different self-regulatory strategies between closed versus open-loop exercise protocols, and this has been borne out experimentally (2). Our subjects were explicitly informed their exercise sessions would last exactly 20 minutes once target heart rate was reached. We could augment our protocol and software in the future to remove this preliminary knowledge and explore performance during different exercise lengths of unknown duration. In conclusion, heart rate biofeedback is an effective vehicle for improving self-regulation at moderate exercise
intensities while direct use of biofeedback improves compliance to a moderate heart rate target zone immediately.

ACKNOWLEDGEMENTS

The authors do not have any conflicts of interest to declare. This study was supported by the Australian Postgraduate Award (A. Shaykevich), the Australian Research Council (B. Jackson), and the National Health and Medical Research Council (B. Grove). The results of the present study do not constitute endorsement by the American College of Sports Medicine.

REFERENCES


CHAPTER 5

The previous studies focused on the application of augmented feedback to entrain self-regulation during moderate intensity exercise. Software instrumentation substantially increased participant autonomy during this work leading to the ambition that one day such applications could be used to improve the exercise experience of the general population. A major impediment to such a goal, however, is the requirement to individually prescribe moderate intensity exercise limits. In the previous work, this was done either with a max effort test (Study 2) or by using a formula-based estimate (Study 3). Recent work in the field of heart rate variability (HRV) has suggested that individual moderate intensity may be objectively defined by the assessment of physiological thresholds associated with cardiac autonomic activity using submaximal testing protocols. HRV is a diverse, mathematically complex, and active field of study. Once again, the need for general mobile software instruments was identified and developed. The present study describes the design and implementation of a robust, reusable software library for HRV analysis, a complete mobile application suitable for research, and pilot testing to identify individual moderate intensity against a gold standard VO₂ max assessment.

Note: A portion of the material presented in this chapter was accepted for poster presentation (Appendix E.4) at the IADIS 2012 conference. See:

ABSTRACT

**Purpose.** The purpose of this study was to develop and validate a set of mobile software instruments for real-time analysis of heart rate variability (HRV). **Methods.** A software library (HRVKit) has been created for the analysis of heart rate variability on a variety of hardware platforms. The library implements both time- and frequency-based techniques common to HRV analysis and performs all necessary data preparation steps including filtering, detrending, and resampling. Accuracy has been assessed by means of intra-class correlation using a popular desktop HRV analysis software package as a reference. Additionally, a mobile software application (HRVLab) has been developed which captures relevant physiological data from heart rate sensors, uses HRVKit for analysis, and provides a continuous graphical representation of the results. A case study using HRVLab for real-time analysis during a graded exercise test is reported. **Results.** Overall, high levels of agreement have been found between HRVKit and the reference application with ICCs $\geq .81$. Results of the case study are consistent with existing literature and suggest anaerobic threshold may be determined in real time using HRVLab. **Conclusion.** HRVKit and HRVLab are novel software instruments that may be useful in the general study of heart rate variability.

KEYWORDS

heart rate variability, iOS, Android, mobile, Java, anaerobic threshold

INTRODUCTION

Heart Rate Variability (HRV) analysis is a common technique for assessing the state of the cardiac autonomic nervous system (ANS), and it has wide applications in a
variety of disciplines including health (3,8,24), psychophysiology (10,17,31), and athletic training (4,14,20,22). Although once believed to beat steadily, almost metronomically, the human heart displays a remarkable variety in its rhythm that can be studied to reveal underlying aspects of physiological state and health. HRV parameters, unlike more concrete indices such as blood pressure or resting heart rate, are the result of mathematical calculations performed on a signal composed of the heart’s interbeat intervals (IBIs). A key insight regarding the interpretation of spectral components of the heart rate signals came about through the work of Akselrod and colleagues using pharmacological modulation of cardiovascular functions (1). This research suggested that low frequency (LF), generally defined between .04 and .15Hz, and high frequency (HF), .15 - .4Hz, spectral components of the HRV power spectral density (PSD) decomposition are mediated by the cardiac sympathetic and parasympathetic nervous systems, respectively. However, more recent findings indicate it is more accurate to regard LF energy as a measure of baroreflex function rather than sympathetic activation (21).

Recent work focusing on athletic testing (4,14,16,20) suggests HRV analysis may be a viable alternative for determining physiological thresholds associated with aerobic exercise. Numerous studies have used HRV to identify the anaerobic threshold, also referred to as the ventilatory threshold, (4,14,15,20), a critical physiological indicator marking the transition from moderate to vigorous intensity exercise (35). Likewise, HRV has also shown promise in detecting the respiratory compensation point (RCP) (14,15). The RCP, also referred to as the second ventilatory threshold, represents an intensity at which a given effort becomes unsustainable due to CO₂ production from increased respiration (hyperpnea) (34,35). The two thresholds in effect delineate exercise effort into three intensities (i.e., moderate, vigorous, high). Precise knowledge
of these individual training intensities has implications for exercise prescription in terms of physiological (9) as well psychological (18) outcomes. While current best practice for determining these thresholds requires the use of expensive, invasive laboratory equipment to analyze exhalation gases and blood, HRV analysis is a promising alternative to simplify the procedure and make it broadly available.

The tools available to researchers for performing HRV analysis consist of desktop applications such as Kubios (University of Eastern Finland) (26) and aHRV (Nevrokard, Slovenia), software libraries such as RHRV (29), or ad-hoc computer codes. The principle drawback of these HRV tools is that they limit the user to post-hoc analysis, since IBIs must first be completely gathered before they can be analyzed. Recent trends in the commercial fitness industry have enabled mobile devices to receive accurate IBI intervals through inexpensive, readily available commercial hardware from a variety of vendors (e.g., Wahoo Fitness, 60 Beat, Zephyr Technology). This has created an opportunity to develop a completely mobile, ecologically valid platform for HRV analysis. With this goal in mind, a suitable software library has been considered incorporating several key characteristics. The library should obviously be compatible with one or more ubiquitous mobile platforms for which heart rate sensors are available. It should implement common time- and frequency-based techniques and present a straightforward interface so that developers can easily integrate it into derivative works. It must be performant since mobile devices are still largely resource constrained relative to personal computers and CPU or memory-intensive operations can easily overwhelm other key software elements such as the user interface. Lastly, the library should support continuous, real-time analysis so that developers have the option of planning software that reacts in some way to the incoming HRV data. Bearing these goals in mind, we have created such a software library, named HRVKit. It should be noted that while
several mobile applications have emerged in the consumer market for performing HRV analysis (iThlete, SweetBeat, BioForce HRV) none of these vendors have presented any published literature indicating which analytical techniques they implement or how they compare with more established HRV tools. The present study will describe the procedure by which the library performs its analysis and provide code examples of how it may be used by 3rd party developers. HRV calculations on an existing data set will be presented using both HRVKit and Kubios, and the results will be compared. We will also report performance benchmarks across various platforms and discuss differences. A complete mobile software application, HRVLab, which integrates real-time IBI capture with HRVKit analysis will be presented. Lastly, we will report the results of a case study using HRVLab during an incremental exercise test to assess ventilatory thresholds.

METHODS

Software Library. HRVKit has been implemented separately in both Objective-C and Java. Objective-C and Java are the principle languages for writing applications targeting Apple’s iOS (Apple Inc., Cupertino, CA) and Google’s Android (Google Inc., Mountain View, CA) devices, respectively. The vast majority of mobile devices in use today are supported by one of these two languages and it is now estimated that Android and Apple share 95.7% of the mobile market as of the 4th quarter of 2013 (2). Java, which runs on nearly all major operating systems, ranks as the second most widely used programming language and narrowly trails C (33). In addition, the popularity of these languages has created a large pool of developers capable of building applications. Our Objective-C implementation is packaged as a universal static library that can be run in either a simulation environment (XCode Simulator) or on an iOS device. The Java implementation is bundled as a JAR file and integrated with Android or traditional Java
projects through Java’s standard method of CLASSPATH library linking. A developer working with HRVKit has the option of embedding the software directly into an application or creating a service in the “cloud” capable of accepting IBIs over a network and returning calculations performed by HRVKit. Listing 5.1 illustrates how a 3rd party developer might make use of the Objective-C implementation while Listing 5.2 gives a Java example. The principle difference between the two is the way in which they broadcast results. Objective-C implements a “message bus” directly into the language, through NSNotificationCenter, while Java requires a more traditional delegate callback pattern.

**HRV Analysis.** Figure 5.1 demonstrates the steps by which HRVKit operates. Analysis involves multiple stages beginning with optional filtering of ectopic beats using a modified low pass filter (25). Data are accumulated until 64 seconds worth of IBIs are available, at which point the root mean square of successive deviations (RMSSD) and standard deviation (STDEV) are calculated. A 64-second window was chosen as a good compromise between spectral and time resolution given the continuous, real-time goals of the library. Accumulated IBIs are then resampled at 4 Hz using cubic spline interpolation resulting in 256 points. These points are subsequently detrended using the smoothing priors (32) approach with \( \lambda = 300 \) creating a high pass filter with a cutoff of .045 Hz. This is sufficient to remove the very low frequency (VLF) components of the subsequent spectrum. A Hann window is applied and a 256-point FFT taken. The PSD is then computed using the Welch’s periodogram method. Accumulated low frequency (LF) energy defined between .04 and .15 Hz and high frequency (HF) energy defined between .15 and .4 Hz are calculated through integration of the PSD through these respective frequency ranges. LF \( (f_{LF}) \) and HF \( (f_{HF}) \) peaks, the frequencies at which maximum LF and HF energy occur, are also recorded.
The ranges for LF and HF calculations correspond to the widely accepted values first observed by Akselrod (1) and generally in use today. They are Kubios’ defaults as well. It is worth noting, however, that since the complete PSD spectrum is made available during every iteration, 3rd parties are free to perform LF and HF summation using boundaries of their own choosing. Likewise, other statistics such as normalized values of LF and HF or alternative calculations of spectral peaks may be computed as well. The overall procedure is repeated using a 3-second shift of overlapping IBI windows such that, after the first 64-second initialization, new HRV results, including the complete PSD distribution, are broadcast every 3 seconds encapsulated within a time-stamped object, HRVResult (Listings 5.1, 5.2). These design choices further support efficiency since data from previous windows are discarded and the in-memory footprint of the library remains constant. In addition, several optimizations were implemented to
improve performance. The Objective-C version uses hardware-accelerated libraries for matrix and FFT operations (Apple’s Accelerate Framework) and both libraries use caching where possible.

```objective-c
#import "HRVKit.h"
#import "HRVResult.h"

HRVKit* hrv = [[HRVKit alloc] init];

// register for notifications
[[NSNotificationCenter defaultCenter] addObserver:self
selector:@selector(handleHF:) name:HRV_KEY object:nil];

double rr = 0.; // obtain rr intervals live from device or text file
[hrv addRR:rr];

// continue adding RR intervals until completion, then obtain a cumulative result
HRVResult* result = [hrv calculateResult];
[hrv release];

NSLog(@"LF: %g", result.lf);
NSLog(@"HF: %g", result hf);
NSLog(@"fHF: %f", result.fHF);
NSLog(@"Ratio: %f", result.lf/result.hf);

//...
-(void)handleHF:(NSNotification*)notification {
    NSDictionary* dict = notification.userInfo;
    HRVResult* result = [dict objectForKey:HRV_DICT_KEY];
}
```

Listing 5.1. HRVKit Integration Using Objective-C

```java
import HRVAnalysis;
import HRVResult;
import HRVAnalysisDelegate;

//...

HRVAnalysis hrv = new HRVResult();
hrv.setDelegate(new HRVAnalysisDelegate() {  
    @Override 
    public void hrvResultComputed(HRVResult result) {
        //...
    }

    @Override 
    public void avgHrvResultComputed(HRVResult result) {
        //...
    }
}
```

98
double rr = 0.; // obtain rr intervals live from device or file
hrv.addRR(rr);
HRVResult result = hrv.calculateResult();

Listing 5.2. HRVKit Integration Using Java

**Lomb-Scargle Periodogram.** While FFT approaches to HRV analysis like the Welch’s Periodogram are widely used, computationally efficient, and lend themselves logically to time-frequency analysis, a major weakness lies in the need to first resample the inherently non-stationary heart beat signal into regular intervals. Quality of data collection and human pathologies may contribute to irregular (i.e., ectopic) heartbeats that must be addressed during the resampling phase prior to FFT analysis. This manipulation, though, has been shown to introduce significant errors into the final analysis (12). The preceding study, however, also demonstrated that a non-FFT spectral technique, the Lomb-Scargle Periodogram (LSP), offers superior performance when removal of ectopic beats is required. We have, therefore, included an LSP alternative based on the algorithm first reported by Press and Rybicki (27) and later implemented by Press, Teukolsky, Vetterling, and Flannery (28). This LSP implementation is currently only available in the iOS version of HRVKit and is not suitable for time-frequency analysis within the library. In other words, it can only provide a comprehensive PSD over the entire range of IBIs but without any temporal resolution. Sample usage of the LSP implementation in HRVKit is provided in Listing 5.3.
Loess Smoothing. Local regression, also known as Loess, is a mathematical technique specifically useful for smoothing data (11). In practice, we have found that Loess smoothing makes it substantially easier to inspect trends in HRV data, particularly in the somewhat noisy $f_{HF}$ signal which is of specific interest in HRV research as it has been correlated to both respiration rate (5,7) and to cardiolocomotor coupling (6) during exercise. HRVKit, therefore, includes utilities to allow 3rd parties to easily apply Loess smoothing.

Mobile Software. HRVLab is a mobile software application written in Objective-C utilizing HRVKit for data analysis and able to run on all Apple mobile devices supporting iOS 4.3 and above. The application uses the Wahoo API (Wahoo Fitness Inc., USA) to capture IBI data either from the company’s Wahoo Key or from heart rate monitors supporting Bluetooth 4.0. The Wahoo Key is an Apple mobile-compatible 30-pin “dongle” which can receive biometric input from a variety of sensors using the Ant+ wireless protocol broadcasting at 2.4 GHz. Ant+ is a widely adopted industry standard with broad hardware support, most notably Garmin (Garmin Ltd., Schaffhausen, Switzerland). Bluetooth 4.0 is a newer wireless data protocol supported natively by current-generation mobile devices, thus eliminating the need for any external hardware.
Compatible heart rate transmitters worn around the thoracic region are widely available (Garmin, CardioSport, Timex, Polar) and provide the 1-millisecond IBI resolution considered necessary for accurate spectral HRV analysis (19). An iOS device running the HRVLab software combined with the appropriate heart rate sensing hardware creates a small, self-contained, mobile system capable of capturing IBI data, performing HRV analysis, and displaying the results in real-time at 3-second intervals (see Figure 5.2). A history of HRV recordings, complete with full power spectral densities, is kept in an internal database, and each recording can be exported or emailed as a comma-separated values (CSV) file. The portability of the system, the general robustness of consumer mobile devices, and their relatively long battery life allow HRV analysis in a variety of ecologically valid settings. Lastly, HRVLab supports offline analysis of user-supplied IBI interval data mirroring the functionality of existing applications such as Kubios.
**Validation.** Fifteen sets of IBI intervals from a previous study (14) were used to compare results between Kubios and HRVKit. The original data were obtained from competitive male cyclists and triathletes performing an exhaustive, incremental cycling ergometer test. Exercise testing was performed two to three hours following a light breakfast in an air conditioned room using an electronically braked cycle ergometer (Ergoline 900, Schiller Medical SAS, Busy St. Georges, France). Cyclists began with a load of 75 watts increasing 25 watts \( \cdot \) min\(^{-1}\) while triathletes started at 60 watts using 15 watts \( \cdot \) min\(^{-1}\) increases. ECG data were collected using a Power device (ADInstruments Ltd, Chalgrove Oxfordshire, UK) and beat-to-beat intervals were extracted.

HRVKit results were obtained by processing IBI files (simple text files with a single IBI per line recorded in milliseconds) using HRVLab’s offline analysis function. Kubios settings were set to the default using 4 Hz resampling, a 256-point window, and smoothing priors detrending with a cut-off of .045 Hz. Results for STDEV, RMSSD, LF, HF, LF/HF, \( f_{LF} \), and \( f_{HF} \) were obtained from each method and compared using intra-class correlation (ICC).

**Performance Benchmarking.** Test cases for each language and on each platform were constructed such that HRVKit performed 5000 sets of time and frequency calculations on separate 64-second windows. An average duration for a single operation was calculated using the overall time to completion. Both language implementations were run on a laptop personal computer (Apple Macbook Pro/2.3 GHz Core i7/8 GB RAM/OSX 10.7.2). The Objective-C and Java implementations were further tested on compatible mobile devices, an Apple iPhone 4 (iOS 5.1/1 GHz ARM v7) and a Samsung Galax S GT-I9000 (Android 2.2/1 GHz ARM Cortex A).

**HRVLab Case Study.** A 33-year old male completed a graded exercise task on a stationary ergometer. Ethics approval was received from the Human Research Ethics
Office at the University of Western Australia prior to the study, and the subject provided written informed consent. Initial resistance was defined at 100 Watts and incremented by 40 Watts every 3 minutes until volitional exhaustion. The subject was outfitted with a wireless heart rate transmitter communicating with the HRVLab software running on a 5th generation iPod Touch. HRV parameters were calculated and stored continuously at 3-second intervals during the exercise task. Capillary blood (35 μl) was drawn from the fingertip at the end of each stage to determine blood lactate levels using a blood-gas analyzer (ABL 725, Radiometer, Copenhagen, Denmark). Exhalation and inhalation gases were collected through a mouthpiece connected to a Hans Rudolph valve and tubing flowing through a computerized gas-analysis system (Meta 2000, School of Sports Science Exercise and Health, University of Western Australia). The volume of inspired air was analysed by a ventilometer (Morgan, Kent, United Kingdom) while Ametek Applied Electrochemistry S-3A/I oxygen and CD-3A carbon dioxide analysers (AEI Technologies, Pittsburgh, PA) measured the fraction of O2 and CO2, respectively, in expired air. The ventilometer was calibrated according to the manufacturer’s specification before use and verified using a known concentration of reference gas.

Lactate threshold was determined by the onset of blood lactate accumulation method at 4 mM by visual inspection. Ventilatory thresholds (VT1 and VT2) were determined by an independent expert using the ventilatory equivalents method (34,35). The Loess-smoothed $f_{HF}$ signal calculated by HRVLab was converted from 3-sec to 15-sec intervals to match the ventilometer intervals by linear resampling using a commercial software package (MATLAB R2012a, The MathWorks Inc., Natick, MA). The subsequently resampled $f_{HF}$ and ventilatory equivalent ($V_E$) signals were compared using one-tailed Pearson correlation. RMSSD and $f_{HF}$·HF were plotted over time and
visual inspection was used to estimate the first ventilatory threshold according to HRV (HRVT₁) using previously described techniques (14,23). These HRV-based detection methods rely on identifying the occurrence of a minimum corresponding to a complete withdrawal of parasympathetic activation after which the signal either begins to gradually rise or remains attenuated for some period of time. Currently, inherent noise, often manifesting as oscillations, in the HRV signals requires visual inspection and an ultimately subjective classification.

RESULTS

Intra-class correlation results for HRV parameters are presented in Table 5.1. ICCs between Kubios and HRVKit exceed .81 with a significance of $p < .01$. Performance benchmark findings are presented in Table 5.2.

<table>
<thead>
<tr>
<th>Measure</th>
<th>RMSSD</th>
<th>STDEV</th>
<th>LF</th>
<th>HF</th>
<th>LF/HF Ratio</th>
<th>LF Peak</th>
<th>HF Peak</th>
</tr>
</thead>
<tbody>
<tr>
<td>Intra-class Correlation</td>
<td>.86</td>
<td>.97</td>
<td>.84</td>
<td>.84</td>
<td>.93</td>
<td>.81</td>
<td>.93</td>
</tr>
</tbody>
</table>

**TABLE 5.1.** Intra-class correlation results between Kubios and HRVKit on key statistics.

<table>
<thead>
<tr>
<th>Language Implementation</th>
<th>PC (ms)</th>
<th>iPhone 4 (ms)</th>
<th>Android (ms)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Objective-C</td>
<td>.779 ± .043</td>
<td>23.1 ± 5.5</td>
<td>--</td>
</tr>
<tr>
<td>Java</td>
<td>.177 ± .41</td>
<td>--</td>
<td>331 ± 23</td>
</tr>
</tbody>
</table>

**TABLE 5.2.** Average single window operation performance results in milliseconds across language implementations and platforms

Figure 5.3 illustrates the results of the VO₂ max test. Lactate threshold (LT) was identified at 641 seconds, while the first (VT₁) and second (VT₂) ventilatory thresholds were determined to have occurred at 615 and 735 seconds, respectively. Visual inspection of both the $f_{HF} \cdot HF$ and RMMSD plots identified a nadir for both signals at 629 seconds that was taken to be the HRVT₁ estimate. $V_E$ and smoothed $f_{HF}$ showed significant correlation, $r = .92$, $p < .001$, as can be observed in Figure 5.3B.
DISCUSSION

The high intra-class correlation among statistical parameters between the two instruments is encouraging in the case of HRV analysis, since absolute numbers are rarely used. Instead, trends over time, such as pre- and post- intervention, are often reported. Differences between the two instruments are due to specific implementation details, particularly FFT parameters, which are sensitive to small changes such as window size, window selection, resampling strategies, and normalization. Absolute comparison is difficult in this case as the exact implementation of statistical techniques used by Kubios is not publically available. The suitability of HRVKit for use on different hardware platforms, particularly in resource constrained and real-time settings, depends on fast execution that does not interfere with other operations such as the user interface. On the PC, both implementations averaged on the order of $10^{-4}$ seconds per single operation. Surprisingly, the pure Java implementation slightly outperformed its Objective-C counterpart on the PC despite the latter’s use of hardware-accelerated libraries. The disparity may be due to a small architectural difference related to language-specific messaging features. The very large standard deviation observed on the Java desktop is likely due to intermittent garbage collection. Since both implementations performed well, no further optimization was sought. On the mobile devices, the Objective-C implementation was nearly an order of magnitude faster than the Android version. The lack of hardware accelerated support for FFT and matrix processing on Android very likely hurt its performance, though the speed may still be sufficient for smooth operation. Overall, execution performance was sufficient to demonstrate the fitness of the library for use in desktop, server, and mobile real-time applications across both Java and Objective-C platforms.
From the results in Figure 5.3A, we can observe the evidence of parasympathetic withdrawal with the attenuation of the $f_{HF}$·HF signal in agreement with previous literature (14,15). Moreover, the times at which no further decline in RMSSD or $f_{HF}$·HF could be detected were not only coincident with one another, but with both VT1 and LT as calculated from the gas exchange data. This is in agreement with previous studies (14,15,20,23,30). Figure 5.3B provides evidence of the correlation between $V_E$ and smoothed $f_{HF}$. Once again, this is consistent with previous work examining the relationship between HRV spectral properties and breath rate (5,7). Although this result is encouraging, we obviously cannot draw any final conclusions from this lone case. However, it suggests, at the very least, that applying Loess smoothing to $f_{HF}$ warrants further investigation.

**Figure 5.3A.** RMSSD and smoothed $f_{HF}$·HF during a VO2 max. Occurrence of ventilatory and lactate thresholds are identified by vertical, dotted lines. X-axis: time(seconds). Left-axis: smoothed $f_{HF}$·HF in ms2·Hz, solid line. Right-axis: RMSSD(seconds), dotted line. **Figure 5.3B.** Comparison of $V_E$ from the ventilometer and smoothed $f_{HF}$ (i.e., breath rate) calculated by HRVLab. X-axis: time(seconds). Left-axis: $V_E$ (L/min), dotted line. Right-axis: BR (Hz), dotted line.

Though computer applications and software libraries exist for performing HRV analysis, HRVKit represents an opportunity to create real-time, integrated systems for data capture, analysis, and display across multiple platforms. HRVLab extends the usefulness of the library by creating a complete mobile instrument for HRV analysis. The software can be used in ecologically valid settings and integrated into novel
applications allowing researchers to focus on problem domains rather than the low level implementation of HRV analysis.

ACKNOWLEDGEMENTS

The author would like to thank Francois Cottin, Département STAPS (Evry), for providing experimental heart rate interval data and interpretation of metabolic parameters and Sharon Gam, University of Western Australia (Perth), for simultaneous data collection using gas exchange and HRVLab.

REFERENCES


2. Android and iOS Continue to Dominate the Worldwide Smartphone Market with Android Shipments Just Shy of 800 Million in 2013, According to IDC [Internet]. *IDC* 2014;Available from: http://www.idc.com/getdoc.jsp?containerId=prUS24676414


33. TIOBE Software: Tiobe Index [Internet]. TIOBE Software: Tiobe Index [Internet]. *Tiobe Software* 2013;Available from: http://www.tiobe.com/index.php/content/paperinfo/tpci/index.html


CHAPTER 6 - GENERAL DISCUSSION

Introduction

The present work integrates software development and human experimentation specific to the study of exercise. In general, the work proceeded in a systematic and consistent fashion. An experimental question was first identified. Next, a piece of software was developed to facilitate the experimental investigation of that particular question. Lastly, the software was integrated into the overall methodology and an experiment was conducted. In some instances, the software provided a function without which the experiment would be impossible (see Chapters 3 and 5). In others, it facilitated an experimental design that would be far more resource intensive without it (see Chapter 4). An overarching focus on creating general-purpose instrumentation was maintained throughout. Subsequently, a powerful, stand-alone mobile software library (see Chapter 5) and three complete mobile applications (see Chapters 1, 4, and 5) were developed along with a variety of reusable software components that could be used for future development. In the case of the work described in Chapter 4, virtually the entire protocol was implemented within the ad-hoc application suggesting a future direction for conducting “research in the wild” by facilitating autonomy among research subjects. Experimental integration of these instruments served to validate their utility in field trials leading to various refinements focusing on features and usability. Ultimately, the work has yielded general instruments that may be leveraged for future investigation and form the basis for translational applications bringing the benefits of research to the general population.
Study 1

In Study 1, a comprehensive collection of software was developed to deliver feedback and auditory stimuli using mobile devices during physical activity. The work included both individual software components as well a complete mobile application suitable for research. Mobile technology is an extremely attractive medium for biofeedback instrumentation. These devices are, by definition, small, portable and are particularly useful for research in natural (i.e., ecologically valid) settings outside of traditional laboratory environments. They are ubiquitous with economies of scale reducing prices. Thus, multiple devices can be used within the context of a single experiment offering the possibility of greatly multiplying researcher effort as will be described in the following Study 3 discussion. They are, perhaps most importantly, programmable and are, in fact, small, powerful personal computers. When combined with an increasing number of biometric peripherals (e.g., heart rate monitors, power meters, cadence sensors), a mobile application can deliver personalized feedback using any number of protocols programmed by the researcher willing to use the available tools.

Apple’s (Apple Inc., Cupertino, CA) family of mobile devices running the iOS operating system was chosen as a deployment target for a number reasons. Specifically, at the time of development, iOS was unique in its ability to connect to existing digital biometric hardware such as heart rate monitors and cadence meters. Additionally, Apple hardware was the sole mobile platform supporting low latency audio playback, fast decoding of compressed audio streams, and hardware-optimized math libraries. Most importantly, these features are available to third-party developers through a set of software libraries (i.e., APIs) supported and maintained directly by Apple. As with all
modern, mobile devices, the hardware boasts reasonably long battery life, a sturdy design suitable for exercise, and Internet connectivity.

The goals of Study 1 were comprehensive, and much of the development needed to be done from the ground up with little in the way of precedent or existing codebase. Low-level, wireless biometric input was largely delegated to the Wahoo API (Wahoo Fitness Inc, Atlanta, GA), although this was further encapsulated to provide support for future instruments as well as to enable system-wide retrieval of biometric data. Initially, only Ant+ devices were supported, though new Bluetooth 4.0 (BTLE) instruments have appeared as BTLE has become the favored peripheral device protocol for Apple products. Currently, BTLE heart rate monitors and bicycle cadence meters are supported. An upper limit of three simultaneous devices is enforced by the underlying hardware. This does not appear to be an issue thus far as even in a highly instrumented sport such as cycling, a maximum of three simultaneous instruments (heart rate, power, speed/cadence) seems more than sufficient to provide meaningful feedback.

After establishing the capability to receive biometric information during exercise, it was necessary to develop a means of providing auditory feedback. This was complicated by the requirement to not simply deliver pre-recorded audio, but to have real-time control of the audio stream both for effects processing (i.e., pitch and tempo control) as well as custom sound generation. An example of this is a metronome (see Chapter 3), which modifies its tempo according to some external parameters. This is impractical using simple file-based audio playback, as one would have to create every conceivable metronome beforehand. Instead, a producer-consumer architecture was designed and implemented. At its simplest, a low-latency audio playback engine (i.e., the consumer) reads audio data, specifically bytes, from a number of audio sources (i.e., the producers), mixes them, and ultimately renders the mixed stream to the device’s
underlying audio playback hardware. The individual producers need only conform to a simple programming interface, namely, that they provide audio data of certain duration. Multiple implementations of this paradigm were created encapsulating audio files, iTunes music (which is stored in a kind of internal data store rather than a file system), as well as more sophisticated audio sources such as the previously mentioned metronome. In the latter case, since producers provide audio on an “as-needed” basis, the metronome was implemented in such a way that it could dynamically change the audio data it provided to reflect the exact tempo desired. Ultimately, a mobile application tying these various components together was created.

The experimental research presented in Chapters 3 and 4 of this thesis represents only a small example of what is possible with the overall capability that has been developed. Experimental work reported in this thesis focused on heart rate, but the effects of feedback on cycling and running cadence could be also studied extensively using the same tools. Music in exercise remains an active area of research, particularly synchronous music (i.e., music synchronized with cadence) (5,34,44,47), and the study presented in Chapter 2 represents a state-of-the-art capability to manipulate music experimentally. Both researcher- and user-selected music are directly supported as all audio may be drawn directly from a user’s personal music library stored in iTunes. The latter capability is highly relevant. Previous research has identified significant benefits from using personal music (9,41), but the effect has been difficult to exploit owing to the technical hurdles involved in creating musical biofeedback systems and the limitations of previous implementations. For example, while the moBeat system (48) was hailed by researchers for its capabilities (30), it nonetheless relied on electronic music rendering (i.e., MIDI) rather than actual songs users might be familiar with. Other applications such as IM4Sports (51) and D-Jogger (36) could only be run on PCs thus
lacking portability. Surprisingly, there is no mention in the scientific literature of systems exploiting the modern “smart phone” platform to provide feedback during steady-state aerobic exercise, let alone ones incorporating music. Within Tempony, musical volume, pitch, and tempo can be independently controlled at fine-grained intervals of less than 1 second. These changes can be driven by an assortment of variables including biometric input from heart rate monitors and cadence meters. These capabilities can be exploited to facilitate further research. For example, music tempo may be used to both regulate and entrain cadence. Music pitch or volume could be used as an alternative to auditory alarms to regulate heart rate (e.g., increase pitch when heart rate is too high). Moreover, third parties can script algorithms for real-time manipulation of the acoustic signals without needing any further knowledge of the inner workings of the software or any form of recompilation. In conclusion, Tempony is a powerful instrument for acoustic feedback research based on existing mobile hardware.

**Study 2**

The purpose of Study 2 was to evaluate different forms of heart rate-based auditory feedback on self-regulation during moderate intensity exercise. Having developed the Tempony application in Study 1 to facilitate such research, two types of feedback were implemented using the software. The first feedback condition consisted of a boundary-style alarm activated when the participant left the target training zone. A second form of continuous, bandwidth feedback was developed using the audio source paradigm described in Chapter 2. Participants completed three exercise sessions using two forms of feedback and a silent control in a repeated measures fashion. In keeping with previous research (6,21), participants struggled to maintain moderate intensity without feedback, managing only 52% time in zone (TIZ) during the no feedback control condition. In contrast, exposure to feedback improved TIZ dramatically to 94% using
boundary feedback and 99% using continuous feedback. No significant changes in RPE scores across conditions suggested that participants were not negatively influenced by feedback despite a potential increase in cognitive load associated with anticipating and responding to the additional stimuli. This is further supported by the high instrumental and affective attitudinal ratings related to the use of heart rate feedback during exercise and the absence of any significant change in these scores before and after the sessions.

The success of boundary feedback in improving TIZ was greater than initially expected. The original hypothesis that participants would continually “bump” against the boundaries of the target training zone requiring feedback to resume correct intensity was not borne out. Participants not only made rapid, corrective changes in exercise effort after receiving feedback, but also appeared to internalize it so as to require little overall stimuli, thus improving overall effort perception. The ultra short acoustic feedback, on the order of 3 seconds, used for the boundary condition may explain the absence of any effect on dissociation or association when compared to the control condition. On the contrary, continuous feedback significantly reduced dissociation over both control and boundary conditions. Research suggests that association/dissociation strategies are mediated by expertise (7). Given the greater performance of continuous feedback as measured by TIZ, this approach may be superior in situations where a very high level of self-regulation is required. On the other hand, boundary feedback may offer the best efficiency with no discernable psychological impact, improvements in adherence to target exercise intensity, and minimal stimuli frequency compared to overall exercise duration.

Generally speaking, the software instrument performed extremely well in practice supporting its continued use in future research. Participants were largely autonomous throughout testing as the software managed the lifecycle of the exercise sessions.
prompting them with appropriate feedback, notifying them upon the completion of
exercise sessions, and recording heart rate data throughout. In the context of feedback
research, where even subconscious researcher behavior can significantly bias subject
performance, the ability to largely remove the researcher from the experimental
procedure proved valuable and is explored more fully in Chapter 4 and the review of
that work. Once a specific feedback condition was selected and recording begun, testing
proceeded without any further intervention from the researcher. Specific control of the
volume of the continuous feedback metronome was successfully implemented through
the external scripting mechanism described in Chapter 2. Other metronomes are
likewise possible as is the application of similar protocols to the regulation of running
and cycling cadence. Anecdotally, some subjects reported engaging directly with the
continuous feedback, raising or lowering their heart rates through intensity adjustments
to elicit an acoustic response, since changes in activity levels had an almost immediate
impact on auditory stimuli. This may be an example of “musical agency”, a
phenomenon only recently explored in the context of exercise (24,25), but which
already shows potential for improving mood and reducing perceived exertion. In this
paradigm, an individual is able control aspects of the acoustic signal by altering
behavior, acting somewhat like a musician, though of course in a far more limited
capacity. As the Tempony software offers real-time control over several musical
characteristics, feedback protocols integrating music and potentially incorporating
musical agency should be considered for future work. Encapsulating regulatory
feedback information directly into music, through amplitude, pitch, or tempo
manipulation, is an appealing prospect and one for which the Tempony software is well
suited.
Study 3

The purpose of Study 3 was to explore whether self-regulation of exercise intensity could be entrained using automated biofeedback. A new, ad-hoc software instrument was required to perform this work and was subsequently developed using portions of the software components developed in Study 1. Application screen shots may be seen in Appendix D.3. Elements of this software had already been used in Study 2, establishing the applicability of such instrumentation during exercise testing. Whereas Study 2 focused on the direct in-task performance effects of using biofeedback, Study 3 expanded on this notion to examine the long-term impact of regular feedback use. The hypothesis was formulated that repeated exposure to feedback defining the upper and lower heart rate boundaries of a target training zone could entrain an ability to self-regulate at the same intensity without further use of feedback.

Study 2 offered further guidance regarding the form this feedback should take. Borrowing from motor learning literature, there is ample evidence that feedback should be delivered conservatively (42,43,52). That is, although feedback is undoubtedly required to gain a correct knowledge of result, excess feedback can lead to a degradation of performance. Although results from Study 2 showed that continuous feedback was superior to boundary in regulating TIZ, the difference was small. Subsequently, a form of boundary feedback was implemented in the protocol for this study.

Results from Study 3 confirmed the hypothesis that entrainment of heart rate self-regulation is possible through a feedback intervention. Upon completing 10 sessions using feedback, participants’ self-regulation ability improved dramatically to the point where performance as measured by TIZ was no longer significantly different from the sessions during which feedback was available. Moreover, the three post-intervention
assessments were statistically indistinguishable from one another showing no sign of decay at up to four weeks post-training. A previous study by Conley, Gastin, Brown, and Shaw (14) with similar aims and instrumentation, albeit in a population of children, failed to show similar results. The findings in that study, however, may have been compromised by the cognitive limitations of the participants and by the lack of any mechanism to help them internalize effort-perception relative to the feedback they received. Though few investigations aside from Conley et al. have used instrumented feedback to entrain self-regulation during moderate-intensity exercise, a number of studies have focused on using participants’ RPE (19,23,35) as the entrainment mechanism. In this methodology, participants first perform exercise at different work rates noting RPE relative to known heart rate or VO2 max percentages. This is commonly referred to as the estimation trial. In the subsequent production trial, participants use the previous experiential mapping between RPE and work rate to reproduce specific levels of effort. This technique has been used successfully to reproduce average heart rate between estimation and production trials in relatively short (less than or equal to 5 minutes) duration efforts with entrainment and testing separated by between 2 and 14 days (19,23,35). The study reported in Chapter 4 advances this work in two critical areas by incorporating a more realistic exercise duration, on the order of 20 minutes, and by demonstrating entrainment a full 4-weeks post-intervention. To the author’s knowledge, this is the first successful demonstration of such a long-term result regardless of the feedback mechanism used.

In keeping with the results of Study 2, boundary feedback proved highly effective ensuring intensity stayed within the individually prescribed target heart rate zone. In fact, the improvement during the feedback sessions themselves was striking. TIZ more than doubled, from 43% to 90%, consistent with findings from Study 2 where TIZ rose
from 52% in the no-feedback control to 94% with boundary style feedback. As in the previous study, this improvement was observed as soon as feedback was applied, with no significant difference across all 10 feedback sessions. The software developed in Studies 1 and 2 made this form of boundary feedback relatively easy to implement and allowed for the clear distinction between upper and lower boundary alarms. These findings further support the direct use of heart rate monitor-based feedback whenever precise regulation of exercise intensity is desired. Affective and instrumental attitudes towards the mobile software employed in this investigation were consistently high and did not change significantly throughout the course of the study suggesting that (a) participants perceive value in this technology, and (b) their perceptions of the value of this technology were not compromised through repeated use.

The entrainment findings documented in Study 3 combined with the ongoing technological capability being developed over the course of all the studies introduces a range of future directions for research. An absence of any significant reduction in performance at four weeks post-training leaves the question of decay unanswered. A longer post-intervention period, perhaps open ended, will be required to assess the lasting effects of entrainment. With a better understanding of such decay/retention dynamics, it may be possible to quantify the relationship between entrainment time and post-intervention self-regulation ability. The HRTrainer software guided participants into the center of their target training zone in both the pre- and post-intervention assessments. Now that successful entrainment has been demonstrated, the next logical step is to remove the initial feedback in post-intervention sessions to assess whether participants can find the previously entrained heart rate zone independently. This was avoided in the study in question to ensure equivalence between pre- and post-intervention sessions and because significant entrainment could not be assumed.
beforehand. Successful entrainment of the two related forms of self-regulation of interest (i.e., the ability to find the target zone and to remain there) would move this work closer to practical translation within general exercise.

Moving further beyond the specifics of the Study 3 design, even more questions emerge. Different protocols for entrainment should be investigated. For example, can similar results be accomplished with fewer feedback sessions? Is there, perhaps, a minimal viable entrainment period? The influence of individual feedback session duration on post-feedback performance also warrants investigation. For example, can training with 15-minute feedback sessions entrain the ability to self-regulate during 60-minute exercise bouts? Different ecological settings for entrainment and testing are also worth exploring since testing outside the structured environment of a laboratory is vital for any conclusions about real-world suitability. One of the strengths of using mobile software instrumentation based on “off the shelf” commercial components is the ability to perform research in different environments since results can vary between the laboratory and the field (11). For example, research suggests that external factors such as temperature (29,39) and “optic flow” (40), (i.e., the rate at which scenery passes by while exercising outdoors) affect effort perception. However, these effects are typically not present in research settings when participants exercise on stationary equipment such as treadmills and rowing machines in climate controlled surroundings. Subsequently, conclusions reached in the laboratory under ideal conditions may be irreproducible in the normal settings in which exercise takes place. As the software developed in Study 3 is completely portable, experiments conducted in different ecological environments can be easily accommodated to include the effects of extraneous parameters otherwise isolated in the exercise laboratory. This potential for greater diversification has obvious implications for real-world adoption of techniques resulting from this research.
Implementing virtually the entire experimental protocol within the HRTrainer software conferred several advantages. Researcher effort was greatly multiplied through the use of identical instruments allowing a single researcher to conduct up to 8 simultaneous exercise sessions complete with instructions, appropriate auditory feedback, collection of subjective responses, and data recording. In all, 280 individual exercise sessions were accommodated using this approach. Moreover, since the software managed all feedback and data recording functions, the researcher was able to remove himself from the testing environment to a large degree. This was particularly important during the assessment sessions where even subconscious researcher bias could potentially influence subject performance and act as an alternate form of external feedback. Once trained on the equipment, the subjects prepared themselves at the start of each session with minimal intervention. The inclusion of written and audio instructions as well as a workflow validating subjective responses helped ensure consistent adherence to the research protocols while providing subjects with a large degree of autonomy. Such semi-automated testing protocols warrant further investigation and could become a new paradigm. As previously mentioned, the apparatus consists entirely of mobile, off-the-shelf components and is ideal for use outside the laboratory. In conclusion, the current work has provided both a successful initial investigation as well as a set of tools to continue unraveling the details of entrainment of self-regulation during aerobic exercise.

**Study 4**

The preceding studies were focused on examining the effects of feedback on exercise intensity using ad-hoc software and hardware instruments. Specifically, moderate intensity exercise was the focus as this intensity level conforms to recent recommendations for public health and disease prevention (28) as well as performance
in sport (10). Moreover, there is also a psychological motivation to accurately identify exercise intensity. Unsurprisingly, affective attitudes towards physical exertion are highly influenced by intensity (20), with a significant decline in feelings of pleasure associated with transitioning into high intensity efforts (22). Establishing individual moderate intensity in the preceding work required either direct testing (Study 2) or estimation (Study 3) to translate “moderate” percentages (i.e., 70-80% of maximum heart rate) into objective heart rate targets. The former approach requires a graded-exercise test completed under researcher supervision, whereas the latter method may lack the accuracy necessary for certain types of efforts, particularly those focused on fitness changes or oxygen kinetics.

Heart Rate Variability (HRV) analysis was identified as a possible means to address the current limitations in prescribing exercise intensity for a broad, diverse population. A developing body of work has provided evidence to suggest that HRV can be used to identify the anaerobic threshold (AT) (15,16,27,31,33), a critical physiological marker that delineates the transition from light to moderate intensity exercise (2). Likewise, HRV has also been used to identify the respiratory compensation point (RCP) (15,16). The RCP, also referred to as the second ventilatory threshold, demarcates an intensity at which CO₂ production from increased respiration (hyperpnea) makes the current level of effort unsustainable (49,50). HRV, therefore, represents a technology with potential to objectively discern individual moderate intensity. Moreover, the technology necessary for HRV analysis is widely available in the form of inexpensive, wireless heart rate monitors (26) and modern mobile devices which can be programmed to receive and process the heart rate signal. A robust software library (HRVKit) and mobile application (HRVLab) were developed (see Chapter 5) on top of this consumer hardware foundation to perform HRV analysis in
real time during exercise creating the first completely mobile platform capable of such continuous analysis, display, and recording.

HRVKit implements an extensive capability for general HRV analysis in a software library that can easily be integrated into third-party applications on the two dominant mobile platforms (iOS and Android). Requiring only a stream of interbeat intervals (i.e., the times between individual heart beats), either in real-time or offline, the library performs all steps necessary for analysis including optional filtering (37), detrending (46), and the calculation of both time and frequency statistics. The library performs well when compared to a current “gold standard” tool such as Kubios (38) with overall high levels of agreement between the two on all key statistics (i.e., intra-class coefficients >= .81). HRVKit also benefits from a number of optimizations allowing for suitably fast calculation for real-time applications as borne out by benchmark testing.

HRVLab was developed to fully exploit the capabilities of HRVKit and to ultimately pursue the original line of inquiry seeking to identify physiological thresholds during exercise. As reported in Chapter 5, pilot testing proved extremely promising with several notable findings. The withdrawal of parasympathetic activation during a VO\textsubscript{2} max test could be clearly observed in the attenuation of the $f_{\text{HF}}$ signal in agreement with previous literature (15,16). Likewise, anaerobic threshold identified from HRV parameters (i.e., RMSSD and $f_{\text{HF}}$) was coincident with benchmark identification from gas exchange and blood lactate. These findings are also consistent with literature (15,18,27,31,33). The application of Loess smoothing (13) to the noisy frequency-domain statistics made subjective evaluation considerably easier. Smoothing also led to a high correlation, $r = .92$, between overall ventilation and smoothed $f_{\text{HF}}$, an HRV parameter previously correlated to breathing frequency (3,4).
The convergence of exercise technology and ubiquitous mobile computing is spawning new technology that may extend the work presented here. Wearable sensors (e.g., activity trackers, glucose meters, pulse oximeters, etc…) continue to evolve and new types of heart rate monitors based on photoplethysmography are becoming available (e.g., Scosche Rhythm, Mio, Basis). Vendors such as Zephyr offer integrated breath rate detection as well as heart rate. As new sensors become available, they can be integrated with the existing work to create an increasingly robust model of the biomarkers characterizing different physiological states during exercise.

A new generation of programmable cycling ergometers (e.g, the Wahoo Kickr) represents technology that is particularly relevant to the threshold determination work presented here. The resistance on this unit can be controlled programmatically in real time from a mobile device using BTLE. Whereas ramp tests typically employ incremental loading of resistance in fixed increments, a procedure coupling HRV and load parameters to systematically drive parasympathetic withdrawal may yield more consistent results and ultimately lead to a fully automated system for anaerobic threshold determination. A future direction for this work may include automatic classification of AT and RCP points delineating exercise effort into moderate-vigorous intensity levels on an individual basis. One can also imagine real time HRV analysis during regular training, providing feedback during every specific exercise bout, and thus constantly accommodating the user’s individual physiology relative to fatigue and physical stress. This, possibly combined with data from other sensors, may ultimately lead to a system capable not only of correctly regulating in-task exercise intensity but also intelligently prescribing effort levels based on desired outcomes (e.g., recovery, increased lactate threshold, cardiovascular health).
Accordingly, although initial development was driven by an interest in exercise self-regulation, the present toolset has wide-ranging applications in other domains where HRV has shown relevance. A growing body of work is using HRV parameters as a biomarker of human health (1,8,32) and, likewise, these metrics remain a fixture within psychophysiological investigations (12,17,45). HRVKit may be integrated into other applications, combining HRV analytics to other functionality, while HRVLab can be used as a stand-alone mobile instrument in a variety of settings and protocols. In conclusion, the HRVKit and HRVLab package that was developed and tested in Chapter 5 will alleviate the analytical burden associated with HRV analysis allowing researchers to focus on novel applications of this physiological indicator.

Conclusion

The work reported in this thesis documents software development and novel empirical evidence related to the self-regulation of moderate intensity exercise, and details both the instantaneous as well as the long-term effects of using acoustic feedback. This work underscores the relatively poor self-regulation ability of untrained individuals consistent with existing literature and provides evidence of the dramatic improvements that are possible through feedback intervention. From an applied perspective, this work has led to the first successful long-term entrainment of exercise self-regulation using objective instrumentation reported in the literature. Moreover, in terms of methodological innovation, the preceding experimental work was realized through the use of novel software instruments leveraging consumer mobile technology. By implementing good software practice focusing on component-driven design and reusability, a broad capability to deliver and study acoustic stimuli, including music, in ecologically valid exercise settings has been created. Looking toward the future of exercise self-regulation, this thesis demonstrates the development and validation of a
real-time mobile system focusing on computational physiology and HRV analysis. Future work can leverage this tool to individually classify exercise effort ultimately replacing expensive, invasive laboratory testing. Of course, different lines of enquiry using HRV and focusing on diverse domains are equally supported. In summation, the inclusion of mobile technology into the study of exercise within this thesis has not only proven successful, but also represents a nearly limitless capability to support further study that allows for more sophisticated, individualized, and contextually diverse investigation.

REFERENCES


APPENDICES

APPENDIX A – Physical Activity Readiness Questionnaire

Pre-Exercise Questionnaire – (CODE #IM-DIF)

Physical Activity Readiness

Becoming more active is very safe for most people, but if you’re in doubt, please complete the questionnaire below. Some people should check with their doctor before they start becoming much more physically active. Start by answering the seven questions below. If you are between the ages of 15 and 69, the PAR-Q will tell you if you should check with your doctor before you start. If you are over 69 years of age, and are not used to being very active, definitely check with your doctor first.

1. Has your doctor ever said that you have a heart condition and that you should only do physical activity recommended by a doctor? YES NO
2. Do you feel pain in your chest when you do physical activity? YES NO
3. In the past month, have you had chest pain when you were not doing physical activity? YES NO
4. Do you lose your balance because of dizziness or do you ever lose consciousness? YES NO
5. Do you have a bone or joint problem that could be made worse by a change in your physical activity? YES NO
6. Is your doctor currently prescribing drugs (for example, water pills) for your blood pressure or heart condition? YES NO
7. Do you know of any other reason why you should not do physical activity? YES NO

If you answered YES to one or more questions, please advise the researcher as there may be a need for you to consult your doctor before participating in further exercise.

General Questions

1. Please indicate your gender: M / F
2. Please provide your age: _______

131
Appendix B – Ethics Approval for Studies 2 & 3

Our Ref: RA/4/1/5270

28 May 2012

Associate Professor James Dimmock
Sport Science, Exercise & Health (School of)
MBDP: M408

Dear Professor Dimmock

HUMAN RESEARCH ETHICS APPROVAL - THE UNIVERSITY OF WESTERN AUSTRALIA

Acute effects of continuous heart rate audio feedback in overweight individuals.

Student(s): Alex Shaykerich - PhD - 20905121

Ethics approval for the above project has been granted in accordance with the requirements of the National Statement on Ethical Conduct in Human Research (National Statement) and the policies and procedures of The University of Western Australia. Please note that the period of ethics approval for this project is five (5) years from the date of this notification. However, ethics approval is conditional upon the submission of satisfactory progress reports by the designated renewal date. Therefore initial approval has been granted from 28 May 2012 to 01 June 2013.

You are reminded of the following requirements:

1. The application and all supporting documentation form the basis of the ethics approval and you must not depart from the research protocol that has been approved.
2. The Human Research Ethics Office must be approached for approval in advance for any requested amendments to the approved research protocol.
3. The Chief Investigator is required to report immediately to the Human Research Ethics Office any adverse or unexpected event or any other event that may impact on the ethics approval for the project.
4. The Chief Investigator must inform the Human Research Ethics Office as soon as practicable if a research project is discontinued before the expected date of completion, providing reasons.

Any conditions of ethics approval that have been imposed are listed below:

Special Conditions

None specified

The University of Western Australia is bound by the National Statement to monitor the progress of all approved projects until completion to ensure continued compliance with ethical standards and requirements.

The Human Research Ethics Office will forward a request for a Progress Report approximately 60 days before the due date. A further reminder will be forwarded approximately 30 days before the due date.

If your progress report is not received by the due date for renewal of ethics approval, your ethics approval will expire, requiring that all research activities involving human participants cease immediately.

If you have any queries please do not hesitate to contact the Human Research Ethics Office (HREO) at hreo-research@uwa.edu.au or on (08) 6488 3703.

Please ensure that you quote the file reference – RA/4/1/5270 and the associated project title in all future correspondence.

Yours sincerely

[Signature]

Peter Johnstone
Manager
APPENDIX C.1 – Study 2 Participant Information Sheet

Exercising with and without Biofeedback – Participant Information Sheet

At The University of Western Australia we are currently running a psychology research project focusing on biofeedback and exercise. This work is being performed by PhD student Alex Shaykevich under the supervision of the principal investigator, James Dimmock. Participants in this project will be asked to perform a one-time initial maximum heart rate test by cycling on a stationary bicycle at increasing intensity until voluntarily stopping. We will be asking basic screening information to ensure your safety, but study volunteers must also make the researchers aware of any pre-existing medical conditions prior to participation. During this project we will be asking individuals to exercise on a stationary bicycle while listening to several forms of auditory biofeedback and wearing a chest strap heart rate sensor and unobtrusive mobile hardware worn on an armband. The goal will be to use the feedback to maintain moderate exercise intensity, defined as 70-80% of individual maximum heart rate. These sessions will consist of a 5 minute warm-up, a 20 minute exercise session, a 10 minute break during which participants will complete a questionnaire, and finally an additional 5 minute exercise session. During the session, the participant’s heart rate will be recorded at one second intervals. Each individual will be asked to perform three of these sessions spaced at least one week apart.

Participation in this research is entirely voluntary and you are free to withdraw from the study at any time without prejudice. The results of this study may be published in the future through academic journals and presentations. Once again though, no individual will be identifiable, and all results will be completely anonymous. PLEASE BE HONEST when answering questions. THERE ARE NO RIGHT OR WRONG ANSWERS.

We would like to thank you for your help with the study. If you have any questions concerning the project please feel free to talk these over with me at any time.

Many thanks,

James

Email: james.dimmock@uwa.edu.au
Phone: 6488 1384
ashayk1@yahoo.com
Phone: 0432963196
APPENDIX C.2 – Study 2 Volunteer Consent Form

Exercising with and without Biofeedback – Participant Consent Form

• I have read the information provided and any questions I have asked have been answered to my satisfaction.

• I agree to participate in this research, realising that I may withdraw at any time without reason and without prejudice.

• I understand that all information provided is treated as strictly confidential and will not be released by the investigator unless required to by law.

• I have been advised as to what data is being collected, what the purpose is, and what will be done with the data upon completion of the research.

• I agree that research data gathered for the study may be published provided my name or other identifying information is not used.

Signed: __________________________________________________________

Date: _______ / _______ / _______
APPENDIX C.3 – Study 2 Preliminary Questionnaire

Preliminary Questionnaire

On this page there are a number of statements concerning the reasons people often give when asked why they exercise. Whether you currently exercise regularly or not, please read each statement carefully and indicate, by circling the appropriate number, whether or not each statement is true for you personally, or would be true for you personally if you did exercise. If you do not consider a statement to be true for you at all, circle the ‘0’. If you think that a statement is very true for you indeed, circle the ‘5’. If you think that a statement is partly true for you, then circle the ‘1’, ‘2’, ‘3’ or ‘4’, according to how strongly you feel that it reflects why you exercise or might exercise.

Remember, we want to know why you personally choose to exercise or might choose to exercise, not whether you think the statements are good reasons for anybody to exercise.

<table>
<thead>
<tr>
<th></th>
<th>Not at all true for me</th>
<th>Very true for me</th>
</tr>
</thead>
<tbody>
<tr>
<td>To stay slim</td>
<td>0 1 2 3 4 5</td>
<td></td>
</tr>
<tr>
<td>To avoid ill-health</td>
<td>0 1 2 3 4 5</td>
<td></td>
</tr>
<tr>
<td>To have a healthy body</td>
<td>0 1 2 3 4 5</td>
<td></td>
</tr>
<tr>
<td>Because my doctor advised me to exercise</td>
<td>0 1 2 3 4 5</td>
<td></td>
</tr>
<tr>
<td>To lose weight</td>
<td>0 1 2 3 4 5</td>
<td></td>
</tr>
<tr>
<td>To prevent health problems</td>
<td>0 1 2 3 4 5</td>
<td></td>
</tr>
<tr>
<td>Because I want to maintain good health</td>
<td>0 1 2 3 4 5</td>
<td></td>
</tr>
<tr>
<td>To help prevent an illness that runs in my family</td>
<td>0 1 2 3 4 5</td>
<td></td>
</tr>
<tr>
<td>To help control my weight</td>
<td>0 1 2 3 4 5</td>
<td></td>
</tr>
<tr>
<td>To avoid heart disease</td>
<td>0 1 2 3 4 5</td>
<td></td>
</tr>
<tr>
<td>To feel more healthy</td>
<td>0 1 2 3 4 5</td>
<td></td>
</tr>
<tr>
<td>To help recover from an illness/injury</td>
<td>0 1 2 3 4 5</td>
<td></td>
</tr>
<tr>
<td>Because exercise helps me to burn calories</td>
<td>0 1 2 3 4 5</td>
<td></td>
</tr>
</tbody>
</table>

Using mobile phone software to provide heart rate feedback during exercise would be...
(Please circle the most appropriate response)
Your Current Exercise...
For the following questions we are interested in planned, structured leisure activity performed outside of structured sport commitments...
1. Over the previous 7 days (i.e., week), how many times did you do the following kinds of exercise for more than 15 minutes...
   
   A) **STRENUOUS EXERCISE** (sweating; heart beats rapidly) ___________times
      e.g., running, jogging, vigorous cycling, vigorous swimming

   B) **MODERATE EXERCISE** (light sweating; not exhausting) ___________times
      e.g., easy cycling, easy swimming

   C) **MILD EXERCISE** (no sweating; minimal effort) ___________times
      e.g., yoga, archery, golf, easy walking

How often do you use a heart rate monitor during exercise?
1  2  3  4  5  6  7
(Never) (Half the time) (Always)
APPENDIX C.4 – Study 2 Task Questionnaire

PLEASE COMPLETE THESE QUESTIONS IN RELATION TO THE EXERCISE SESSION

This is a scale used to determine exertion, which is intensity of effort, stress, or discomfort felt during exercise. Please rate your level of exertion on the exercise task on a scale from 6-20, with 7 = No Exertion at All and 19 = Maximal Effort. There are no right or wrong answers.

6
7 Very, very light
8
9 Very light
10
11 Fairly light
12
13 Somewhat hard
14
15 Hard
16
17 Very hard
18
19 Very, very hard
20

If this exercise session were to be replicated in the gym, how much do you think this exercise session would cost?

$ ____________

If this exercise session were to be replicated in the gym, how much would you be willing to pay for this exercise session?

$ ____________

Please rate how much you engaged in the following activities during the exercise session you just completed.

<table>
<thead>
<tr>
<th>Activity</th>
<th>I did not do this at all</th>
<th>I did this all the time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Letting your mind wander</td>
<td>1 2 3 4 5 6 7</td>
<td></td>
</tr>
<tr>
<td>Monitoring specific body sensations (e.g., leg tension, breathing rate)</td>
<td>1 2 3 4 5 6 7</td>
<td></td>
</tr>
<tr>
<td>Trying to solve problems in your life</td>
<td>1 2 3 4 5 6 7</td>
<td></td>
</tr>
<tr>
<td>Activity</td>
<td>I did not do this at all</td>
<td>I did this all the time</td>
</tr>
<tr>
<td>-------------------------------------------------------------------------</td>
<td>--------------------------</td>
<td>-------------------------</td>
</tr>
<tr>
<td>Paying attention to your general level of fatigue</td>
<td>1 2 3</td>
<td>4 5 6 7</td>
</tr>
<tr>
<td>Focusing on how much you are suffering</td>
<td>1 2 3</td>
<td>4 5 6 7</td>
</tr>
<tr>
<td>Singing a song in your head</td>
<td>1 2 3</td>
<td>4 5 6 7</td>
</tr>
<tr>
<td>Focusing on staying loose and relaxed</td>
<td>1 2 3</td>
<td>4 5 6 7</td>
</tr>
<tr>
<td>Wishing the exercise would end</td>
<td>1 2 3</td>
<td>4 5 6 7</td>
</tr>
<tr>
<td>Thinking about school, work, social relationships, etc.</td>
<td>1 2 3</td>
<td>4 5 6 7</td>
</tr>
<tr>
<td>Focusing on your performance goal</td>
<td>1 2 3</td>
<td>4 5 6 7</td>
</tr>
<tr>
<td>Wondering why you are even exercising in the first place</td>
<td>1 2 3</td>
<td>4 5 6 7</td>
</tr>
<tr>
<td>Making plans for the future (e.g., grocery list)</td>
<td>1 2 3</td>
<td>4 5 6 7</td>
</tr>
<tr>
<td>Getting frustrated with yourself over your performance</td>
<td>1 2 3</td>
<td>4 5 6 7</td>
</tr>
<tr>
<td>Writing a letter or paper in your head</td>
<td>1 2 3</td>
<td>4 5 6 7</td>
</tr>
<tr>
<td>Paying attention to your form or technique</td>
<td>1 2 3</td>
<td>4 5 6 7</td>
</tr>
<tr>
<td>Reflecting on past experience</td>
<td>1 2 3</td>
<td>4 5 6 7</td>
</tr>
<tr>
<td>Paying attention to your rhythm</td>
<td>1 2 3</td>
<td>4 5 6 7</td>
</tr>
<tr>
<td>Thinking about how much you want to quit</td>
<td>1 2 3</td>
<td>4 5 6 7</td>
</tr>
<tr>
<td>Focusing on the environment (e.g., your surroundings)</td>
<td>1 2 3</td>
<td>4 5 6 7</td>
</tr>
<tr>
<td>Thinking about competitive strategy or tactics</td>
<td>1 2 3</td>
<td>4 5 6 7</td>
</tr>
<tr>
<td>Counting (e.g., objects in the environment)</td>
<td>1 2 3</td>
<td>4 5 6 7</td>
</tr>
<tr>
<td>Monitoring your pace</td>
<td>1 2 3</td>
<td>4 5 6 7</td>
</tr>
<tr>
<td>Thinking about how much the rest of the exercise session will hurt</td>
<td>1 2 3</td>
<td>4 5 6 7</td>
</tr>
<tr>
<td>Meditating (focusing on a mantra)</td>
<td>1 2 3</td>
<td>4 5 6 7</td>
</tr>
<tr>
<td>Encouraging yourself to exercise fast</td>
<td>1 2 3</td>
<td>4 5 6 7</td>
</tr>
<tr>
<td>Trying to ignore all physical sensations</td>
<td>1 2 3</td>
<td>4 5 6 7</td>
</tr>
<tr>
<td>Concentrating on the exercise</td>
<td>1 2 3</td>
<td>4 5 6 7</td>
</tr>
<tr>
<td>Wondering whether you will be able to finish the exercise session</td>
<td>1 2 3</td>
<td>4 5 6 7</td>
</tr>
<tr>
<td>Thinking about pleasant images</td>
<td>1 2 3</td>
<td>4 5 6 7</td>
</tr>
<tr>
<td>Monitoring the time of the exercise</td>
<td>1 2 3</td>
<td>4 5 6 7</td>
</tr>
</tbody>
</table>
For each of the following statements, please indicate how true it is for you in relation to the *exercise session* you just completed.

<table>
<thead>
<tr>
<th>Statement</th>
<th>Not at all true</th>
<th>Somewhat true</th>
<th>Very true</th>
</tr>
</thead>
<tbody>
<tr>
<td>I enjoyed doing this session very much</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>I think I am pretty good at this session.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>I put a lot of effort into this.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>I believe this session could be of some value to me.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>This session was fun to do.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>I think I did pretty well at this session, compared to others.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>I didn't try very hard to do well at this session.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>I think that doing this session is useful.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>I thought this was a boring session.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>After working at this session for a while, I felt pretty competent.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>I tried very hard this session.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>I think this is important to do.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>This session did not hold my attention at all.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>I am satisfied with my performance at this task.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>It was important to me to do well at this task.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>I would be willing to do this again because it has some value to me.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>I would describe this session as very interesting.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>I was pretty skilled at this session.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>I didn't put much energy into this.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>I think doing this session could help me.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>I thought this session was quite enjoyable.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>This was a session that I couldn't do very well.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>I believe doing this session could be beneficial to me.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>While I was doing this session, I was thinking about how much I enjoyed it.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
<tr>
<td>I think this is an important session.</td>
<td>1</td>
<td>2</td>
<td>3</td>
</tr>
</tbody>
</table>
APPENDIX C.5 – Study 2 Final Questionnaire

Using mobile phone software to provide heart rate feedback during exercise would be... (Please circle the most appropriate response)

<table>
<thead>
<tr>
<th>Harmful</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>Beneficial</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pleasant</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>Worthless</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>Enjoyable</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>Desirable</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>5</td>
<td>6</td>
<td>7</td>
</tr>
<tr>
<td>Uncomfortable</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
<td>Comfortable</td>
</tr>
</tbody>
</table>

Please rate your typical level of exertion when you undertake aerobic exercise on a scale from 6-20, with 7 = No Exertion at All and 19 = Maximal Effort. There are no right or wrong answers.

6
7 Very, very light
8
9 Very light
10
11 Fairly light
12
13 Somewhat hard
14
15 Hard
16
17 Very hard
18
19 Very, very hard
20
APPENDIX D.1 – Study 3 Participant Information Sheet

At The University of Western Australia we are currently running a research project focusing on biofeedback and exercise. This work is being performed by PhD student Alex Shaykevich and Assistant Professor Grant Landers. For this study, we are seeking healthy adults over the age of 18 and with a BMI no greater than 29. BMI will be calculated within the application based on the information you provide. Participants in this study will be asked to perform 14, 20 minute exercise sessions on a stationary bicycle at a moderate intensity. Your individual moderate intensity will be calculated based on your age. These sessions will take place twice per week at SSEH in the G.05 physiology labs. You may choose a **Mon/Wed** or **Wed/Fri** schedule in one of two time blocks, **11:30 – 12:15** or **12:15 – 1:00**. During exercise, the software will provide you with audio feedback relative to your heart rate, very much like the way a sport watch might work. You’ll hear a fast, high-pitched series of beeps when your heart rate is too high, and a low, slower set when it is too low. Your goal will be to maintain moderate exercise intensity using the feedback to help guide you. We need you NOT to use any other kind of heart rate feedback during other exercise you may perform during the same testing period. You should only be getting heart rate biofeedback from our application for the duration of your testing.

Participation in this research is entirely voluntary and you are free to withdraw from the study at any time without prejudice. The results of this study may be published in the future through academic journals and presentations. Once again though, no individual will be identifiable, and all results will be completely anonymous.

We would like to thank you for your help with the study. If you have any questions concerning the project please feel free to talk these over with me at any time.

Many thanks,

Grant & Alex

Email: grant.landers@uwa.edu.au
Phone: 6488 2362
biofeedbackuwa@gmail.com
Phone: 0432963196
APPENDIX D.2 – Study 3 Volunteer Consent Form

Phd Candidate Alex Shaykevich,
School of Sport Science, Exercise and Health
The University of Western Australia
35 Stirling Highway, Crawley WA 6009
Email: biofeedbackuwa@gmail.com
Phone: 0432963196

Auditory Biofeedback and Exercise

- I have read the information provided and any questions I have asked have been answered to my satisfaction.
- I agree to participate in this research, realising that I may withdraw at any time without reason and without prejudice.
- I understand that all information provided is treated as strictly confidential and will not be released by the investigator unless required to by law.
- I have been advised as to what data is being collected, what the purpose is, and what will be done with the data upon completion of the research.
- I agree that research data gathered for the study may be published provided my name or other identifying information is not used.

Print Your Name:
__________________________________________________________

Signed:
__________________________________________________________

Date: _________ / _________ / _________
Validation of Real Time Mobile Software for Determining Ventilatory Threshold Based on Heart Rate Variability – Participant Information Sheet

At The University of Western Australia we are currently running a computational physiology research project focusing on identifying ventilatory threshold through analysis of heart rate variability (HRV). This work is being performed by PhD student Alex Shaykevich under the supervision of the principal investigator, James Dimmock. As part of a separate procedure, you will be undergoing VO2 max testing. Participants in this study will additionally be outfitted with a chest strap heart rate transmitter which will broadcast heart rate data to a mobile device running our software during the VO2 testing period. The heart rate data will be analyzed and a set of HRV indices will be created which will then be compared against the results from the VO2 apparatus. In this way, we hope to validate a mechanism of ventilatory threshold determination based only on the HRV signal.

Participation in this research is entirely voluntary and you are free to withdraw from the study at any time without prejudice. The results of this study may be published in the future through academic journals and presentations. Once again though, no individual will be identifiable, and all results will be completely anonymous.

We would like to thank you for your help with the study.

If you have any questions concerning the project please feel free to talk these over with me at any time.

Many thanks,

James

Email: james.dimmock@uwa.edu.au
Phone: 6488 1384

ashayk1@yahoo.com
Phone: 0432963196
I have read the information provided and any questions I have asked have been answered to my satisfaction.

I agree to participate in this research, realising that I may withdraw at any time without reason and without prejudice.

I understand that all information provided is treated as strictly confidential and will not be released by the investigator unless required to by law.

I have been advised as to what data is being collected, what the purpose is, and what will be done with the data upon completion of the research.

I agree that research data gathered for the study may be published provided my name or other identifying information is not used.

Signed: 

_________________________________________________________

Date: _________ / _________ / _________
APPENDIX E.3 – HRV Case Study Ethics Approval

Our Ref: RA/4/1/6033

04 April 2013

Associate Professor James Dimmock
School of Sport Science, Exercise & Health
MBDP: M408

Dear Professor Dimmock

HUMAN RESEARCH ETHICS APPROVAL - THE UNIVERSITY OF WESTERN AUSTRALIA

Validation of Real Time Mobile Software for Determining Ventilatory Threshold Based on Heart Rate Variability

Student(s): Alex Shaykevich - PhD - 20905121

Ethics approval for the above project has been granted in accordance with the requirements of the National Statement on Ethical Conduct in Human Research (National Statement) and the policies and procedures of The University of Western Australia. Please note that the period of ethics approval for this project is five (5) years from the date of this notification. However, ethics approval is conditional upon the submission of satisfactory progress reports by the designated renewal date. Therefore initial approval has been granted from 04 April 2013 to 01 April 2014.

You are reminded of the following requirements:

1. The application and all supporting documentation form the basis of the ethics approval and you must not depart from the research protocol that has been approved.
2. The Human Research Ethics Office must be approached for approval in advance for any requested amendments to the approved research protocol.
3. The Chief Investigator is required to report immediately to the Human Research Ethics Office any adverse or unexpected event or any other event that may impact on the ethics approval for the project.
4. The Chief Investigator must inform the Human Research Ethics Office as soon as practicable if a research project is discontinued before the expected date of completion, providing reasons.

Any conditions of ethics approval that have been imposed are listed below:

Special Conditions

None specified

The University of Western Australia is bound by the National Statement to monitor the progress of all approved projects until completion to ensure continued compliance with ethical standards and requirements.

The Human Research Ethics Office will forward a request for a Progress Report approximately 60 days before the due date. A further reminder will be forwarded approximately 30 days before the due date.

If your progress report is not received by the due date for renewal of ethics approval, your ethics approval will expire, requiring that all research activities involving human participants cease immediately.

If you have any queries please contact the HREO at hreo-research@uwa.edu.au.

Please ensure that you quote the file reference – RA/4/1/6033 – and the associated project title in all future correspondence.

Yours sincerely

Dr Mark Dixon
Associate Director, Research Ethics and Biosafety
APPENDIX E.4 – IADIS 2012 HRV Poster

Summary
A software library (HRKvit) for performing heart rate variability (HRV) analysis and capable of running on Apple’s iOS mobile hardware platforms has been developed. The software implements both time and frequency analysis techniques common to HRV in real time and also performs all necessary data preparation steps including filtering, detrending, and resampling. Results have been compared using Kubios as a reference and overall high levels of agreement have been found.

Purpose
Heart Rate Variability analysis is a common technique for assessing the state of the autonomic nervous system (ANS) and has wide applications in disciplines such as biofeedback and psychology. Recent trends in the commercial fitness industry have enabled mobile devices to receive accurate IBI intervals through inexpensive, readily available commercial hardware (Wahoo Fitness, Inc). This has created an opportunity to develop a completely mobile, ecologically valid platform for HRV analysis.

Features
+ Compatible with a ubiquitous mobile platform (iOS) for which heart rate sensors are available.
+ Implements time and frequency based techniques (RMSSD, STDEV, LF, HF, PSD) (Fig. 1).
+ A user-friendly interface, easy to develop against (Listing 1).
+ Supports continuous, real-time analysis so developers can plan software which reacts to incoming HRV data (Fig. 2).
+ Optimization acknowledges mobile platform limitations. Single window operations are performed on the order of 10-1 sec. Constant memory footprint.

Methods
Figure 1. HRV Analysis - implementation Workflow

Data Analysis
Fifteen sets of IBI intervals from a previous study² were used to compare results between Kubios and HRKvit. The data set represents results from competitive male cyclists and triathletes performing an exhaustive, incremental cycling ergometer test. Intraclass reliability procedure used to compare against Kubios, a widely cited HRV application. Findings confirm very good agreement, ICCs = .84, between Kubios and HRKvit.

<table>
<thead>
<tr>
<th>Measure</th>
<th>RMSSD</th>
<th>STDEV</th>
<th>LF</th>
<th>HF</th>
<th>LF/HF</th>
<th>LF Peak</th>
<th>HF Peak</th>
</tr>
</thead>
<tbody>
<tr>
<td>ICC</td>
<td>1.0</td>
<td>1.0</td>
<td>.84</td>
<td>.84</td>
<td>.93</td>
<td>.81</td>
<td>.93</td>
</tr>
</tbody>
</table>

Figure 2. HRVlab - Example of Application Development with HRKvit

Listing 1. Objective-C Usage

```
```