Doctoral Dissertation

Human Factors in Computer-aided Systems to Change Health Behavior and Promote Physical Exercise

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Abstract

In this thesis, I investigate human factors in computer-aided system design to promote physical well-being and regular practice of exercise. Health problems associated with sedentary lifestyles are undeniably critical issues of our time. Computer-aided approaches are promising instruments for resolving these issues through theoretical and practical progress of sports science. Scholars consistently employ interdisciplinary informatics for training, coaching, testing, and educating individuals. However, common design principles often fail to address human factors and unique characteristics of physical exercise at the same time. In response, I utilize a human-computer interaction perspective and investigate fundamental cognitive elements of exercise psychology in computer-aided system design. I conduct three case studies to individually evaluate self-efficacy, outcome expectancy, and risk factors in physical exercise. First, I investigate age-related differences in exergame difficulty adjustments to promote self-efficacy and enhance motivation for regular physical exercise. Next, I consider a situated visualization approach for pedaling in cycling to address outcome expectancy by realizing a qualitative-quantitative monitoring procedure. Finally, I study knee overuse injuries in cycling to address risk perception in exercise. Altogether, I consider these factors critical for solving problems associated with physical inactivity through computer-aided systems and essential for achieving a further increase in regular practice of physical exercise to bolster healthy lifestyles.

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Keywords:

Health behavior change, human factors, human-centered computing, human-computer interaction, interaction design, information visualization, exercise motivation, exergames, aging.

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CHAPTER 1

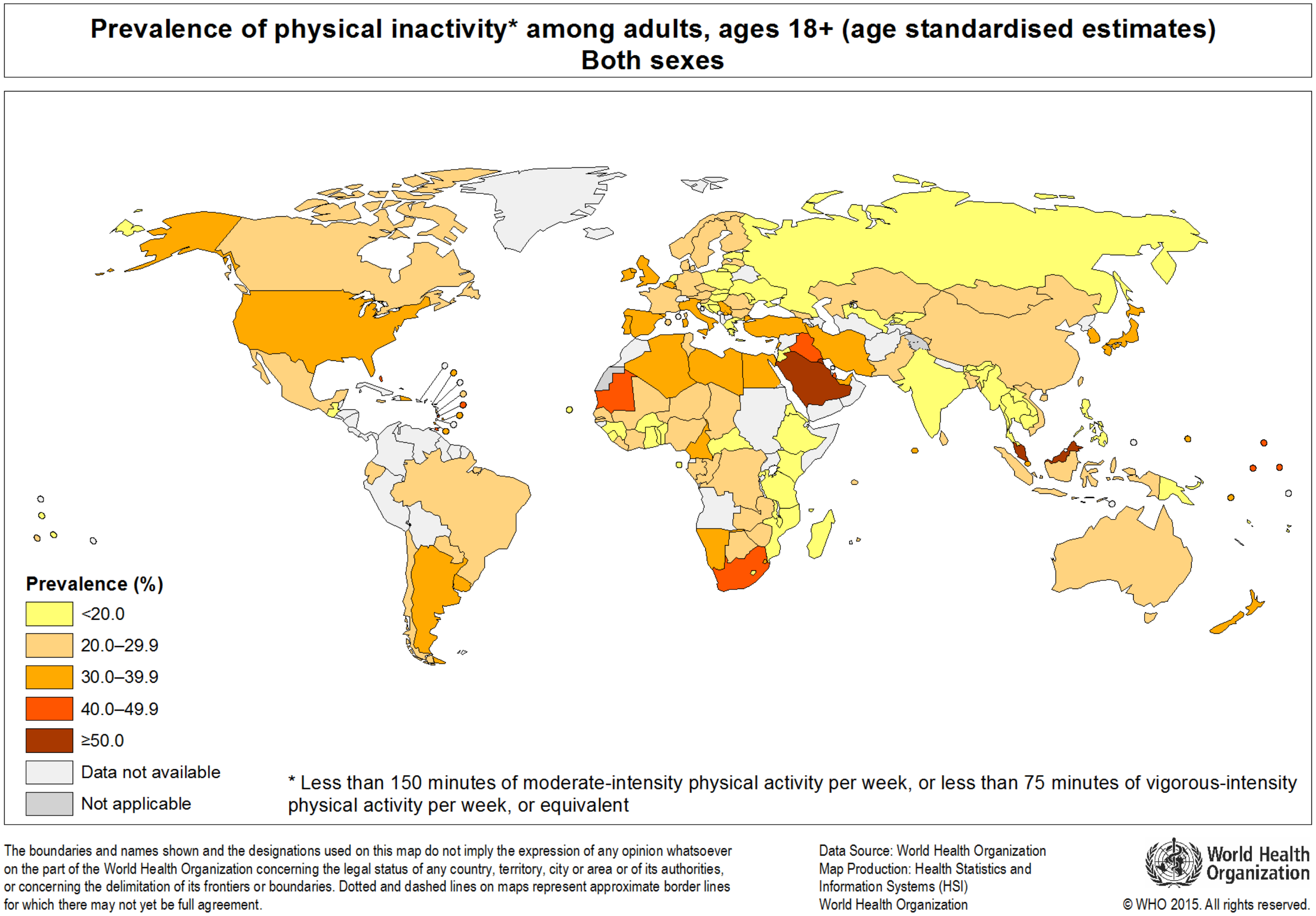
Introduction

The history of technology is fueled by the socio-economical changes that affected our lives in irreversible ways [30]. Over the last decades, humanity witnessed this yet again in the form of *"The Third Industrial Revolution"*, or also known as *"The Digital Revolution"* [151]. The beginning of information age brought a massive shift from mechanical and analogue to digital where various technological advancements capitalized on the development of computational hardware, software, and novel paradigms [151]. This ongoing evolution rapidly introduced numerous improvements into our daily lives. Nowadays, we cover great distances in just a few hours which took months for our ancestors [29]. We produce more by using less materials with great efficiency [29]. We live longer thanks to the advancements in modern medicine and health care industry [179]. However, present-day societies are also facing unique problems as a result of the same developments. Most of us are prisoners to our network enabled gadgets from the very moment we wake up [106]. Humanity is more connected than ever before, yet social problems associated with diminished face-to-face interaction like depression are on the rise [106]. Gun violence, school shootings, and terrorism receive major media coverage all around the United States [120]. Shifting economies, poverty, and increasing income inequality are serious global maladies [48]. Last but not least, growing number of people are transitioning to less physically active lifestyles due to the consistently shifting and ever demanding nature of their everyday lives [198]. Proportionally, it is increasing the risk of numerous non-communicable diseases and making health problems associated with sedentary lifestyles such as obesity critical issues of our time (Figure A.1, A.2, A.3, A.4) [198].

1.1. The Physical Inactivity Pandemic

The World Health Organization (WHO) defines physical inactivity as performing less than 150 minutes of moderate-intensity or 75 minutes of vigorous-intensity physical activity per week [197]. In 2010, the WHO classified 23% of the world population over 18 years old physically inactive (Figure 1.1) [195]. This number grows to a striking 81% among adolescents aged 11 to 17 year-old [195]. One out of four individuals was physically inactive in 2016 [71]. Increased physical inactivity levels often correlate with high gross national product, resulting in more physically inactive societies in high-income countries compared to low [195]. All these circumstances contribute to a significant global problem because insufficient physical activity is one of the major causes of high mortality rates around the world. Every year, lack of regular physical exercise and sedentary lifestyles lead to approximately 3.2 million deaths on a global scale [198]. People who exercise on a regular basis have a 20% to 30% lower risk of death from various diseases compared to people who do not [188]. Chronic conditions associated with physical inactivity such as heart diseases, cancer, and diabetes are responsible for 1.7 million deaths every year in the United States alone [22]. Medical costs associated with physical inactivity reach up to a massive $67.5 billion on a worldwide scale [49]. Research supports the idea that physical inactivity negatively affects our mental health and diminishes our cognitive ability to learn [76]. Despite the world-wide recognition of its detrimental effects, physical inactivity continues to threaten public health and modern societies continue to adopt sedentary behaviors coupled with unhealthy dietary habits.

Researchers have consistently studied this pandemic to come up with efficient solutions and identified several determinants associated with urbanization that discourage people from committing to regular physically activity [195]. Accord-



Prevalence of physical inactivity* among adults, ages 18+ (age standardised estimates)
Both sexes

* Less than 150 minutes of moderate-intensity physical activity per week, or less than 75 minutes of vigorous-intensity physical activity per week, or equivalent

The boundaries and names shown and the designations used on this map do not imply the expression of any opinion whatsoever on the part of the World Health Organization concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. Dotted and dashed lines on maps represent approximate border lines for which there may not yet be full agreement.

Data Source: World Health Organization
Map Production: Health Statistics and Information Systems (HSI)
World Health Organization

World Health Organization

Figure 1.1: 2010 Global Health Observatory data on prevalence of physical inactivity [197]

ing to World Health Organization, fear of violence, high crime rates, high-density traffic, low air quality, environmental pollution, lack of public space and recreation facilities are globally accepted environmental factors [195]. Lack of time and family responsibilities have been consistently referred barriers among working individuals. Old adults often raise health issues and age-based physical limitations as deterrents to regular exercise. Young individuals frequently cite lack of motivation as a barrier to more regular participation in physical exercise [23]. Wide availability of leisure time activities requiring less physical activity is also an inherent cause of this pandemic. Small-sized social networks and low-paying jobs are also correlated with less physical activity [157].

Conventional approaches used to tackle this health crisis typically concentrate on reducing personal and environmental factors associated with physical inactivity such as obesity, stress, fatigue, associated cost, lack of time, and irregular sleep cycles. [37, 102, 126, 131, 176]. Educational institutions consistently utilize physical training classes to teach children about the benefits of healthy living and an active lifestyle [103]. The World Health Organization regularly publishes recommendations on regular physical activity for health [196]. A growing body of knowledge on high-intensity interval training (HIIT) protocols aims to resolve problems associated with time constraints through low volume high intensity endurance exercise interventions [11]. Possibly the most well-known of them all to general public, computer-aided approaches such as video games that require physical activity, has been gaining significant attention among research communities [99, 116].

1.2. Computer-aided Approaches

The number of studies using computer-aided systems in healthcare have steadily increased over the last decade (Figure 1.2) [81]. Despite the negative effects associated with our tremendous dependency on information technologies, computers have revolutionized the means of health maintenance and management [81]. Nowadays, we are transitioning away from clinician oriented processes to conservative and self-regulatory approaches in terms of consistently observed negative outcomes associated with physical inactivity [133]. Global Positioning System

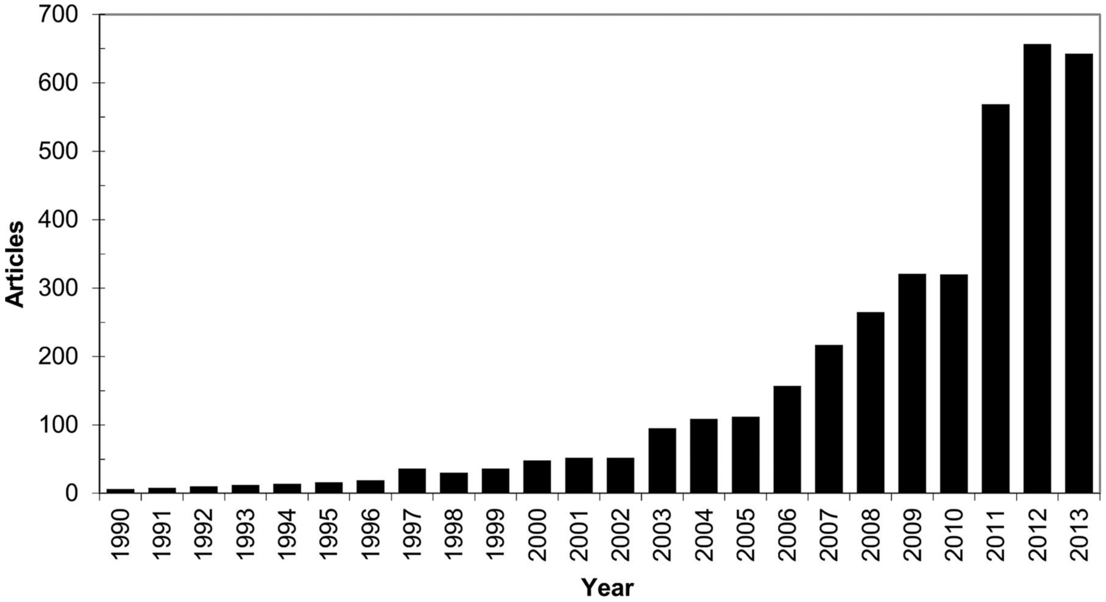


Figure 1.2: Number of publications using accelerometers in exercise settings [180].

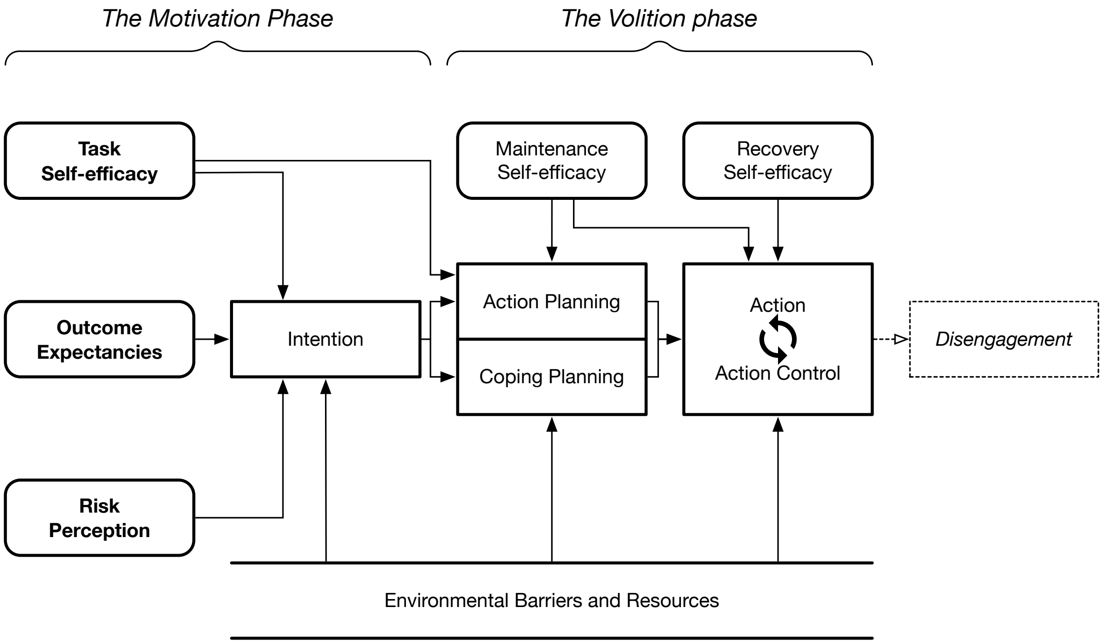
(GPS), pedometers, inertial measurement units (IMU), heart rate monitors and body motion trackers (MoCap) offer cost-efficient solutions [133]. These devices allow individuals to monitor certain syndromes associated with poor physical condition and promote appropriate exercise routines with satisfactory health benefits. Moreover, wearables such as wireless body area network (WBAN) allow energy expenditure estimation for realizing appropriate exercise load or carrying out real-time physical performance evaluations [93]. Likewise, significant improvements achieved in motion capture technology currently allow us to recognize facial expressions, emotions, and bodily movement with great accuracy; which in turn led to a better understanding of exercise physiology and psychology [17, 160]. Furthermore, interactive video games utilizing bodily movement as gameplay elements are gaining significant attention from both public and research communities. Games such as Dance Dance Revolution (DDR), Wii Sports, Kinect Dance Central, and Beat Saber are designed to administer engaging gameplay experiences through adoption of in-game physical elements [11, 171]. Research supports the beneficial and motivational aspects of these games in low to moderate level exercise and encourages the use of similar persuasive technologies to motivate masses in increasing their adherence to regular physical exercise [67, 169]. Most work in this field utilizes computer-aided systems designed to promote multiplayer interaction for removing social barriers and promoting collective exercise [98]. Subsequently, immersive technologies are offering significant improvements in exercise adherence and effectiveness over conventional approaches [28, 70].

Despite the existing systematized body of knowledge and considerable amount of resources devoted to its cause, most computer-aided approaches are so near and yet so far from preventing lack of physical activity on a global scale. I raise our fragmentary comprehension on human factors as a fundamental cause and approach the phenomenon in discussion from a human-computer interaction perspective. I employ a human-centered approach to computer-aided system design and concentrate on exercise psychology for promoting physical activity.

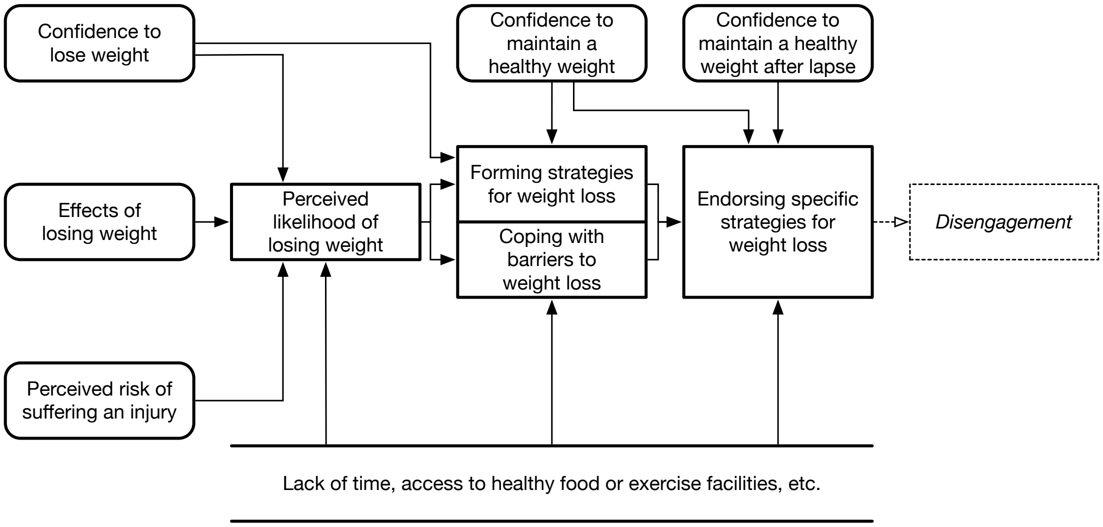
1.3. Human Factors and Exercise Psychology

Humans are inherently different beings with dynamically changing needs and desires to be satisfied. We are intricate creatures due to our diverging attributes such as socio economic background, genetic traits, or political values. These basic assumptions about human nature play an important role in computer-aided system design. Defined as human factors in computing systems, or commonly referred as human-computer interaction (HCI), is an essential field of study that exceeds simple questions such as which one is the best menu design [77]. The combined effort of countless scholars devoted to this field plays a substantial role in reducing the risk of injuries, death, or catastrophic outcomes associated with human errors in computer systems, which was painfully proven in partial core meltdown at Three Mile Island and crash of American Airlines Flight 965 in December 1995 [32, 58, 152]. Although the HCI community have substantially increased our understanding on most human factors in computer-based system design, we continue to operate with limited amount of knowledge regarding our innate tendencies for promoting regular physical exercise.

As an attempt to resolve this problem, recent work focus on our evolutionary nature to avoid inessential physical exertion for explaining negative affective response to exercise [109]. The existence of this trait is explained by our ancestors' need to conserve energy for primitive activities such as pursuing prey in an envi-



(a) Graphical outline of HAPA



(b) Weight loss expressed in terms of HAPA as a practical example.

Figure 1.3: The Health Action Process Approach (HAPA). Bold text emphasizes the constructs that I focus in this thesis.

ronment where nutrition was scarcely found. We continue to observe the effects of this trait as research clearly shows that humans adapt movement patters in a way that minimizes energy expenditure even while the lower extremities are constricted [72, 75]. This has serious implications for internalization of sedentary lifestyles since most of us perceive physical activity as an imposition rather than pleasant and essential. Therefore, under suitable circumstances, humans are inclined to choose sedentary behavior over healthy but stressful alternatives such as physical exercise.

However, this inherent tendency does not mean it is insusceptible to positive transformation. Over the last decades, scientists studied various aspects of human psychology in exercise to better understand the intrinsic determinants that lead to changes in health behavior [130]. Well established psychological theories of physical activity such as Social Cognitive Theory [14], Theory of Planned Behavior [3], or Transtheoretical Model [142] provide evidence-based strategies for achieving positive outcomes in health promotion programs [130]. As a more recent theory, the Health Action Process Approach (HAPA) uses an integrated model to extend previous theories and defines the predictors of change from health-compromising to health-enhancing behaviors (Figure 1.3) [153]. HAPA divides the process of adoption, initiation, and maintenance of health behaviors into motivational and volitional phases. The first phase is mainly effected by three psychological factors, task self-efficacy, outcome expectancies, and risk perception. Self-efficacy and outcome expectancies are seen as the major predictors of forming an intention and risk perception may have an indirect role and induce detrimental effects on behavioral motivation [153]. I consider these three factors essential in computer-aided system design and study each predictor of health behavior change from an HCI perspective to promote regular practice of physical exercise.

1.4. Three Pillars of Potent Systems

In this thesis, I conduct three case studies to individually examine each major construct of intention suggested by the HAPA (Figure 1.4). First, I introduce a role for age in difficulty adjustments of exercise games to better promote self-efficacy and motivate individuals to engage in regular physical exercise. Next, I

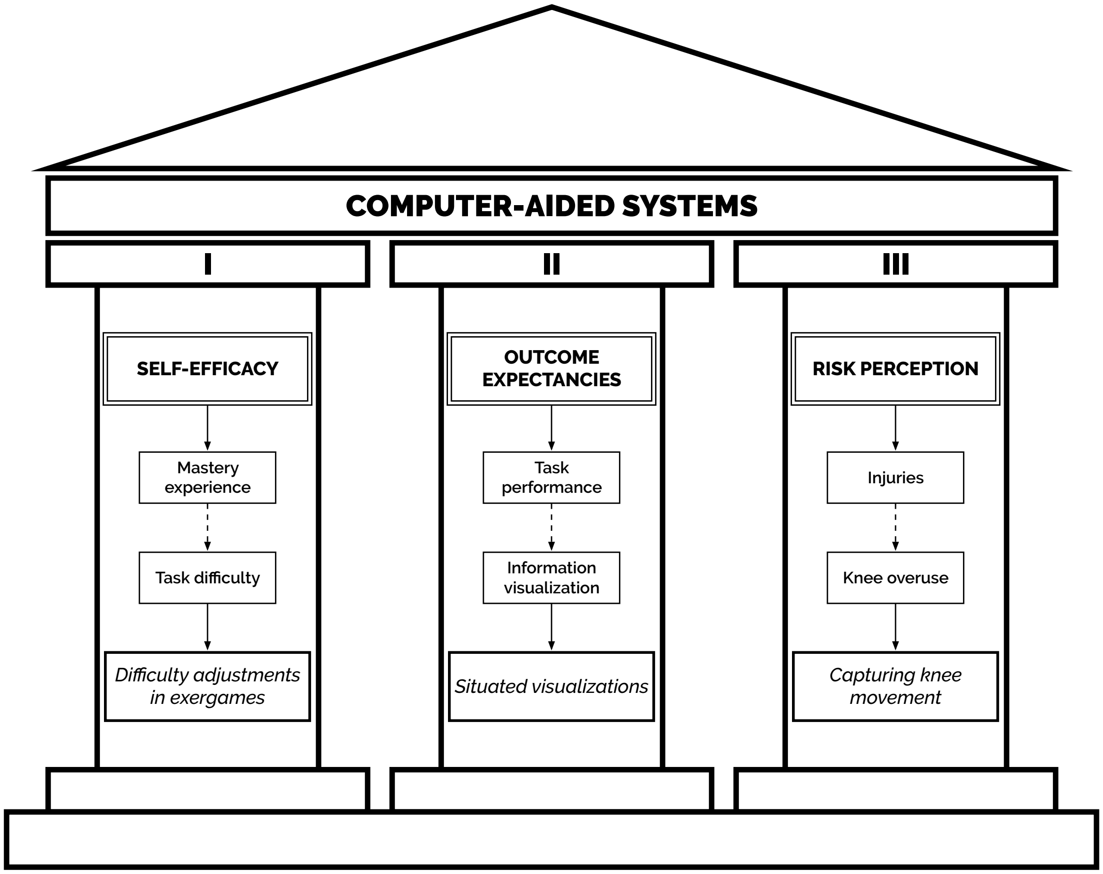


Figure 1.4: Conducted studies in conjunction with the three cognitive constructs.

investigate situated visualizations to satisfy the outcome expectancy of cyclists to a greater extend. Finally, I consider a similar approach to knee movement visualizations for reducing the perceived risk of overuse injuries.

1.4.1 Self-efficacy

Sports professionals consider any physical exertion good for overall health [74]. Yet, not all activity is considered exercise and exercising once cannot undo all effects of a prolonged sedentary lifestyle [36]. Therefore regular physical exercise is important for reducing risks of non-communicable diseases (NCDs), maintaining a healthy body weight, reducing stress, minimizing anxiety, avoiding depression, and strengthening one's immune system [74]. Despite all these benefits, staying motivated to exercise regularly is a cognitive challenge in itself [143]. Research supports the major contribution of self-efficacy, one's belief in his or her abilities and capability to produce desired outcomes, on maintaining a high level of motivation [15]. Mastery experience which is highly correlated with increased self-motivation is defined as the most effective source of self-efficacy [15]. Since successes are the main contributors of mastery experience, adequate task difficulty plays an important role in computer-aided systems for achieving positive health behavior change between individuals. Therefore, I investigate difficulty adjustment methods in digital exercise games, or commonly referred as exergames, for motivating individuals and increasing their adherence to regular physical exercise. I address aging-related changes in exergame design and introduce a role for age in consistently utilized difficulty adjustment methods to substantially increase motivation for physical exercise.

1.4.2 Outcome Expectancy

Outcome expectancy is typically defined as our expectation that a behavior is always followed by positive or negative results [193]. Renowned social cognitive models such as self-efficacy theory [14], the transtheoretical model [142], the theory of planned behavior [3], and protection motivation theory [114] utilize outcome expectancy as a fundamental construct for explaining changes in human behavior. Physical activity studies employing these theories analyze outcome expectancy and motivation in exercise settings, and most of them report significant correlation between the two [145, 147, 194].

The computer-aided system design consistently address outcome expectancy in physical exercise settings by providing adequate feedback on individual's performance for any given activity [5]. Consequently, effective information visualization becomes a substantial element of design to provide low-cost and unobtrusive means for the evaluation of these results [57]. Existing approaches often focus on novel visualization techniques to achieve effortless extraction and communication of information [57]. Yet, most approaches solely concentrate on visualization design and fail to address the peculiar components of exercise such as bodily form or cognitive load. Therefore, I study situated visualizations in physical exercise settings to stimulate outcome expectancy while supporting both physical and cognitive aspects of exercise. For realizing this goal, I work with professional athletes due to their extensive knowledge about information visualization and their familiarity with the common techniques used to evaluate performance in physical exercise.

1.4.3 Risk Perception

Risk perception involves an individual's cognitive and emotional assessment on any behavior concerning its benefits and consequences. It is often targeted in social cognitive models thanks to its commonly recognized role in achieving positive health change behaviors [24, 156]. The critical role of this construct can be observed in physical exercise where injuries are perceived as significant risk factors for any individual attempting to renounce a sedentary lifestyle [91]. Aside from possible falls and accidents, intricate factors such as muscle imbalances, fatigue, hormone levels, over-training, poor equipment, lack of nutrients, or change in climate are consistently cited sources of injuries in physical exercise [38, 78]. Fortunately most of functional or structural injuries are avoidable with proper exercise form and body alignment [177]. On the other hand, assessing an individual's form or technique is an ill defined process due to this problem's personal nature and individual differences in movement pattern. Moreover, existing body of knowledge on human motion largely depends on indoor scenarios where environmental factors significantly differ in terms of outdoor exercise [122]. Taken together, I study knee overuse injuries in cycling to better understand their nature and determine the required actions for achieving a decline in degree of risk perception. Additionally, I aim to reduce their likelihood by promoting self-assessment through intuitive visualizations which can support both indoor and outdoor training environments.

1.5. Thesis Structure

This thesis consists of five chapters (Figure 1.5).

First, I establish the what, why, and how of my research work and briefly explain the resulting contributions in Chapter 1.

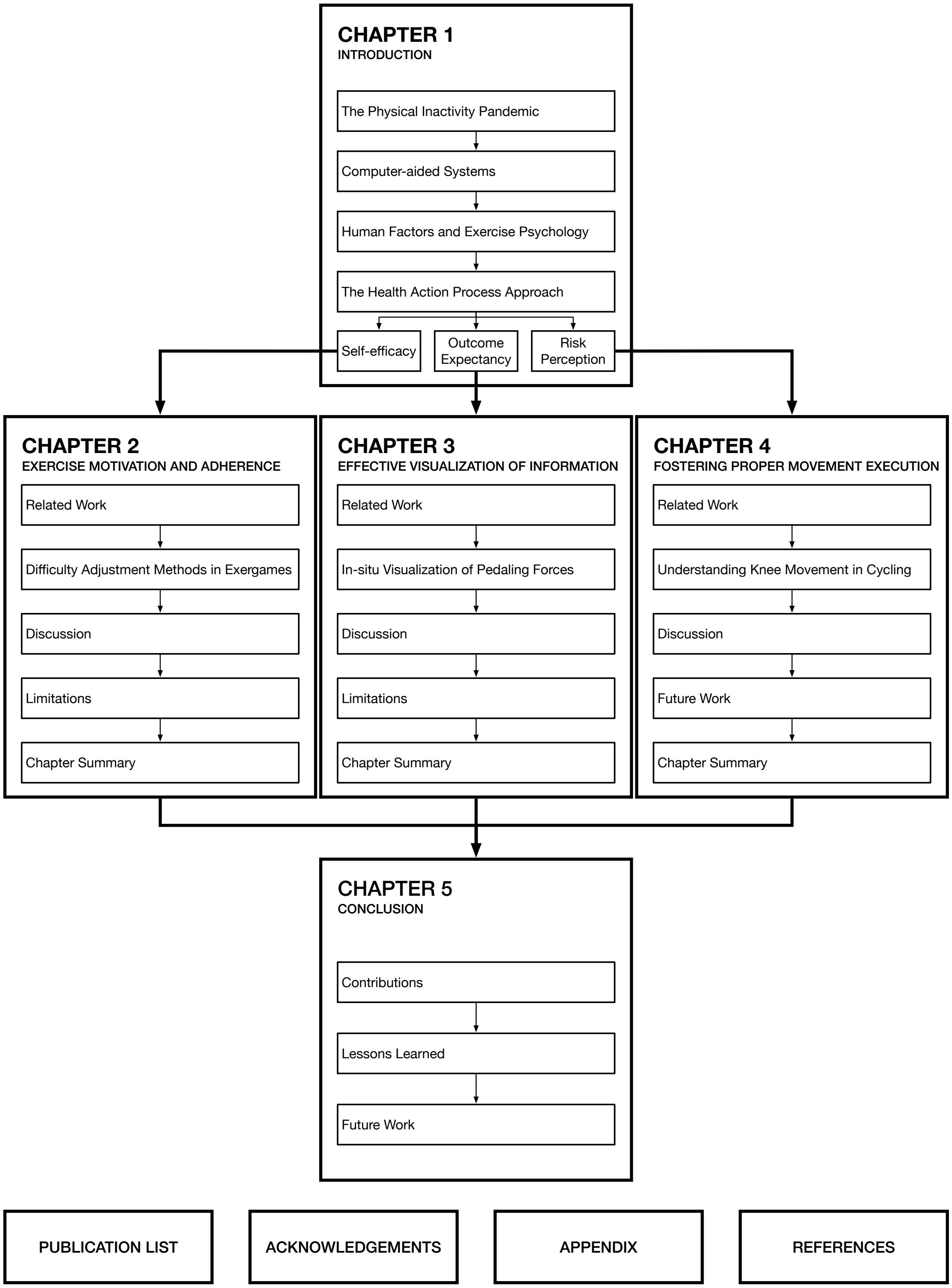


Figure 1.5: Graphical outline.

Second, I introduce my work on exergame difficulty adjustment and promoting motivation for regular physical exercise in Chapter 2. I also include an in-depth literature review on serious games and difficulty balancing to enhance our understanding on the topics in discussion.

Next, I propose a situated pedaling visualization to cycling exercise in Chapter 3. Additionally, I discuss the importance of qualitative monitoring in conjunction with quantitative, and how situated visualizations have a potential to promote outcome expectancy by simultaneously supporting both practices.

Afterwards, I demonstrate the capabilities of an existing video-based deep learning toolbox in Chapter 4 for indoor-outdoor tracking of knee joint in cycling. I describe the prevailing methods used to assess knee movement in cycling and explain why their indoor-only nature is questionable. Furthermore, I employ my knowledge from Chapter 3 to come up with a visualization framework which also provides a robust unobtrusive approach to indoor-outdoor tracking of knee movement in cycling.

Finally, I conclude my findings and contributions in Chapter 5 . I also propose several future work that may be of service to information and sports scientists alike.

CHAPTER 2

Exercise Motivation and Adherence

Persistence is an essential feature for promoting health and physical fitness through successful exercise programs. However, approaches for encouraging people to commit regular physical exercise often end up in failure due to lack of motivation [143]. Drop-out rates reach up to 50% within first six months between people who were introduced to a regular exercise program [6]. Researchers justified the value of self-efficacy as a prominent solution to exercise adherence problem [47, 115, 118]. In his social cognitive theory, Bandura defines self-efficacy as one's belief in his or her ability to succeed in specific situations and achieve certain goals (Figure 2.1) [14]. Therefore, self-efficacy is positively correlated with exercise adherence and it is an essential construct in human psychology for motivating participants to commit regular physical exercise.

Existing body of knowledge encompasses a number of psychological factors for developing self-efficacy within exercise scenarios. Among all, mastery experience, or simply performance outcome, stands out as the most influential factor and characterized by an individual's past personal success, goal setting, and appropriate exercise program design [86]. I explore the last part of this factor from an human-computer interaction perspective considering exergames. A portmanteau of exercise and gaming, exergames are frequently utilized to provide means

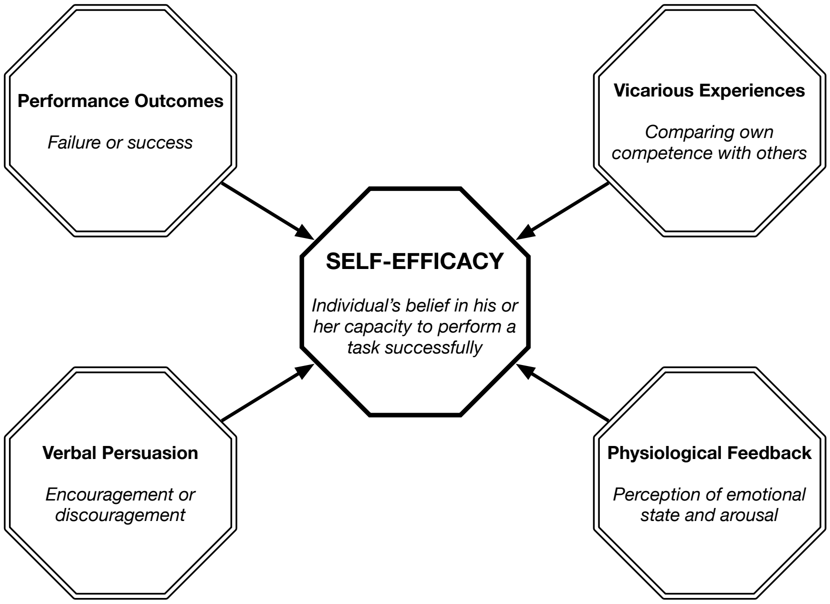


Figure 2.1: Sources of self efficacy.

of engagement in physical and social activities that are also a form of exercise [25, 64, 66]. Although the health benefits of exergames are still subject to debate [18, 43, 107, 135], many studies confirm their potential as a motivator in committing regular physical exercise [168, 169, 170, 171].

While research into exergames mainly explored its application areas, design, and benefits, achieving optimal play experience through game difficulty balancing according to player skill continues to remain unclear. As a crucial component of the modern game design pipeline, difficulty balancing aims to minimize the effects of skill variations through challenge adjustments to optimize player experiences [12]. Commonly referred to as difficulty adjustments, recent work examined the effects of static and dynamic techniques in both exergame and non-exergame settings [65, 165]. However, shortage in comparative empirical studies and utilization of homogeneous player groups aged between 18 to 30 fails to justify their applicability to broader audiences including old individuals [112, 167].

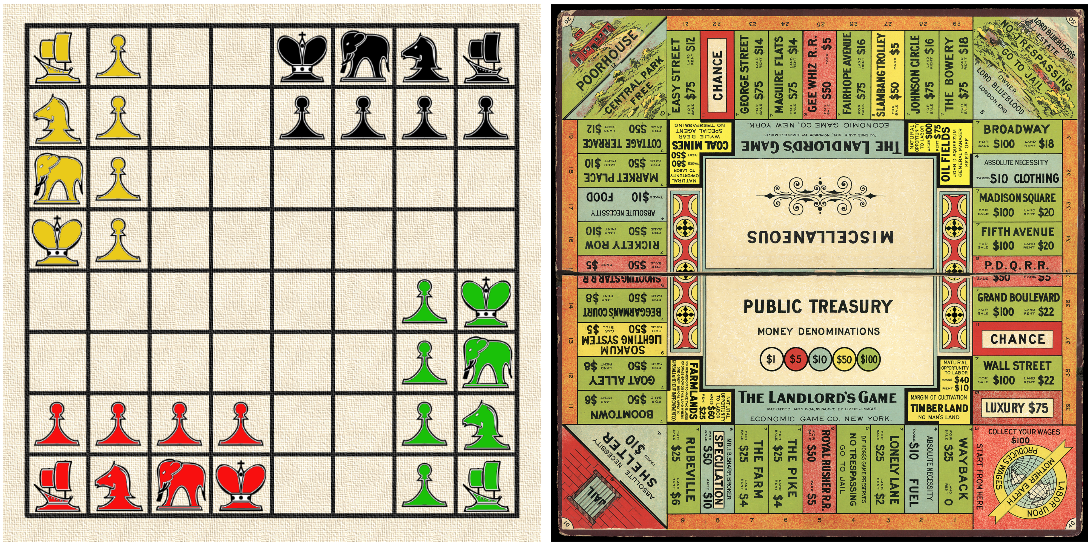
To address these issues, and motivated by adequate exergame applications, I compare flow of young and old individuals using four consistently utilized difficulty adjustment methods to introduce a role for age in exergame difficulty adjustment preference and design. I contribute to the growing field of serious games by advancing our understanding on factors associated with appropriate task difficulty and optimal play experience. Taken together, I enable designers to make informed decisions for administering satisfactory exergaming experiences; which in return might lead to a further increase in regular practice of physical exercise to bolster healthy lifestyles.

2.1. Related Work

2.1.1 History of Serious Games

Serious games is an interdisciplinary field of study that its origins can be traced back to Plato's fundamental discussions on role of play in child development [8, 44]. Frequently described as games with an implicit objective beyond entertainment, first uses of the term can be found in Clark Abt's seminal work with the same title [1]. However, a rich historical trend in purposing of games can also be observed way before his time [119, 129, 155, 187]. Throughout the annals of play, both analogue and digital serious games have been utilized extensively in therapeutic, educational, commercial, and social settings [25, 98, 144, 146]. The earliest application of gaming to purposes other than entertainment can be seen in 7th Century India. Chaturanga which is seen as a precursor to chess was the first known game to utilize militaristic metaphors in a board game (Figure 2.2a) [134]. Similarly, Landlord's Game from 1902 is precursor to modern Monopoly and it was designed to depict dangers of capitalist approaches to land taxes and property renting (Figure 2.2b) [134].

Given that Plato's critical thinking and notions on purposing of play, traditionally the focus of digital serious games has always been on training and education. As a classical example, Math Blaster used simple equations as game elements to build knowledge in basic subjects such as addition, subtraction, multiplication, and division [85]. World Without Oil aimed to educate players on how an oil crisis might affect their lives [199]. IBM designed City One to simulate the complexities of urban planning from water management to finance [82]. Microsoft's Flight Simulator has been a comprehensive simulation-based learning experience of civil aviation since 1982 [41]. United States Army used Ameri-



(a) Chaturanga [21]

(b) The Landlord's Game [104]

Figure 2.2: Analogue serious games.

cas Army as a recruitment tool which simulated military training exercises and combat missions [110].

Following this period, re-purposing of games gained much attention from multinational corporations due to their potential in advertisement. Pepsi Invaders was developed to boost morale among sales employees of Coca-Cola [50]. Kool-Aid Man and Chex Quest were games designed specifically for brand promotion through game consoles [50].

It was recently that scholars of this emerging field identified the powers of gaming in health related contexts. Several unsuccessful early attempts such as Project Puffer of Atari interfaced an exercise bicycle with their own home entertainment system as a novel and desirable market for company to enter in 1982 (Figure 2.3) [9]. The major advance in this field started with the first Games for Health conference in 2004 which triggered investigations into potential of games in health care applications [99]. Since then there has been a rapid rise in gamification of physical activity and exercise.

Figure 2.3: Atari's early attempt to combine exercise with gaming. [9]

(a) Nintendo Wii [137]

(b) Microsoft Kinect [83]

Figure 2.4: Two video game consoles utilizing dance as a form of exercise.

2.1.2 Purposing of Games for Health

Over the last decade we have witnessed a rapid rise in the use of novel digital concepts that combine exercise and games, such as Nintendo Wii and Microsoft Kinect (Figure 2.4). Labeled active games, exertainment, or exergames, Mueller et al. defined this genre as digital games where the outcome of the game is predominantly determined by physical effort [123]. We adhere to this definition and use the term *exergames* for referring to these games in our investigation of the vast amount of existing literature. We divide our investigation into two age based groups: young and old individuals.

Researchers have been widely investigating the physiologic and psychological effects of exergames on young individuals that can contribute to short or long-term weight maintenance. Straker and Abbott compared traditional and physically active gaming among nine to twelve years old children and found increased cardiovascular response and energy expenditure during latter scenario [172]. Graves et al. compared physiological cost and enjoyment of exergaming on Nintendo Wii Fit with aerobic exercise and found it stimulating in light-to-moderate intensity exercise [69]. Staiano et al. examined physical and psychological effects of a 20-week exergame intervention on overweight and obese adolescents, and reported the effectiveness of cooperative exergames on weight loss among young individuals [169]. Althoff et al. studied location-aware multiplayer games that combine gameplay with the physical world and reported increased physical activity levels among players [4]. Douris et al. compared physiologic and psychological responses to 30-minutes of treadmill walking with Nintendo Wii Fit Free Run and described the latter as a potent alternative to traditional moderate-intensity exercise [53]. Staiano and Calvert outlined the literature on exergames used in physical education courses in schools and provided several physical, social, and academic benefits as related outcomes [170]. Staiano et al. also reported an increase in cognitive skills of adolescents as an outcome of competitive exergames and found a relationship between this increase and weight loss [168].

Old individuals have also been gaining much attention from exergame community due to their lack of motivation for physical activity, physical fitness, and mobility in extremities [139]. Billis et al. developed a game platform using Nintendo Wii Balance Board in an attempt to increase exercise motivation and physical well being among older individual groups [20]. Pedram et al. addressed social, environmental, and physical issues of the elderly by designing an augmented dancing environment and provided design guidelines for creating similar interactive designs [98]. Gerling et al. evaluated the effects of age-related impairments on exergaming experience of frail old individuals and indicated their need to be considered in game design process [66]. Ijsselsteijn et al. identified augmented and virtual reality exergames as stimulating on intrinsic motivation for regular exercise [84]. Durick et al. explored and presented alternative approaches to aging myths in exergames for older individuals [55]. Skjæret et al. carried out investigations into motion characteristics of older individuals in stepping exergames designed to increase movement quality through fall preventive exercises [162]. Gerling et al. examined exergame design for institutionalized older individuals and reported increased quality of life among players [67]. Romero et al. demonstrated how inclusion of family members or caretakers into exergame design could lead to persuasive solutions among older individuals, and increase motivation for social and physical activities [144]. Brox et al. focused on multiplayer exergames for older individuals and highlighted their power in preventing loneliness through social interaction in physical activity [25].

2.1.3 Difficulty Adjustments in Exergames

Balancing of game difficulty based on player skill has been widely recognized as a crucial element of game design to avoid boredom or frustration among players. Liu et al. pointed out the unsuitable and interruptive nature of static difficulty adjustment methods in realizing optimal play experience [112]. They designed a real-time, anxiety-based affective feedback mechanism for dynamic difficulty adjustment (DDA). Smedding et al. used adaptive difficulty parameters for speed, accuracy, and range of motion to design a challenging yet suitable exergame for Parkinson disease patients [165]. Baldwin et al. conducted a formal review of existing competitive multiplayer games and suggested a preliminary framework for classifying Multiplayer Dynamic Difficulty Adjustment (mDDA) instances [13]. Baldwin et al. also investigated the effects of multiplayer DDA awareness on play experience and found a negative relationship between the two [12].

Although research in game difficulty adjustments gained a significant momentum over the last years, to our knowledge, research on difficulty adjustment in exergames is scarce. Most studies follow a similar practice as [112] and focus on designing instruments or models for adjustment optimization. Hunicke described the design requirements of effective DDA systems that do not disrupt or degrade the play experience [80]. Jennings et al. suggested the use of level generation and machine learning techniques to achieve a DDA method that can change both structural and personalized difficulty elements [88]. Moreover, due to an inclination to adopt homogeneous and young sample groups, there is still considerable ambiguity with regard to impact of age related changes on difficulty adjustments mechanisms [167].

Much work has consistently been focusing on aging-related decline of physical or cognitive functions instead of game difficulty optimization. Interventions to prevent falls in older individuals is a common area of interest for researchers working on exergames. Lange et al. used a dancing game to administer step based exercises to reduce falls in older individuals [105]. De Groot et al. outlined motivating factors and barriers for older individuals to adhere to group exercises for fall prevention [46]. Uzor and Baillie described the use of tailored exergames to prevent falls and conducted a long-term study where observed better exercise adherence in participants who used exergames compared to standard care [183].

2.2. Age and Difficulty Adjustments in Exergames

2.2.1 Hypotheses

There is still much controversy surrounding aging and difficulty adjustment mechanisms in exergames. My goal in this study was to answer the following research questions:

Q1. Do traditional approaches fail to provide a satisfactory play experience?

Q2. Do play experience of young and old individuals differ from each other under similar exergaming conditions?

Q3. Is there a difference between difficulty adjustment preference of young and old individuals?

Accordingly, I formulate the following hypotheses after reviewing the existing literature on aging and exergame difficulty adjustments:

H1. Flow refers to an equilibrium between challenge presented by the game and respective skill set of players where maximum enjoyment is achieved. For example, in Wii Sports Tennis, players experience flow when the skill level of the non-playable characters (NPC) are on par with their own. Since controlling player skill is a mundane task, we achieve flow by adjusting game difficulty and modifying game elements such as NPC speed, health, gameplay duration, or power-up frequency. Traditional methods used for these adjustments follow a steady increase in difficulty, mostly in steps represented as game levels. Growth or amount of the adjustment depends on player's self-assessment of his perceived skill and selection of difficulty from a given set of choices such as easy, normal, and hard. This schema causes a decline in flow and leads to a diminished gaming experience [12, 13, 64, 112, 165]. Accordingly I form our first hypothesis as follows: *Constant difficulty will fail to provide a satisfactory exergaming experience compared to ramping, performance-based, and biofeedback-based difficulty adjustments.*

H2. Aging-related changes have become a central topic in exergame design for older individuals. As an example, diminished motor control and neural functions affect various aspects of designing exergame experiences for this specific target group. However, effects of these changes on difficulty adjustment preference are still not clearly defined. I think that technology experience and gaming perception of young and old generations differ significantly, which is likely to have a substantial effect on preferred level of difficulty. Combined with varying game preferences, I believe that exergaming experience of young and old generations will demonstrate a considerable amount of dissimilarity under same conditions. Based on this background, my second hypothesis is: *Measured exergaming experience of the two age groups will show a significant difference based on Jackson and Marsh's Flow State Scale (FSS) [87].*

H3. Based upon the first and second hypotheses, I predict significant differences between difficulty adjustment preference of the two age groups. Building upon this interaction, I form my final hypothesis as follows: *The two age groups will favor different difficulty adjustment methods.*

2.2.2 System Design

Throughout the design process, I followed the Waterfall model which is a sequential software engineering approach. First, I gathered requirements by working with Japan's only national sports college and observing traditional exercise classrooms for older individuals at multiple locations such as community halls and

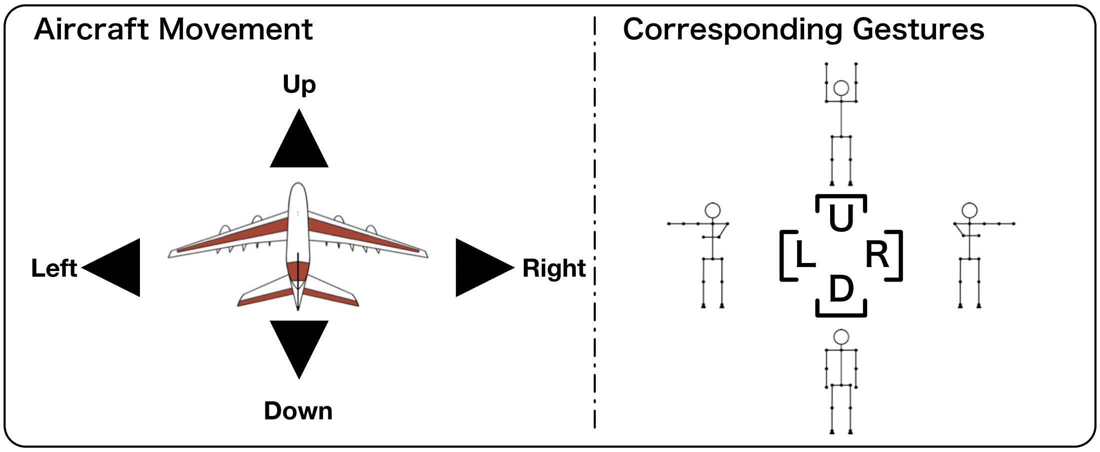


Figure 2.5: In-game controls and corresponding gestures.

rehabilitation hospitals. Consequently I opted for a competitive game design to address upper extremity exercises due to their widespread admission in physical therapy for older individuals. During my initial studies I developed three exergames and finally I chose the game we used in this study due to its conformity to entertainment criteria derived from the ElderGames project [63].

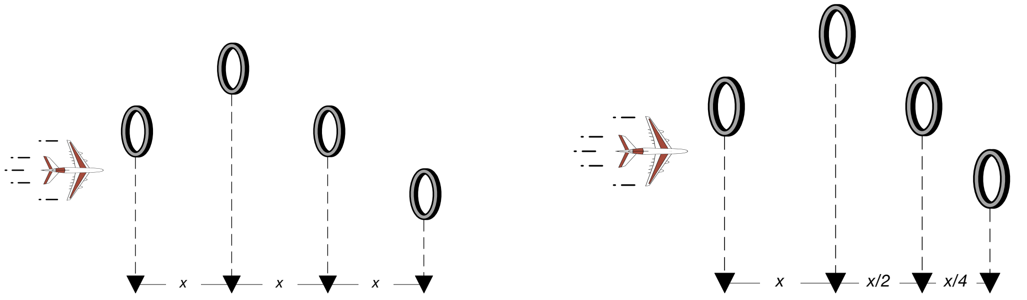
In my game, players control an aircraft by utilizing predefined discrete arm gestures to pass through rings placed on its path. I used a metaphorical relationship between in-game gestures and their real-life representations to overcome the infamous chocolate covered broccoli problem [26]. As a result, I utilized four arm gestures that were based on aircraft marshaling movements as in game controllers (Figure 2.5). I conducted preliminary studies with young and old individuals to determine a suitable range of motion (ROM) for each gesture.

Rings were color coded and randomly placed at four locations in correspondence with gestures used to represent movement direction. The distance between each ring was utilized as the game's difficulty and was modified by the game in accordance to the selected difficulty adjustment method (Figure 2.6). Under constant difficulty mode the distance between each ring was set to a static value before beginning the game. Ramping adjustments reduced the distance over time regardless of player performance. Performance based adjustments reduced the distance between each ring based on the ratio of current and maximum score. Biofeedback mode utilized readings from an electrocardiography (ECG) based heart rate monitor to track physiological condition of participants and adjust difficulty accordingly (Figure A.9, A.10). I chose ECG over photoplethysmography (PPG) because of its high reliability in measuring RR interval directly from QRS complex. Although algorithms to indirectly measure RR interval from PPG measurements exist [111], they support longer monitoring such as 5 minutes, thus ECG remains as industry standard. Furthermore, any other method or signal could have been used to achieve the same purpose, I chose RR interval because of its cost effectiveness in terms of time and availability combined with high accuracy in measuring heart activity. Based on this rationale, I modified the distance according to the fluctuations of the readings I acquired from heart rate monitor; which I used with a method analogous to formula established by Karvonen [97]. Figure 2.7 represents this real-time process where I directly used Polar H7 output on inter-beat interval (RR interval) to dynamically modify the game difficulty. I utilized the ratio between current and resting RR interval which was measured at the beginning of the experiment while participant was instructed to perform 4-7-8 breathing technique. I increased the maximum possible distance between rings by 50% for older individuals to accommodate the aging related decline of physical and neurological functions. Table 2.1 represents the distance settings I used with each adjustment method in terms of aircraft travel time, which in return determined the frequency of upper-extremity gestures executed by the participants.

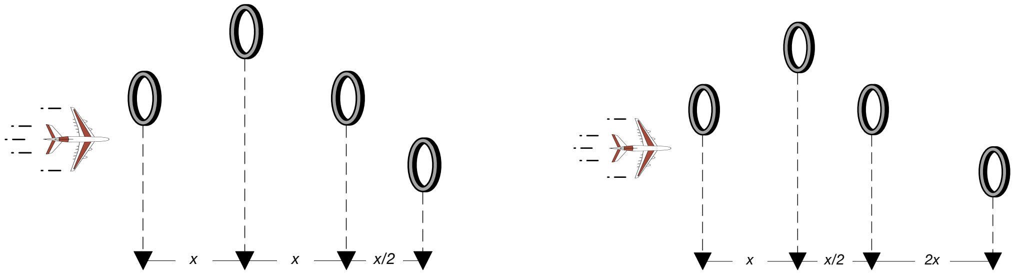
I set game's success criteria as ratio of successful passes through rings. Each successful pass resulted in a one point increase in player's total score. I used this information to calculate the ratio between accumulated points and total number of rings. This quantitative indicator of success was shown to players at the end of each game session and recorded along with point progression for evaluation purposes.

2.2.3 Measures

I utilized Jackson and Marsh's Flow State Scale *(FSS)* to evaluate player's game experience [87]. It consists of nine scales that represent dimensions of flow discussed by Csikszentmihalyi [42] and each scale incorporates four items. These scales are defined as challenge-skill balance, action-awareness merging, clear goals,



(a) Constant (b) Ramping



(c) Performance (d) Biofeedback

Figure 2.6: Difficulty adjustment methods. a) Fixed. b) Reduced over time. c) Reduced upon success. d) Adjusted dynamically based on RR interval.

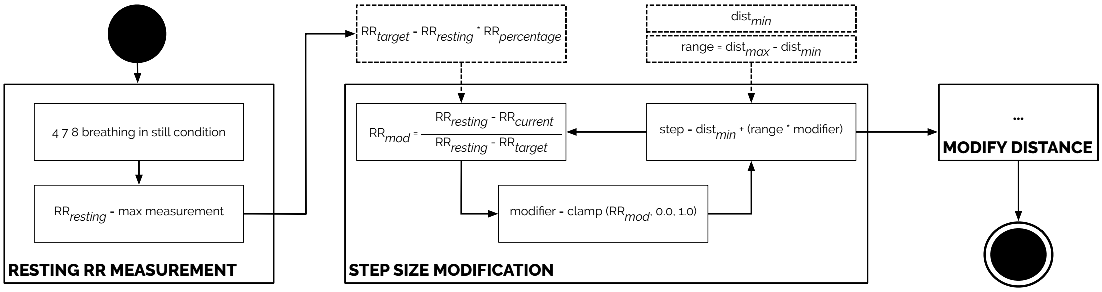


Figure 2.7: Difficulty modification process based on RR interval. This procedure was executed with each frame to react changes in RR interval in a timely manner.

Table 2.1: Distance modifications based on difficulty adjustment methods.

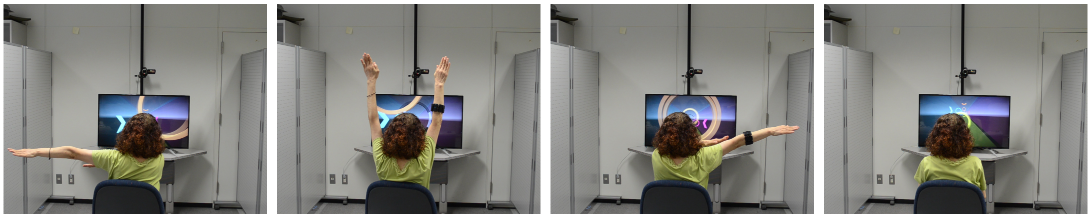
Method	**Modification**	**Distance (in seconds)**	
		Young	**Old**
Constant	Fixed	1.0”,0.75”,0.5”	1.5”,1.0”,0.5”
Ramping	Reduced over time	1.0” ∼ 0.5”	1.5” ∼ 0.5”
Performance based	Reduced on success	1.0” ∼ 0.5”	1.5” ∼ 0.5”
Biofeedback	Dynamic based on HRV	1.0” ∼ 0.5”	1.5” ∼ 0.5”

unambiguous feedback, concentration on task at hand, sense of control, loss of self-consciousness, transformation of time, and autotelic experience. Each item measures a dimension of the player’s flow on a traditional 5-point Likert scale where 1 represented strongly disagree and 5 represented strongly agree.

In addition to FSS, I recorded in-game data; including point progression, percentage based score, arm movements, heart rate, and RR interval. I also recorded gameplay videos of participants during each session.

2.2.4 Experiment Procedure

I started with a naive health screening process by using the Physical Activity Readiness Questionnaire (PAR-Q) with the young participants [178]. Health screening of old participants was conducted and guaranteed by the recruiting organization. After confirming participant eligibility, I explained the experiment protocol in detail and obtained informed consent in both age groups. Then, I installed the heart rate monitor and gesture armband on their respective body locations. Afterwards, I seated participants in a front facing posture and measured their resting RR interval while the participant was following on-screen instructions regarding 4-7-8 breathing method. I put each participant through a series of practice sessions using constant difficulty setting. I introduced the four difficulty adjustment methods in randomized order after participant demonstrated a sufficient understanding of the game interface and utilized in-game gestures (Figure 2.8). During the experiments, participants had to use arm gestures to steer the airplane through a series of rings, where the color of each ring corresponds to the gesture that will be needed to reach it. Participants played three consecutive



(a) Left (b) Up (c) Right (d) Down

Figure 2.8: Upper extremity gestures.

games before filling out the FSS for the respective method. This task was repeated with each difficulty adjustment method and sufficiently long breaks were given in between sessions to eliminate residual effects. After completing all tasks, participants were debriefed and discussions were held for 10 to 20 minutes before their dismissal. I conducted my study in accordance with Declaration of Helsinki and the protocol was approved by the Ethics Committee of Nara Institute of Science and Technology, Japan.

2.2.5 Apparatus

The physical setup of my system included a Philips 43” 4K Ultra HD LCD display that was connected to a late 2013 Apple Mac Pro with 3.0GHz 8-Core Intel Xeon E5 processor, 16GB 1866MHz DDR3 ECC memory, and dual AMD FirePro D700 6GB GDDR5 VRAM graphics cards. I connected these two devices with a standard HDMI cable.

I used a Polar H7 to monitor participant condition using ECG technology. I installed the moistened sensor on participant’s chest as instructed in its user guide. The sensor used Bluetooth Low Energy (BLE) to wirelessly transmit the measurements to Apple Mac Pro and I used RR interval data solely to simulate a dynamic difficulty adjustment condition.

I employed a Myo Gesture Control Armband to capture upper body extremity movements. I focused on orientation data provided by the armband’s inertial measurement unit (IMU) to track upper-extremity movements and decide if one of the four gestures are properly being executed or not. The angle range I accepted a gesture as proper was a total of 15 degrees in each direction which was

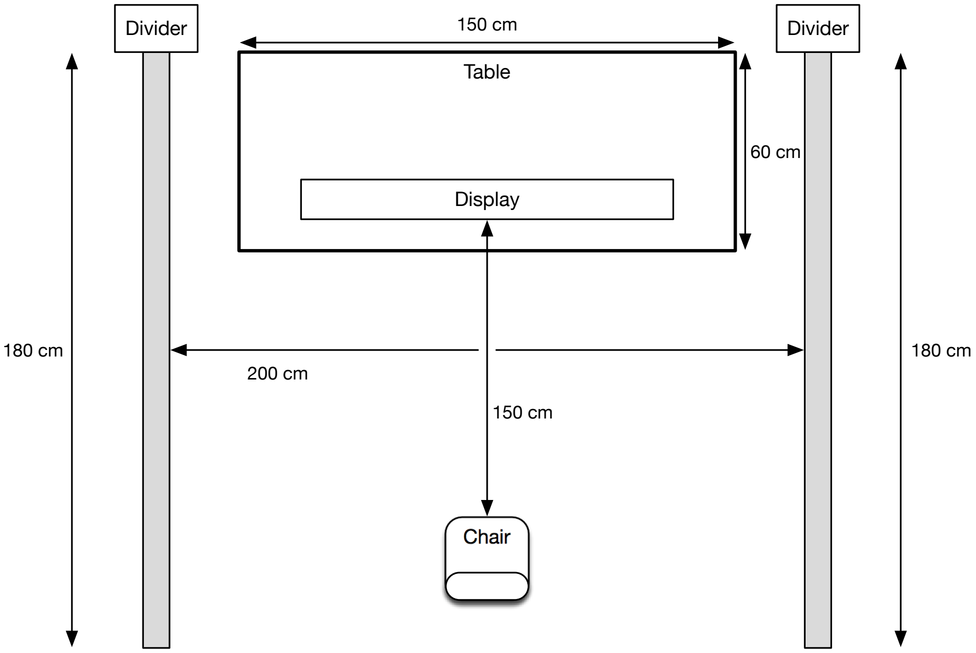


Figure 2.9: Environmental settings.

implemented to ensure correct gesture execution.

I developed our exergame using Unity 2017.3.1f1 Personal 64-bit Edition considering its extensive platform support, ease of hardware integration, and our expertise with its development environment. I mainly relied on its standard asset package and modified it according to our requirements. I used C and Objective-C to create my own Bluetooth plugin for Unity due to its lack of native support.

2.2.6 Environmental Settings

I placed our display on a 150x60x70 cm desk. Participants were seated on a standard 50 cm height chair and positioned 150 cm away from the display in a front facing posture. I used two 90x180 cm room dividers on each side of the experiment space to avoid possible environmental distractions. The distance between left and right dividers was 200 cm. Figure 2.9 illustrates my configuration.

I sat far behind participant throughout the experiment and no interruptions occurred during experiment phases. Video footage of each experiment was recorded with two video cameras. The first camera was located at the middle of

Table 2.2: Descriptive statistics of the sample group

	Male			**Female**			**Total**		
	N	**Mean**	**St.Dev.**	**N**	**Mean**	**St.Dev.**	**N**	**Mean**	**St.Dev.**
Old	10	72.30	2.91	4	72.50	3.70	14	72.36	3.00
Young	10	27.10	3.03	5	26.20	1.64	15	26.80	2.62
Total	20	49.70	23.37	9	46.78	24.53	29	48.79	23.33

the table facing the participant. The second camera was placed one meter behind the participant facing towards the experiment space.

2.2.7 Participant Profile

I recruited 29 participants for my experiments. The sample consisted of 15 young and 14 old individuals with age 26.80 ± 2.62 and 72.36 ± 3.00 respectively (Table 2.2). The young participants were students gathered from various labs at Nara Institute of Science and Technology, Japan. I utilized the services of a local organization that finds temporary or part-time jobs for senior citizens to recruit old participants. I paid a remuneration of 1000 JPY (approximately 9 USD) per hour to all individuals for their participation in my study.

In both groups no participant identified himself as a gamer. Participants had no prior experience or knowledge about the exergame design before the scheduled experiment date. Additionally, they had no personal or professional level relationship with me that might effect the results.

2.2.8 Results

I utilized a fully randomized repeated measures design in order to investigate my hypotheses. I used Generalized Estimating Equations (GEE) with linear scale response model in our three step regression-analysis and preferred Wald test for Chi-square Statistics. I evaluated each FSS scale via Cronbach's alpha and removed concentration on task at hand and transformation of time from my evaluation due to low level of internal consistency (Table 2.3). Additionally, I ex-

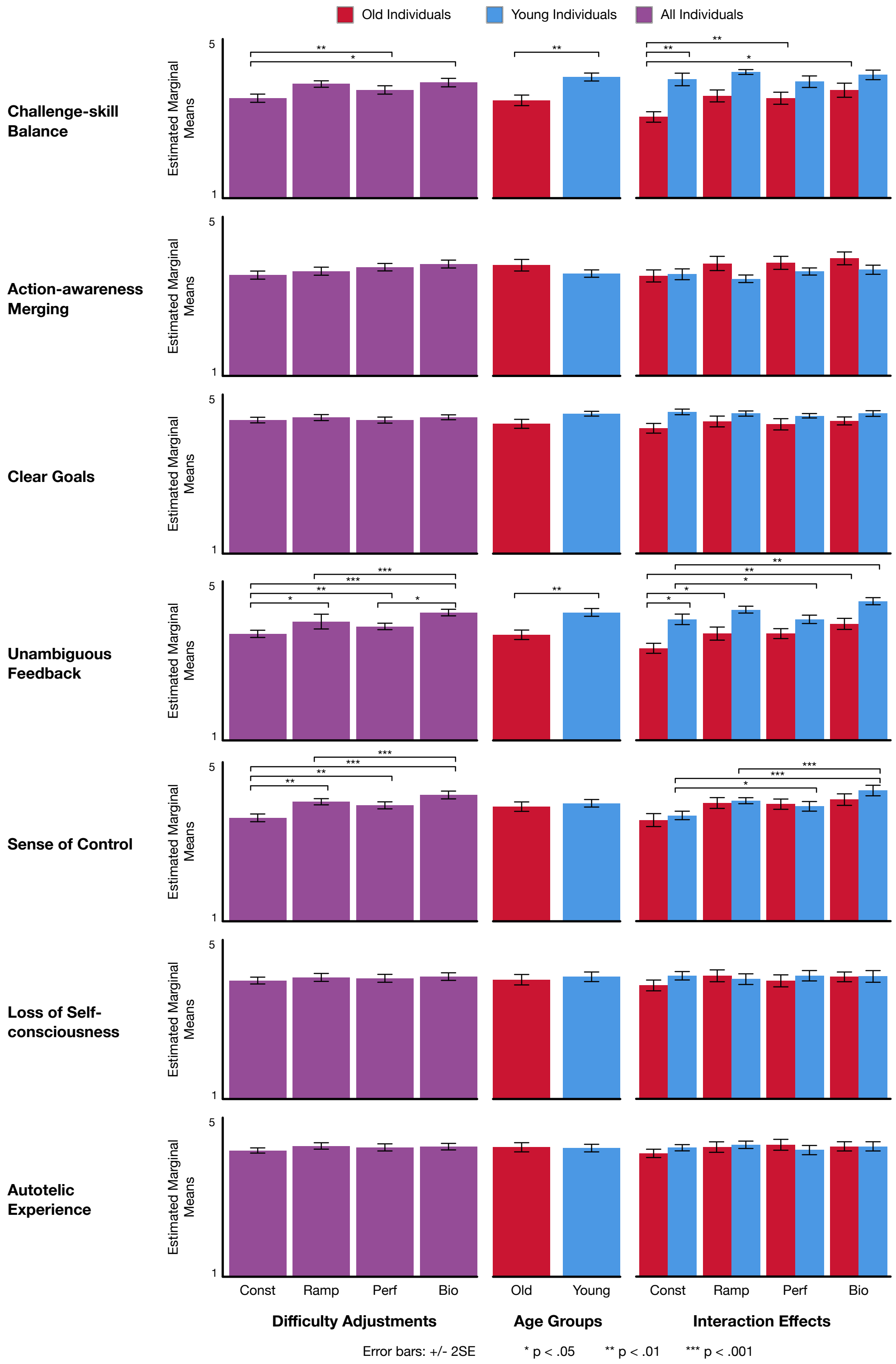


Figure 2.10: Statistical analysis of answers given to Flow State Scale.

Table 2.3: Internal consistency of each scale according to Cronbach's alpha

Scale	α_{const}	α_{ramp}	α_{perf}	α_{bio}
Challenge-skill Balance	0.916	0.931	0.899	0.891
Action-awareness Merging	0.818	0.885	0.902	0.854
Clear Goals	0.943	0.947	0.938	0.874
Unambiguous Feedback	0.874	0.852	0.902	0.891
Concentration on Task at Hand	0.740	0.649	0.701	0.805
Sense of Control	0.883	0.877	0.869	0.923
Loss of Self-consciousness	0.828	0.789	0.825	0.730
Transformation of Time	0.506	0.642	0.728	0.827
Autotelic Experience	0.827	0.933	0.911	0.899

cluded one young male participant's results from my final evaluation as a result of his low level of language proficiency and interruptions leading to differences in experiment procedure. I used difficulty adjustments and age group as factors. I evaluated each FSS scale according to three tests consisting of difficulty adjustment method comparison, age group comparison, and investigation of interaction effects between the two (Figure 2.10).

2.2.8.1 Challenge-skill Balance

Difficulty Adjustments: Utilized method had a significant effect on challenge-skill balance, $p = .013, \chi^2 = 10.737$. Pairwise comparisons using Bonferroni correction revealed that mean scores were significantly lower in constant difficulty compared to performance and biofeedback based difficulty adjustments ($M_{const-perf} = -.446 \pm .137, p = .007; M_{const-bio} = .491 \pm .176, p = .032$).

Age Groups: Age group had a significant effect on challenge-skill balance, $p = .003, \chi^2 = 8.774$ Pairwise comparisons using Bonferroni correction revealed that mean scores were significantly lower between old individuals ($M_{old-young} = -.732 \pm .247$).

Interaction Effects: Difficulty adjustments and age groups had a significant interaction effect on challenge-skill balance, $p < .001, \chi^2 = 52.292$. Pairwise comparisons using Bonferroni correction revealed that mean scores were significantly lower between old individuals under constant difficulty adjustments ($M_{const_{old}-const_{young}} = -1.18 \pm .307, p = .003$). Additionally, mean scores for constant difficulty adjustments were significantly lower than performance-based and biofeedback-based difficulty adjustments between old individuals ($M_{const_{old}-perf_{old}} = -.661 \pm .178, p = .006; M_{const_{old}-bio_{old}} = -.839 \pm .250, p = .022$).

2.2.8.2 Action-awareness Merging

Difficulty Adjustments: Utilized method had a significant effect on action-awareness merging, $p = .047, \chi^2 = 7.965$. Pairwise comparisons using Bonferroni correction revealed that mean scores were not significantly different.

Age Groups: Age group did not have a significant effect on action-awareness merging, $p = .304, \chi^2 = 1.059$.

Interaction Effects: Difficulty adjustments and age groups did not have a significant interaction effect on action-awareness merging, $p = .058, \chi^2 = 13.654$.

2.2.8.3 Clear Goals

Difficulty Adjustments: Utilized method did not have a significant effect on clear goals, $p = .409, \chi^2 = 2.888$.

Age Groups: Age group did not have a significant effect on clear goals, $p = .094, \chi^2 = 2.800$.

Interaction Effects: Difficulty adjustments and age groups had a significant interaction effect on clear goals, $p = .034, \chi^2 = 15.151$. Pairwise comparisons using Bonferroni correction revealed that mean scores were not significantly different.

2.2.8.4 Unambiguous Feedback

Difficulty Adjustments: Utilized method had a significant effect on unambiguous feedback, $p < .001, \chi^2 = 31.518$. Pairwise comparisons using Bonferroni correction revealed that mean scores were significantly lower in constant ($M_{const-ramp} = -.232 \pm .084, p = .033; M_{const-perf} = -.384 \pm .114, p = .005; M_{const-bio} = -.670 \pm$

$.122, p < .001$) and significantly higher in biofeedback difficulty adjustments ($M_{bio-ramp} = -.438 \pm .092, p < .001; M_{bio-perf} = -.286 \pm .098, p = .022$).

Age Groups: Age group had a significant effect on unambiguous feedback, $p = .002, \chi^2 = 9.506$. Pairwise comparisons using Bonferroni correction revealed that mean scores were significantly lower between old individuals ($M_{old-young} = -.705 \pm .229$).

Interaction Effects: Difficulty adjustments and age groups had a significant interaction effect on unambiguous feedback, $p < .001, \chi^2 = 119.871$. Pairwise comparisons using Bonferroni correction revealed that mean scores were significantly lower between old individuals under constant difficulty adjustments ($M_{const_{old}-const_{young}} = -.911 \pm .271, p = .021$). Additionally, mean scores for ramping and biofeedback were significantly lower than constant difficulty adjustments between older individuals ($M_{const_{old}-ramp_{old}} = -.464 \pm .133, p = .014; M_{const_{old}-bio_{old}} = -.768 \pm .215, p = .010$) while this changed to performance and biofeedback difficulty adjustments between young individuals ($M_{const_{young}-perf_{young}} = -.307 \pm .081, p = .005, M_{const_{young}-bio_{young}} = -.571 \pm .114, p < .001$).

2.2.8.5 Sense of Control

Difficulty Adjustments: Utilized method had a significant effect on sense of control, $p < .001, \chi^2 = 26.560$. Pairwise comparisons using Bonferroni correction revealed that mean scores were significantly lower in constant difficulty adjustments ($M_{const-ramp} = -.393 \pm .123, p = .008; M_{const-perf} = -.500 \pm .130, p = .001; M_{const-bio} = -.714 \pm .160, p < .001$). Additionally mean scores were significantly lower in ramping compared to biofeedback difficulty adjustments ($M_{ramp-bio} = -.321 \pm .080, p < .001$).

Age Groups: Age group did not have a significant effect on sense of control, $p = .635, \chi^2 = .225$.

Interaction Effects: Difficulty adjustments and age groups had a significant interaction effect on sense of control, $p < .001, \chi^2 = 90.647$. Pairwise comparisons using Bonferroni correction revealed that mean scores were significantly lower between young individuals under constant difficulty adjustments ($M_{const_{young}-perf_{young}} = -.464 \pm .133, p = .014, M_{const_{young}-bio_{young}} = -.786 \pm .128, p < .001, M_{ramp_{young}-bio_{young}} = -.500 \pm .098, p < .001$).

2.2.8.6 Loss of Self-consciousness

Difficulty Adjustments: Utilized method did not have a significant effect on loss of self-consciousness, $p = .435, \chi^2 = 2.732$.

Age Groups: Age group did not have a significant effect on loss of self-consciousness, $p = .723, \chi^2 = .125$.

Interaction Effects: Difficulty adjustments and age groups had a significant interaction effect on loss of self-consciousness, $p = .230, \chi^2 = 9.332$.

2.2.8.7 Autotelic Experience

Difficulty Adjustments: Utilized method did not have a significant effect on autotelic experience, $p = .109, \chi^2 = 6.048$.

Age Groups: Age group did not have a significant effect on autotelic experience, $p = .920, \chi^2 = .010$.

Interaction Effects: Difficulty adjustments and age groups did not have a significant interaction effect on autotelic experience, $p < .076, \chi^2 = 12.825$.

2.3. Discussion

2.3.1 General Examination of Results

Health problems associated with sedentary lifestyles are critical issues of our time. Exergames present an alternative solution to this health crisis through simultaneous introduction of entertainment and physical activity. However, effects of aging on game difficulty optimization remains unclear. Identification of optimization method preference between age groups will facilitate better game experiences and may improve adherence to regular physical exercise through well-designed exergames.

In this study, I compared the exergame experience of young and old individuals under four frequently used difficulty adjustment methods to better understand differences between their preferences. Through my analysis, I observed a significant decline in multiple aspects of my sample's play experience under constant difficulty adjustments. On the other hand, biofeedback-based difficulty adjustments resulted in higher scores compared to other methods and led to better play experiences. My second analysis showed that perceived balance between presented challenge and player skill was higher between young individuals compared to old. Additionally, ideas on quality of the received feedback differed significantly between age groups. This result provides necessary support for my second hypothesis. Finally, I found interaction effects between utilized difficulty adjustments methods and player age groups. Third analysis identified biofeedback-based difficulty adjustments as preferable in both age groups in addition to performance-based between young and ramping difficulty adjustments between old individuals. As anticipated, this result proves my third hypothesis.

My findings correlate favorably with with Baldwin et al. [12, 13] and further support the role of dynamic difficulty adjustments in delivering satisfactory play experiences. The evidence I found is also in complete agreement with Liu et al. [112] and supports my first hypothesis.

Mean scores of old individuals were consistently lower compared to young individuals except action-awareness merging (Figure 2.10). Although the factual reasons behind this difference was not explored, I think this might be connected to aging related decline in sensory acuity between older individuals. Under constant difficulty adjustments the frequency of movements follow a steady pattern whereas other difficulty adjustment methods lead to changes that might be difficult to anticipate for older individuals.

The superiority of biofeedback-based difficulty adjustments over traditional methods is fairly clear. However, integration of biofeedback or another dynamic difficulty adjustment method into gameplay significantly increases the required engineering effort and introduces additional hardware requirements for consistent monitoring of player state. Despite its benefits, biofeedback-based difficulty adjustments might not be favorable for game designers or players alike and lead to predominance of ramping or performance-based difficulty adjustment mechanisms in exergames. My study highlights the age based differences in player preferences on these mechanisms and suggests performance-based approaches when the target user group is young individuals. On the other hand, my results favor ramping difficulty adjustments in exergames when the player base consists of older individuals.

However, careful attention must also be paid to the connection between play and player characteristics since players with high self-efficacy may prefer consistently difficult play experiences. Additionally, despite the widespread applications of Csikszentmihalyi's flow model to exercise, consistent physical improvement may not be observed while challenge and skill consistently stay in complete balance and show no variation. This outcome may cause a decline in perceived enjoyment and benefits of exergames, eventually leading to reduced participation compared to conventional regular physical exercise approaches. I strongly believe that a combination of multiple difficulty adjustment methods based on administered exercise and player characteristics would lead to superior play experiences while simultaneously contributing to healthy lifestyles.

Given the age related changes in the cardiovascular system, my anticipation was to see more variation in heart rate measurements of older participants compared to young. This was the case in performance-based, ramping, and biofeedback-based methods, but we observed less variation in measurement values of old participants during scenarios with constant difficulty adjustments (Figure A.5, A.6, A.7, A.8). A possible explanation for this result might be found in the affective state of players. Participants showed a tendency to stop performing gestures under performance-based and ramping difficulty adjustment methods when the difficulty level became significantly high. However, this was not the case in constant difficulty since the rhythmicity and predictability of movement patterns allowed them to perform for longer periods of time. This is an important factor since proper exercise routines are designed around reps and sets; referring to number of consecutive repetitions of an exercise and number of cycles where the repetitions are performed. Although dynamic difficulty adjustments may lead to superior gaming experiences, they could also demonstrate a decline in exercise gains and health benefits by introducing randomness to exercise routines performed by players. I think this is a fundamental issue for future research and requires careful investigations into sports science side of exergames.

2.3.2 Post-experiment Discussions

In addition to above findings, older participants also mentioned the metaphorical relationship between aircraft marshaling gestures and their in-game representation. This observation has serious implications in integrating logical design ele-

Figure 2.11: We added multiplayer functionality and deployed our game at a rehabilitation hospital for institutionalized older individuals.

ments to exergames and eliminating the chocolate covered broccoli problem. One possible approach to further expand this relationship is to introduce narratives to exergames. Ever increasing popularity of action role-playing video games (RPG) with exceptional narratives such as Witcher III and Elder Scrolls is a factual example of how good stories might increase motivation to play. Lu examined this idea to bridge the gap between these two important game design domains [113]. Yet, further studies on this topic are required in order to verify its effects and possible benefits.

Despite this, I observed several cases where upper extremity movements of participants deviated from their intended path. Most of the participants believed their movements were exact and as straight as possible, yet when I showed them the videos I captured the apparent error in their gestures was undeniable. It is probable that participants may have erroneously judged their own joint position which can be justified by poor proprioception. In my opinion, there is a strong probability that incorporation of proprioceptive feedback on extremity movements may lead to enhanced awareness of the body in space and increase the likelihood of experiencing flow in exergames.

2.3.3 Deployment at a Rehabilitation Hospital

According to social cognitive theory, people observe others and evaluate the consequences of their behaviors, which can also lead to engagement of the viewer [16]. This theory has a strong association with multiplayer gaming where several players compete or cooperate depending on game objective and its structure. It also lays the groundwork for considerable amount literature and makes social interaction an important factor within exergames to promote physical and psychological health of aging generations [25, 98, 144]. Systematic studies also report social interaction an influential factor for increasing exercise adherence among old individuals [108, 154].

Therefore, I implemented a multiplayer version and deployed it at a rehabilitation hospital for institutionalized older individuals and tested it during a four day period (Figure 2.11). The majority of my participants during this period were older than 85 years old, maximum being 91. The overall response to my exergame was fairly positive, but the difficulty adjustment methods worked properly with very few participants. It is crucial to note that the task difficulty in exergames does not fully depend on gesture frequency, but also required range of motion for their correct execution and their ability to interpret displayed instructions. More than half of our participants had health issues with their shoulders that prevented them from raising their arms to a point where the angle between arms and trunk reaches 120 degrees, which was necessary for our system to separate different movements. This observation shows that difficulty adjustments should consider not only the frequency of actions, but also the range of motion involved in it, and I hope my research will serve as a base for future studies on this topic.

The most surprising result to emerge from our efforts at the hospital is that the oldest participant was also the healthiest in terms of resting heart rate, maximum heart rate variability, and range of motion. Our 91 year-old female participant voluntarily joined our every experiment and demonstrated a consistent increase in game performance with each day. It was interesting for us to observe that the rate of physical and cognitive decline can greatly vary between individuals despite their identical age. Although getting older is inevitable, this has serious implications on importance of aging well to sustain a high quality of life.

2.4. Limitations

I am aware that my study has at least three limitations. The first is the homogeneous structure of our old individual group in terms of nationality. Although I managed to gather young individuals with different ethnic backgrounds, that was not the case for old individuals. Combined with their similar age bracket, same ethnicity may have an effect on their gaming perception and lead to an undesired bias in my results. I am planning to address this issue with a replication study outside of Japan in the future. The second limitation of my study is its short-term repeated measures design. It may be difficult for participants to realize and assess the differences in all dimensions of flow under various difficulty adjustment mechanisms with a study of this design. Yet, this limitation underlines the difficulty of collecting data on elderly. Given that, it is not inconceivable that different evaluations would have led to different conclusions. For example, one significant aspect I failed to address in complete detail was the measurement of arousal between participants. I mainly focused on simulation of difficulty adjustments methods while using RR interval as a form of signal connected to arousal. In reality, multiple stimulus can affect the RR interval values of an individual, such as physical action or health conditions, and it displays a change with age. Therefore, I believe further studies must also consider additional measurements such as facial expression analysis and eye tracking alongside RR measurements to better evaluate emotional arousal and valence. Finally, although the exergame I have designed for this study considerably adheres to recommendations of the ElderGAMES [63], one can argue that it is a mere simulation and games designed with a superior engineering effort may lead to different results. I acknowledge this limitation and encourage future studies with different games and game genres for further investigation.

2.5. Chapter Summary

In this study I have compared multiple dimensions of flow between young and old individuals under four common approaches to exergame difficulty adjustments. My work has led us to the conclusion that difficulty adjustment methods lead to a different exergaming experience based on the age of players. The evidence from this study points towards the idea that likelihood of experiencing flow differs between young and old individuals under same difficulty adjustment methods. Additionally, although biofeedback based adjustments are preferable, old individuals are also expected to experience flow with ramping adjustments whereas performance-based methods are favorable for young individuals. Taken together, these findings implicate a role for age in exergame difficulty adjustments to enhance play experiences, and increase adherence rates to physical exercise for the establishment of healthier lifestyles.

To further my work, I plan to have a long term study in an elderly care center and conduct several replication studies in other countries through the help of our collaborators. I am also currently in the process of investigating high intensity aerobic exercises and massively multiplayer online gaming applications as promising application areas.

CHAPTER 3

Effective Visualization of Information

Outcome expectancy is a central construct in numerous theories developed over the years on human health behavior change [193]. Bandura defines outcome expectancy as *"a person's estimate that a given behavior will lead to certain outcomes"* [14]. According to him, these estimations largely depend on individual judgments of performance in any given situation [14]. Based on this definition, providing feedback on task performance becomes crucial for any computer-aided system designed to promote physical exercise. Additionally, an effortless yet effective communication medium plays an important role in this process considering the physically and mentally demanding aspects of exercise. Therefore, information visualization becomes fundamental for successful design.

In this chapter I focus on these unique aspects of physical exercise and study situated visualizations for satisfying outcome expectancy in computer-aided system design. I utilize an in-situ approach to pedaling training in cycling and try to augment the physical and cognitive skills required for achieving desired outcomes in this type of exercise.

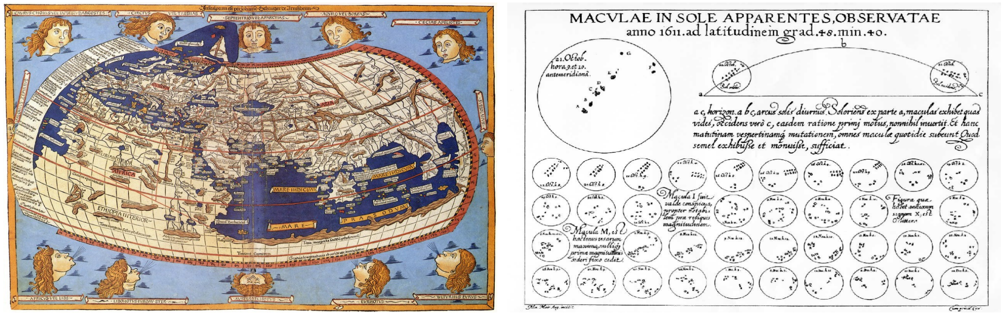
Figure 3.1: Sumerian tablet used for surveying governed silver amount [61].

3.1. Related Work

3.1.1 Information Visualization

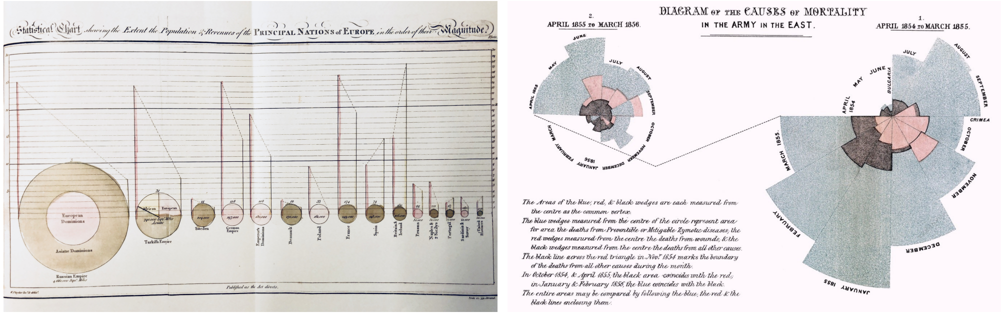
Human visual system occupies 30% to 40% of the cerebral cortex whereas this number shrinks to 8% for somatosensation and 3% for audition [184]. Given its significantly large bandwidth compared to other senses, the emergence and evolution of information visualization was an inevitable step in our history. I follow a two-step approach to define information visualization by individually examining the composing words. According to Few, *information* is acquired through analyzing some type of data, connected to physical or abstract constructs [59]. For example, stock market prices and football statistics are more abstract in nature whereas human anatomy and cell structures of mammals are physical. The latter part of *visualization* refers to representations of data that facilitate the discovery of new insights and knowledge [166]. Combined together, these two words define a paradigm which utilizes graphical portrayal of quantitative data to enhance cognition through vision [35].

The process of representing data in visually meaningful ways to support human cognition is definitely not a new process when it is examined from an his-



(a) Ptolemy's map (b) Scheiner's sunspots

(c) Playfair's line graph (d) Playfair's bar graph



(e) Playfair's pie chart (f) Nightingale's rose diagram

Figure 3.2: Historical examples of information visualization [59, 61, 181].

torical context. Archaeological findings dating back to over 2000 years before the common era (BCE) demonstrate the usage of tables to represent financial data (Figure 3.1) [61]. 15^{th} century depiction of Claudius Ptolemy's spherical map provides a reference to maps used for navigation and exploration; making it one of the information visualization with extreme durability till today (Figure 3.2a) [61]. 17^{th} century saw an increase in visualization of theoretical models such as Christopher Scheiner's depiction of the sunspots (Figure 3.2b) [61]. 18^{th} century

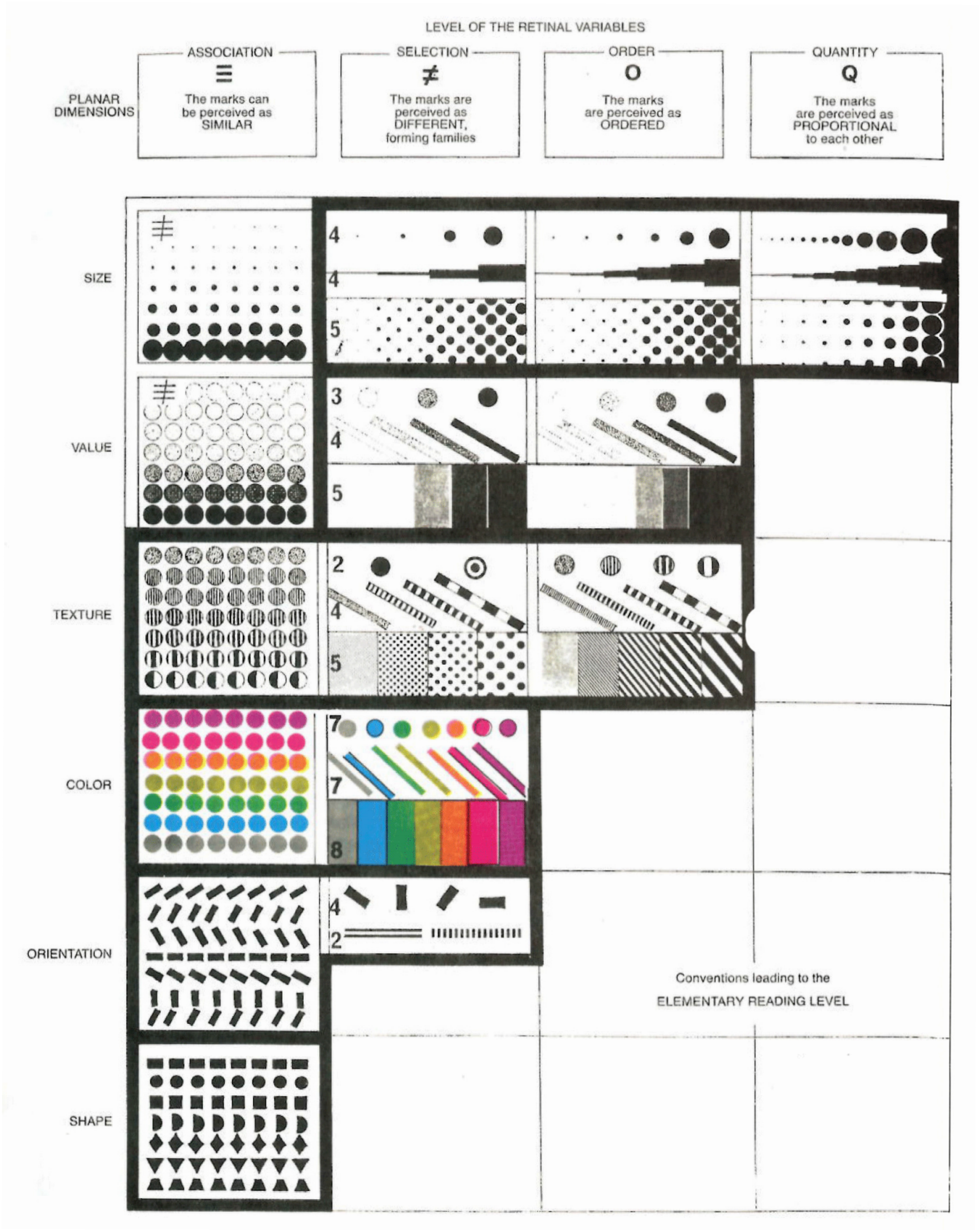


Figure 3.3: Bertin's illustration of the six visual concepts for mapping information to graphics [19].

marked the beginning of information visualization as we currently know it. Playfair invented line, area, and bar charts to represent changes in economical data over time (Figure 3.2c,3.2d) [59]. He also invented pie charts and circle graphs to emphasize part-whole relationships such as the proportions of land governed by the Ottoman Empire in Asia, Africa, and Europe (Figure 3.2e) [59]. Statistical mapping was prevalent throughout the 19^{th} century where Playfair's approach was widely utilized. Florance Nightingale's rose diagram where she visualized the causes of mortality in the army is a famous example of visualizations from this era (Figure 3.2f) [181].

The rapid development of information technologies in second half of 20^{th} century carved the way for expansion of information visualization. Influential works of Tukey and Bertin attracted much attention and allowed information visualization to gain a well-earned recognition between 1950 and 1975. [19, 182]. Consistently building on seminal works of Tufte and Shneiderman, we continuously experienced the emergence of interactive and dynamic information visualization methods till today [158, 181].

3.1.2 Situated Visualizations

Although Sutherland initiated a transformation from textual to graphical with his Sketchpad in 1963, we continue to rely on the same paper based visualization metaphors primarily defined by Playfair even after more than two centuries [174]. This fact alone demonstrates the immense power of his approach. Yet, the advent of technology also showed its effects on approaches to information visualization. The methods of our time are significantly more interactive than before and allow various forms of manipulation for further explorative experiences.

As one of these methods, White introduced *situated visualizations* by combining information visualization with its respective physical environment [190]. He developed SiteLens to visualize virtual data in the context of its physical site [191]. He aimed to support users in sense making, pattern finding, and insight discovery about a physical site and its characteristics by emphasizing the connection between information visualization and its respective environment (Figure 3.4). Takeuchi and Perlin developed ClayVision to address the problems arising from the information bubble trend in Augmented Reality (AR) applications in urban

Figure 3.4: White's situated visualization. Spheres represent carbon monoxide data captured at the exact location to emphasize the effects of environment [190].

navigation [175]. They argued about the shortcomings of current approaches to information visualization in AR and described how it attracts significant amount attention which reduces user's focus on details related to physical world. Instead of pasting information bubbles, they employed free-form transformations on real world elements to convey information related to physical space. Kalkofen et al. introduced interactive visualizations to emphasize exsiting spatial relationships between virtual and real objects in AR applications [94]. They explored the effects of focus and context on users perception when information is presented in its real environment where scenes clutter density is often high. Zollmann et al. designed an interface which augments users view with relevant information to support flight management of micro aerial vehicles [200]. They aimed to provide spatial information about the environment and support the cognitive abilities of users.

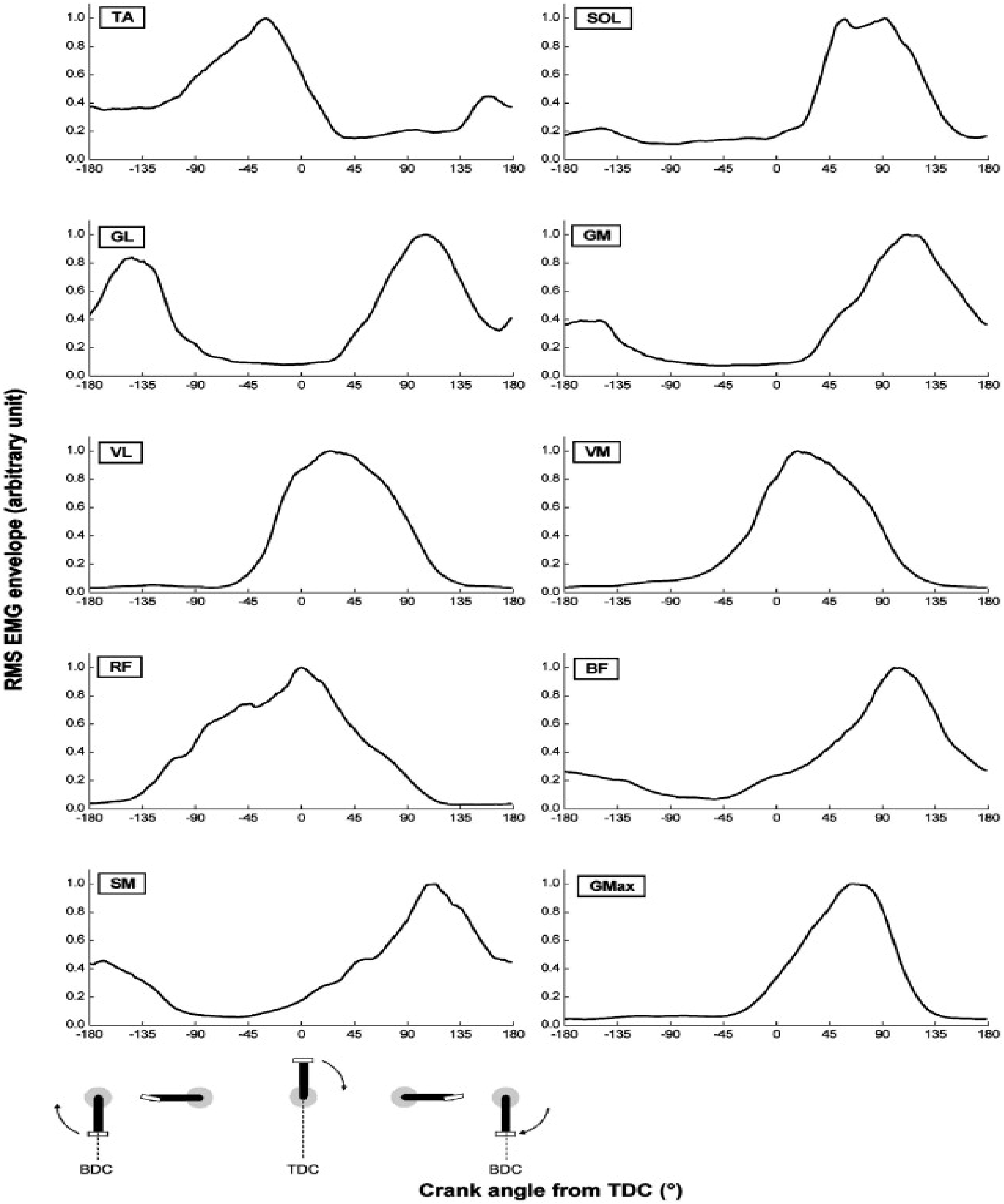


Figure 3.5: EMG measurements for 10 lower limb muscles. TDC, *top dead center (0)*; BDC, *bottom dead center (180)*. GMax, *Gluteus maximus*; SM, *Semimembranosus*; BF, *Biceps femoris (long head)*; VM, *Vastus medialis*; RF, *Rectus femoris*; VL, *Vastus lateralis*; GM, *Gastrocnemius medialis*; GL, *Gastrocnemius lateralis*; SOL, *Soleus*; TA, *Tibialis anterior* [51]

3.1.3 Cycling Dynamics and Pedaling

Despite its straightforward circular appearance, biomechanics of pedaling is a highly complex non-circular lower extremity motion in terms of biomechanics that requires [127]. Its complex structure combined with the lack of ground truth leads to sophisticated problems in cycling specific pedaling visualizations. Therefore designing a visualization to support training in cycling requires a broad understanding of pedaling motion. Scholar of sports science tackled the riddles surrounding cycling dynamics and pedaling for a long time. Dorel and Hug provided an overview of pedaling technique in cycling by using electromyography (EMG) [79]. They described the activation patterns of lower limb muscles and the constraints that effect these patterns including power output, pedaling rate, body position, and fatigue. Their results indicated significant differences between muscle recruitment patterns of professional road cyclists. Dorel et al. also investigated the contribution of each functional sector of pedaling on the total force produced over a complete cycle, including down-stroke, up-stroke, and transition phases [52]. They consistently observed a large positive contribution to total force production during the down-stroke phase and a slight negative contribution during the up-stroke phase. They measured total and effective forces over a complete pedal revolution and observed significant differences when pedaling rates were high.

3.2. In-situ Visualization of Pedaling Forces

In this work, I introduced a situated visualization approach to cycling training and aimed to satisfy outcome expectancy by promoting causality between form and pedaling. I developed a prototype which superimposes numerous visualizations onto simultaneously captured training videos of cyclists.

3.2.1 Initial Studies

My pursuit of situated visualizations for cycling training started with several trips to National Institute of Fitness and Sports in Kanoya to cooperate with cycling professionals. My initial efforts were mainly focused on understanding the needs of cyclists and their utilization of computer-aided systems for training. I interviewed multiple professional cyclists and came to the conclusion that evaluating one's performance was a major challenge for the most. Although current information visualization approaches are fairly common in my field of expertise, cyclists with no particular training regarding these methods were reluctant towards their interpretation of data. Preferably most cyclists used measured training time as an effective factor to gauge their performance. Yet, the simplicity of these evaluations were also not satisfactory enough, which in turn led to interference of subjective opinions and emotions.

I validated the significance of this situation by administering a simple questionnaire of my own design which aimed to gather information on pedaling strategies of professionals. I surveyed 30 cyclists and initially hypothesized to reach a settlement among participants on important sectors of pedaling motion that contribute to an increase in performance. Contrarily, the answers given to questionnaires were rather diverse (Figure A.11). During my one-on-one interviews with some of the participants, they raised the differences in strategies employed to assess their performance as the rationale behind. Most participants utilized the information passed down between generation of cyclists rather than modern approaches to training. When I questioned the same participants about the usage of graphs to evaluate their performance, almost all referred to required learning process as an obstacle. Consequently, I characterized the current trend to information visualization in cycling inadequate for satisfying training needs of users and their outcome expectancies on pedaling.

3.2.2 System Design

Cycling typically encompasses outdoor and indoor training. As implied by its name, outdoor training refers to workouts done by riding outside with a certain exercise schedule or goal. On the other hand indoor training might be understood in two ways. The first one refers to weight training that can be done in absence of any cycling equipment. The second one involves training done with bike rollers or resistance trainers. I targeted the final scenario in this work.

Resistance trainers allow cyclists to train using their own bicycles while it remains stationary. These trainers transform suitable bikes into exercise equipments similar to stationary bicycles used in gyms. They are consistently used by professionals and amateurs alike to train mostly during unpleasant weather conditions. Cyclists also use these trainers to evaluate their form on the bike and their pedaling due to adequate levels of safety they offer by eliminating the risk of falls. I focused on this aspect of their training due to its high level of correspondence with nature of situated visualizations. I expected cyclists to undergo a certain training session and designed three visualizations to support the outcomes desired by the most; force vectors, torque generation, and directional deviation.

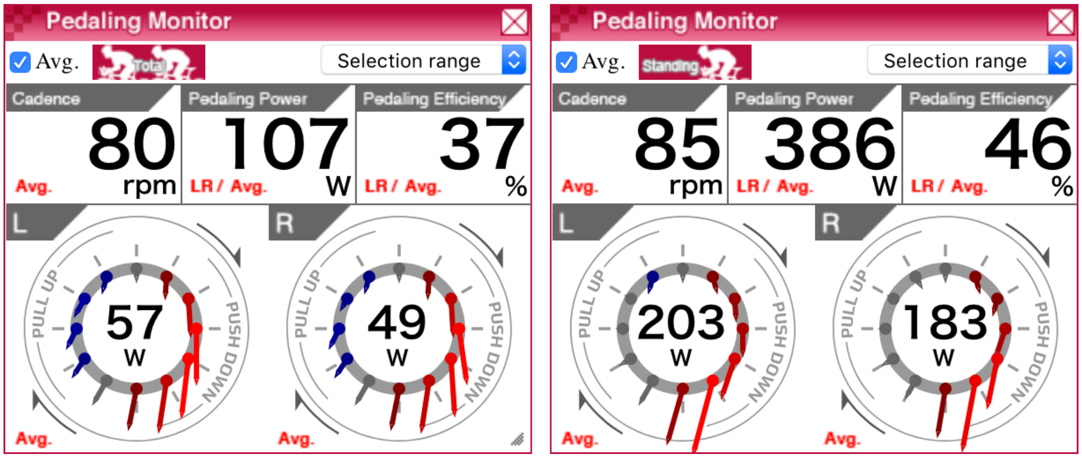
I implemented the force vector visualization based on the default graphs used by the pedaling monitor system (Figure 3.6). Goal of this visualization was to provide information on measured forces during one full pedal stroke using twelve vectors and combine it with physical characteristics of cycling posture (Figure 3.7). I color coded the produced pedaling forces based on each force's effect on crank rotation. I represented positive and negative contribution to torque generation by using blue and red respectively. Additionally, I used white for forces which pass through the axis of rotation to illustrate no torque generation. Furthermore, I employed a combination of vectors and triangles to represent torque generation. Similar to first visualization, I used color coding to provide explicit information on produced force's contribution to rotation.

Finally, I visualized the directional deviation between force and torque vectors by using the same approach from second visualization. I used blue to represent torque and yellow for force with positive contribution to rotation. I visualized force vectors only in case of negative contribution to rotation for visual simplicity.

3.2.3 Apparatus

I used a Pioneer Pedaling Monitor System equipped road bicycle and mounted it to a Tacx Booster T2500 indoor resistance trainer. I extracted tangential and radial components of pedaling forces in every 30° with a complete crank motion. The system was installed on a 52-36T Dura Ace FC-9000 with 172.5 mm crank arm length and coupled with a 11-28T Dura Ace CS-7900.

I used a Logicool (Logitech) HD Pro Webcam C920r to capture training videos and. I utilized an Optitrack Trio V120 to track passive reflective markers attached



Pedaling Monitor
☑ Avg. Total
Selection range
Cadence 80 rpm
Pedaling Power 107 W
Pedaling Efficiency 37 %
L 57 W
R 49 W

Pedaling Monitor
☑ Avg. Standing
Selection range
Cadence 85 rpm
Pedaling Power 386 W
Pedaling Efficiency 46 %
L 203 W
R 183 W

Figure 3.6: Example data captured with pedaling monitor system.

(a) No background (b) RGB video frames (c) Grayscale video frames

Figure 3.7: The vector-based data visualization for representing pedaling forces.

to right pedal. We used the tracking information to calculate pedal trajectory and extract exact 3D locations where pedaling monitor system measured force components. I calibrated these two equipments prior to experiments using a 7x9 checkerboard pattern with passive reflective markers placed at its three corners.

3.2.4 Experiment Procedure

I started the experiments by measuring participant's inseam length and adjusting saddle hight accordingly. Then, I instructed a procedure containing three separate intervals. During the first interval, I asked male participants to generate power equal to seven times of their body weight in watts for one minute. In second interval, I asked them to produce ten time of their body weight in watts

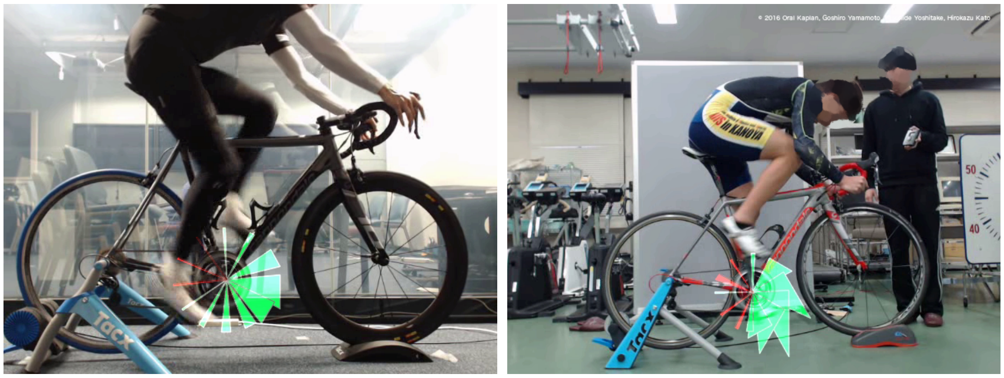
Table 3.1: Experiment settings I used with male participants.

	First Interval			**Second Interval**		
Body Weight (kg)	Power (W)	Rear Gear	Resistance	Power (W)	Rear Gear	Resistance
40	280	2/10	7/10	400	6/10	8/10
50	350	4/10	7/10	500	6/10	8/10
60	420	5/10	7/10	600	8/10	8/10
65	455	7/10	7/10	650	9/10	8/10
70	490	8/10	7/10	700	10/10	8/10
75	525	7/10	8/10	750	10/10	8/10
80	560	7/10	8/10	800	10/10	8/10
85	595	8/10	8/10	850	10/10	8/10

for thirty seconds. During the final interval I request a maximal effort for ten seconds. I took gender-related physical differences into account by reducing the body weight multipliers to six and eight during the first and second intervals with female individuals. I allowed all participants to take a five-minute active recovery break between each interval by pedaling slowly under a low-gear low-resistance combination. I encouraged participants to sustain a steady cadence of 90 rotations per minute (RPM) during the first and second intervals. I did not specify any cadence value for last interval since it was maximal. I used a metronome to assist participants in maintaining a steady cadence. I started the timer for each interval after the participant reached desired cadence of 90 RPM. I modified rear gear and resistance according to Table 3.1.

I had a 15-minute interview in the form free talks with each participant after administering all trials. During the first part, I collected in-detail information on their pedaling technique and frequency of their video usage to satisfy their training needs. After that, I collected their subjective opinions on my visualization method. Finally, I allowed participants to express their suggestions for advancing my research.

(a) Vectors : Preliminary (b) Vectors : Professional



(c) Triangles : Preliminary (d) Triangles : Professional

Figure 3.8: Comparison of my preliminary results with what I observed during my experiments with a professional track cyclist. I observed a great difference in pedaling power which lead to occlusions in my visualizations.

3.2.5 Participant Profile

I evaluated my approach with ten male and two female professional cyclists. Eight participants were regular contenders in national road races and remaining four included three track and one individual time trialist. Average participant age was 20 (age_{min} : 19, age_{max} : 23). The professional background of participants included numerous podium finishes in national competitions of Japan, such as Inter-College 3km Cycling Championship, Inter-College Team Spring, and Road Race Championship Under 23.

3.2.6 Results

All participants reported their experience with using videos or mirrors to assist their training needs. The most common purpose of using these two mediums was to confirm the correctness of their posture on the bicycle. Ankle angle, fore-aft saddle position and aerodynamic upper-body posture were consistently examined features. One female participant reported her usage of videos to confirm adequate clear position. All participants were positive about using videos to assist their training needs. Situated visualizations were favored due to their effectiveness in providing concurrent information on both cycling form and pedaling. One participant acknowledged the possibility of new training paradigms that can be emerged as a result of these visualizations, such as achieving a balance between aerodynamic upper-body posture and resultant pedaling technique.

I also received an unexpected result regarding the situated force visualizations. From an information visualization perspective, I expected vectors to be the most suitable method of pedaling force visualization (Figure 3.8a, 3.8b). Yet, most participants also favored the triangle visualizations in addition to vectors (Figure 3.8c, 3.8d). The most frequent reason given was the increased visibility of charts due to wider area used to draw it. Participants consistently mentioned that given the right design, this increased visibility would make the visualization easy to understand after or during training. This idea was backed by the significant reduction in cognitive functions due to physical and mental fatigue placed upon cyclists' bodies. On the contrary, when I presented the same visualizations to non-cyclist information scientists they had no value over vectors. It is clear that user profile and characteristics of the physical activity are extremely important for designing exercise specific visualizations.

All participants were positive about having a comparison between their current and past performances with my visualization approach to evaluate changes in their pedaling with respect to their form. Several participants mentioned the possible usage of situated visualizations to compare their pedaling between adequate and inadequate form conditions. Overall reactions to comparing one's form with another were mostly negative. Main arguments raised by the participants were differences in body structure and muscle recruitment patterns. Two participants were positive about this kind of comparisons given similar body structures. Yet, same participants also mentioned the difficult nature of adapting new pedaling styles or modifying it according to the style of another individual.

3.3. Discussion

My interviews with professionals clearly revealed that the videos are not the most consistently used medium in cycling training due to limited amount of scenarios where users find them useful. Although some participants occasionally used videos to capture and evaluate their form on the bike, most used videos as infrequently as twice a year. When I presented my approach, all participants were positive about using it for personal training provided with decent ease-of-use. They described the main reason behind their interest as the direct relationship that can be formed effortlessly between cycling form and pedaling. As I mentioned before, current approaches to performance evaluation in cycling mainly focus on the results rather than causes. There is no denial that the current methods are highly useful. Yet, my interest in this work was to combine merits of these methods to allow effortless and effective performance evaluations. Since videos can only provide information that is available to naked eye, videos are suitable for form and motion evaluations. On the other hand, I used pedaling visualizations to represent abstract data. Enhanced training regimes can be established with such rational combinations of distinct visualizations to address the complicated nature of physical activity. As a result, sports and exercise professionals can utilize these visualizations to achieve improved performance during assessment and planning activities.

Participants were keen on both vector and triangle visualizations. Latter approach was mostly favored due to increased amount visibility when I superimposed the graphics on videos. Reduced effort while making rough evaluations was consistently cited and participants indicated the importance of this property given the effects of physical and mental stress on their cognitive functions. They expressed that information comprehension might require less effort with area visualizations. However, visualizing more than one data type as areas was also defined impractical since it might simultaneously increase the complexity. Vector approach were mostly seen useful due to participants familiarity with the

Figure 3.9: Grayscale video frames are combined with independent visualizations of force direction and torque generation. Blue color represent positive contribution to rotation whereas red represents vice versa.

method itself. Features of this result named as mere-exposure principle require an in-depth analysis, which I did not conduct since it was not a part of my study.

As I expected, vectors showed great qualities in analyzing directional information on one's pedaling. Yet, extracting a general movement pattern out of this approach was significantly difficult due to reduced visual acuity. Area visualizations representing torque generation received more attention in this context. Participants successfully identified their torque generation pattern after each interval. However, I observed occlusion problems with professionals when exerted forces pass a certain threshold (Figure 3.8).

Finally, lack of real-time support on movement was a consistently cited problem of outdoor cycling training. Participants were inclined towards measuring and comparing their performance in an outdoor scenario rather than indoor due to its closer connection to actual racing situations. For example, cyclists cannot analyze the effects of body weight usage in pedaling and cycling form in indoor training due to its stationary nature. On the other hand, five participants mentioned the dangers of giving too much attention to form and pedaling in outdoor training. They discussed how occupying a significant portion of human visual system might pose great dangers if cyclists are not fully aware of their surroundings. Further work needs to be carried out to address this problem and I hope my work will serve as a base for many years to come.

As a result, I regard visual acuity and occlusion as two additional factors that become significant on top of Shneiderman's visualization mantra while superimposing pedaling visualizations on correlated training videos. A quantitative analysis on these approaches satisfying the described points has a potential to reveal much needed additional information for my future designs (Figure 3.9).

3.4. Limitations

Throughout my studies on situated visualizations in exercise settings, I have solely focused on a qualitative evaluation to better understand the surrounding human factors. As I mentioned in the previous section, continuing on this path with a quantitative study may produce evidence based strategies which would allow computer-aided system designers to make informed decisions. Unfortunately, I could not follow such a research direction due to time limitations and the need for a shift in research perspective from *outcome expectancy* to *risk perception.*

One possible study of such kind includes the measured change in athlete performance under training scenarios with situated visualizations. Although a comparison between situated and non-situated conditions might be the first thing that comes to mind, I consider this an unfair comparison since non-situated conditions cannot provide qualitative information by default. Instead, my recommendation is to compare the effects of combining qualitative and quantitative components of exercise with situated visualizations. One can consider two scenarios where these components are visualized separately and jointly, and compare changes in certain parameters regarding athlete performance while considering statistical significance. If such study yields positive results, it may be inferred that the combination of qualitative and quantitative feedback leads to a better visualization in support of exercising individuals which is highly preferable.

Another qualitative study that I propose considers the current trend in information visualization for physical exercise. Taking the uniqueness of humans as basis, generalized visualization approaches to qualitative data might not be best method for supporting every single exercising individual. Especially in professional sports, this manifests as a clear distinction between successful athletes who prefer objective performance assessments versus the athletes who train and compete with subjective assessments alone. Situated visualizations may present a perfect middle-ground for both of these groups where an optimal approach can be achieved in various exercise scenarios regardless of individual differences in preference for exercise.

All these cases and related points that I have introduced above are significant points that I could not address throughout my studies and remain as limitations to better understand situated visualizations in physical exercise. Once again, I recommend scholars of both information and sports science to study them for better satisfying the outcome expectancy of exercising individuals. In return, that may lead to a significant change in health behavior for the better and connect to a decline in occurrence of non-communicable diseases attributed to lack of physical exercise.

3.5. Chapter Summary

In this chapter, I introduced a situated visualization approach to pedaling in cycling for addressing outcome expectancy. I combined training videos with various visualizations to better understand fundamental properties of design. I tested my ideas with professional cyclists and received positive feedback about this approach. Participants consistently cited the effects of physical and mental fatigue on their cognitive functions and ability to evaluate consistently utilized visualizations. In conclusion, I consider in-situ visualization methods as feasible solutions to intricate problems of current performance visualizations. They have a potential to promote physical exercise better than traditional visualization approaches thanks to supporting outcome expectancy to a greater degree.

CHAPTER 4

Fostering Proper Movement Execution

Most living organisms face numerous challenges on a daily basis that involve undesirable circumstances, and humans are no exception. Defined as *risk*, this construct is often described as the likelihood of an individual experiencing the effects of danger or loosing something of value [159]. Although numerous scholars studied this concept from different perspectives, uncertainty is accepted as an important psychological construct of risk perception in health-related frameworks [89, 163]. Consecutively, it plays an important role in health management due to its effects on perceived negative outcomes of physical activity, and the evidence based strategies to handle them.

From an heuristic viewpoint, risk perception refers to the subjective judgments that people make about the severity of any risk inducing situation that consists of cognitive and emotional dimensions [132]. In this chapter, I address the cognitive dimension to promote people's knowledge and understanding on possible risk factors in exercise, mainly working on injuries and the their effects on people's motivation to adopt a physically active lifestyle. I primarily focus on knee overuse injuries in cycling due to lack of research-based evidence despite their high recurrence rate and clinical importance. I aim to increase awareness to faulty movement patterns that may initiate injuries, and reduce the associated risk by introducing adequate computer-aided technologies for better evaluation of underlying causes. Therefore, I consider a video-based visualization framework for qualitative and quantitative monitoring of knee movement in cycling to promote subjective and objective analyses, which is essential for reforming movement monitoring in cycling by taking human factors and autonomy into consideration. Additionally, I consider my in-situ approach from Chapter 3 on Shneiderman's visual-information seeking mantra [158] with videos of knee movement, and aim to support subjective and objective practices through qualitative and quantitative data visualizations.

4.1. Related Work

4.1.1 Risk Associated with Injuries in Sports and Exercise

Physical exercise requires a high level of bodily fitness for the execution of physically demanding tasks. No exercise, however, is free from the dangers of exercise-related injuries due to high number of repetitions required to achieve and maintain an adequate fitness level. This makes injuries consistently observed problems between exercising individuals regardless of their expertise level [7]. Each injury type is accompanied with a significant negative impact on physiology or psychology of the individual, which is mainly attributed to the injury type and its effects on performance in exercise. Therefore, research efforts in computer-science and sports medicine gained a significant momentum over the last decades to better understand the underlying factors and eradicate associated problems throughout the world [161, 185, 189]. For instance, Jones et al. measured 391 army trainees to identify intrinsic risk factors to physical exercise-related injuries and found low aerobic fitness as a major factor between female trainees [91]. Jones and Knapik surveyed the data from the US Army on unintentional injuries and disclosed general principles to aid with injury control in civilian sport and exercise programs [92]. Johnston and Carroll tested the psychological impact of exercise-related injuries based on sports and exercise involvement [90]. They found the perceived recovery to be less between individuals who are more involved in sports and exercise despite the reported negative affect had no correlation with involvement

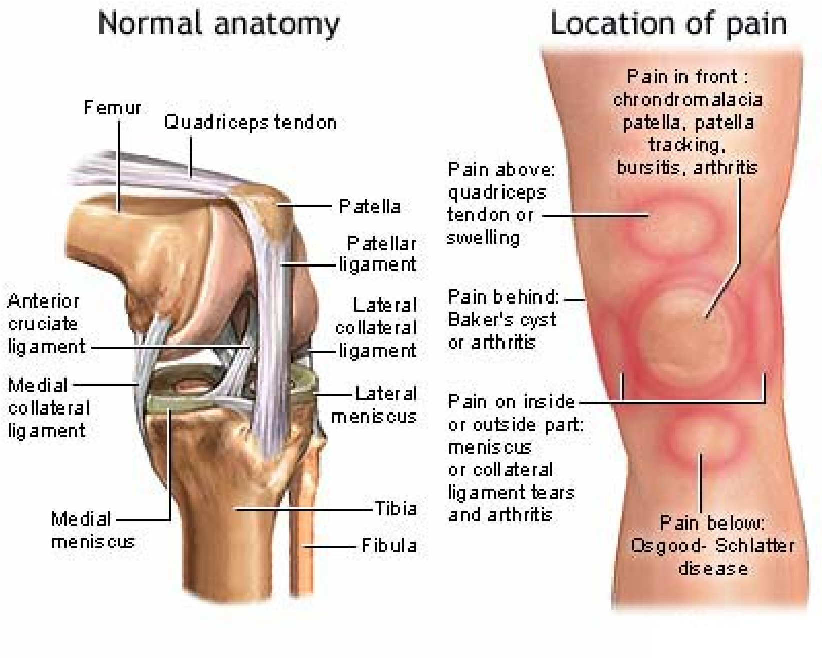


Figure 4.1: Anatomy of knee joint and frequently observed overuse injuries [68].

level or amount. Contrary to one of the most common fitness beliefs, Pope et al. demonstrated that typical muscle stretching protocols performed prior to moderate to vigorous exercise do not lead to clinically meaningful risk reduction in exercise-related injuries [141]. He also suggested fitness level as a significant risk factor between exercising individuals. Small et al. conducted a systematic review of existing literature on static stretching protocols as a form of preventive measure to exercise-related injuries and found moderate to strong evidence that their routine application does not reduce the overall rates of injuries [164]. Nicholl et al. conducted a national study on exercise-related injuries in England and Wales, and surveyed 28,857 individuals aged 16 to 45 years using a postal questionnaire [128]. They reported a striking yearly estimate of 29 million incidents resulting in new or recurrent injuries where sprains and strains of the lower limb muscles were the most frequently reported problems.

4.1.2 Knee Overuse Injuries in Cycling

Cycling is a popular form of sport and exercise that requires a high level of bodily fitness for executing physically demanding tasks. Even though studies consider cycling a low-impact non-weight bearing form of exercise due to body weight being carried by a bicycle [45], it is not free from the dangers of overuse injuries due to high number of repetitions required to achieve and maintain an adequate fitness level. This makes exercise-related overuse injuries consistently observed problems between cycling individuals regardless of their expertise level [121]. Every overuse injury is accompanied with a significant negative impact on physiology and psychology of the individual depending on the injury type and its effects on physical performance. Therefore, research efforts in computer-science and sports medicine gained a significant momentum over the last decades to better understand the underlying injury factors and eradicate associated problems.

Besides falls, the repetitive nature of cycling and monotonous loading of joints are consistently associated with knee overuse injuries such as pain and discomfort around the knee joint [34, 38]. Despite the existing significant body of knowledge, the knee joint continues to be a common site of injury with anecdotal treatment approaches [38]. Complex syndromes such as patellar tendinitis are consistently observed between cycling individuals [34]. Lateral knee pain is a common symptom of iliotibial band friction syndrome, which is attributed to repetitive flexion and extension of lower extremities [56, 100]. Furthermore, studies frequently report training-induced pain and discomfort around knee joint; making knee the second most common overuse injury region following back pain in cycling [34, 45, 62].

Solutions to above problems mainly consider two factors for assessing and treating knee overuse injuries in cycling. First, studies often focus on short and long-term load management to optimize training and rest periods [27] due to the consistently cited association between excessive training load and overuse injuries [54]. Second, optimizing the biomechanics of cycling plays a significant role in achieving an adequate man-machine interaction to reduce the likelihood of injuries. Both intrinsic and extrinsic factors are proven to play a significant role in this process, such as bicycle geometry, muscle imbalances, or functional or anatomical limb length discrepancies [10, 192]. Furthermore, the optimization of

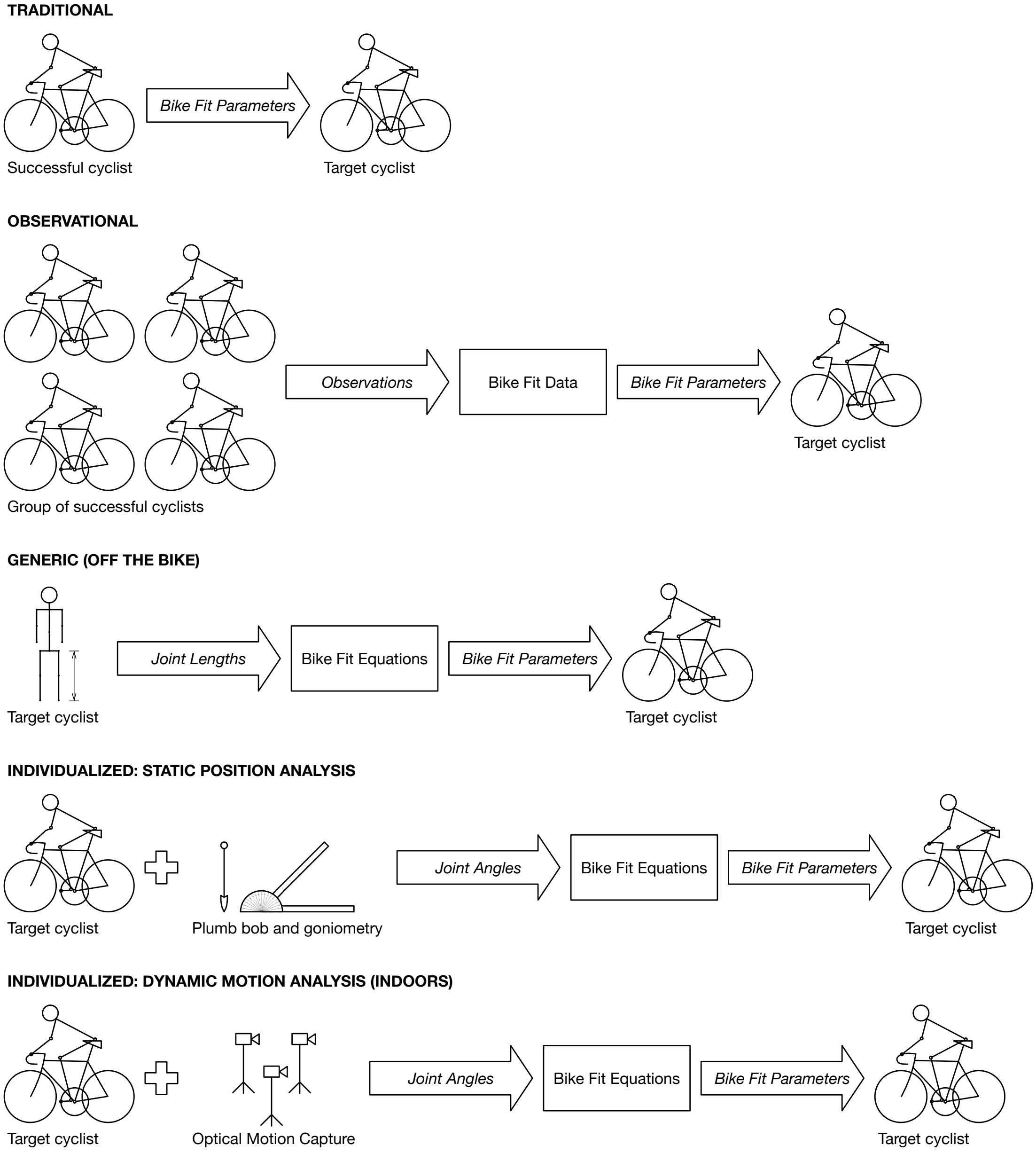


Figure 4.2: Graphical history of bike fit.

closed kinetic chain of cycling, or commonly referred as *bikefit*, is a controversial part of this process which demonstrated a dramatic change over the course of history [33]. Although state of the art computer-aided systems offer better solutions compared to observation driven approaches of 1970s, a significant portion of existing body of knowledge remains unscientific and unsupported by adequate research results (Figure 4.2). Scholars suggest both subjective and objective practices as effective means for monitoring exercise performance and identifying progression towards negative health outcomes [149]. Subjective factors such as self-reporting of workload, mood states, or perceived exertion yield qualitative insights, whereas objective measures such as bodily movement, physiological metrics, or performance statistics provide quantitative measures [33, 40, 149]. However, current approaches to sports data visualization primarily support objective practices while significantly overlooking the benefits of subjective information and qualitative monitoring [136].

4.1.3 Capturing Human Movement

Digitally recording human movement, or commonly referred as motion capture, is a technology that has been fostering significant development in numerous fields over the last decades [173]. From an historical perspective, early techniques used to capture movement focused on creating lifelike hand-drawn animations [173]. Originally invented by Max Fleischer, rotoscoping is an animation technique that enabled realistic human movement in cartoons through frame-by-frame tracing of motion picture footage (Figure 4.3) [173]. Fleischer used rotoscoping to create his own animated character called Koko the Clown [60] and later Walt Disney employed the same technique in 1937 Snow White and the Seven Dwarfs [140]. Although rotoscoping is seen as a proof of concept for modern motion capture systems, Lee Harrison III was the first person to capture human movement as we know it. In 1959, he used a body suit equipped with potentiometers and a cathode ray tube to capture and animate actor movements in real-time (Figure 4.4) [73, 150]. Current state of the art optical systems continue to utilize a similar approach where actors wear a body suit and attach passive reflective markers to capture movement through infrared cameras. These systems offer great accuracy and relatively short setup times compared to their predecessors. SIGGRAPH 2016

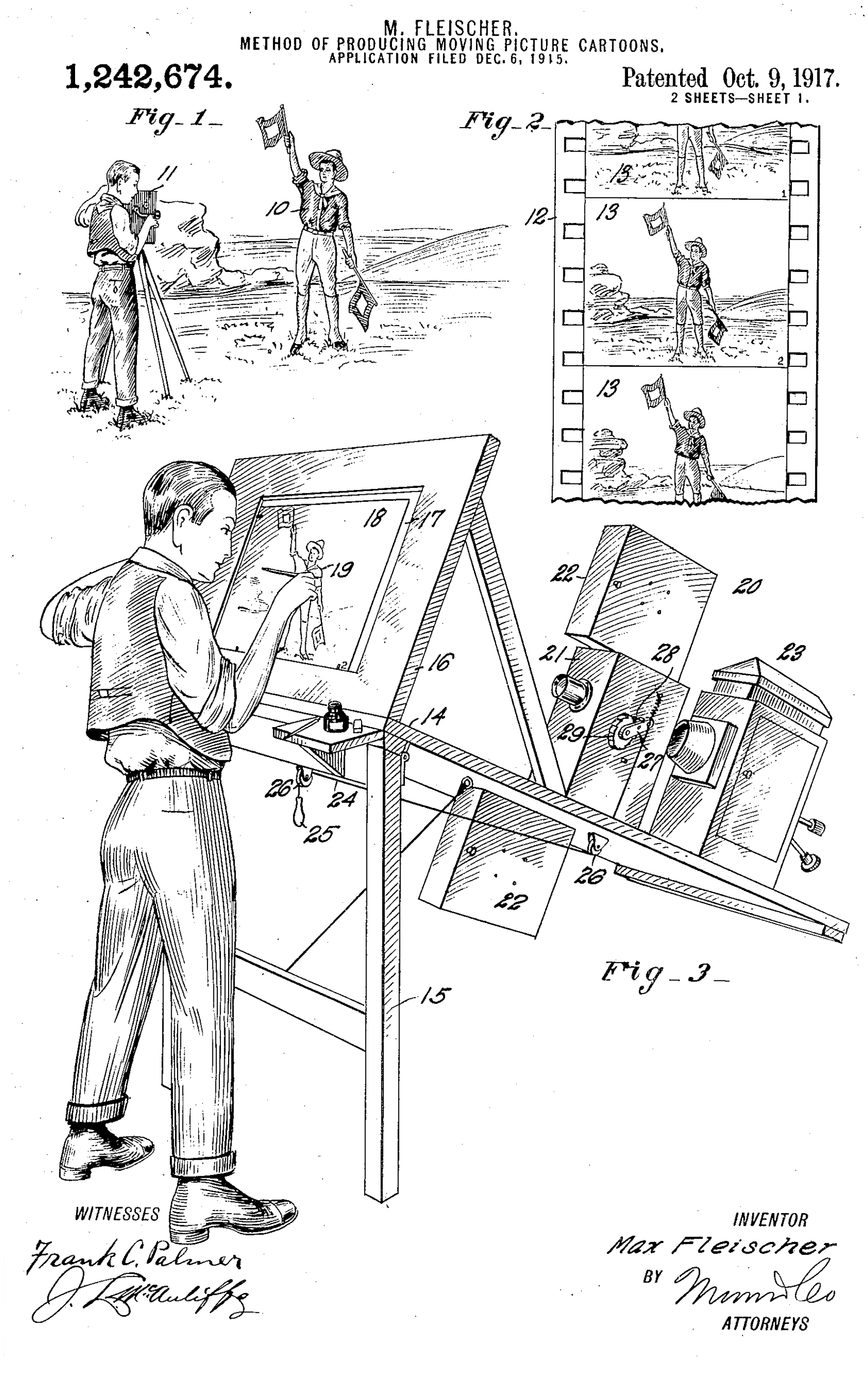


Figure 4.3: Fleischer's method of producing moving-picture cartoons included a typical video camera for capturing actors that performed the same movements to be displayed by the cartoon characters. Resulting videos were projected to a screen and used frame by frame to create hand drawn cartoons [173].

Figure 4.4: The line patterns representing the dancer's motion are altered according to the data received from various sensors attached to the body suit [73, 150].

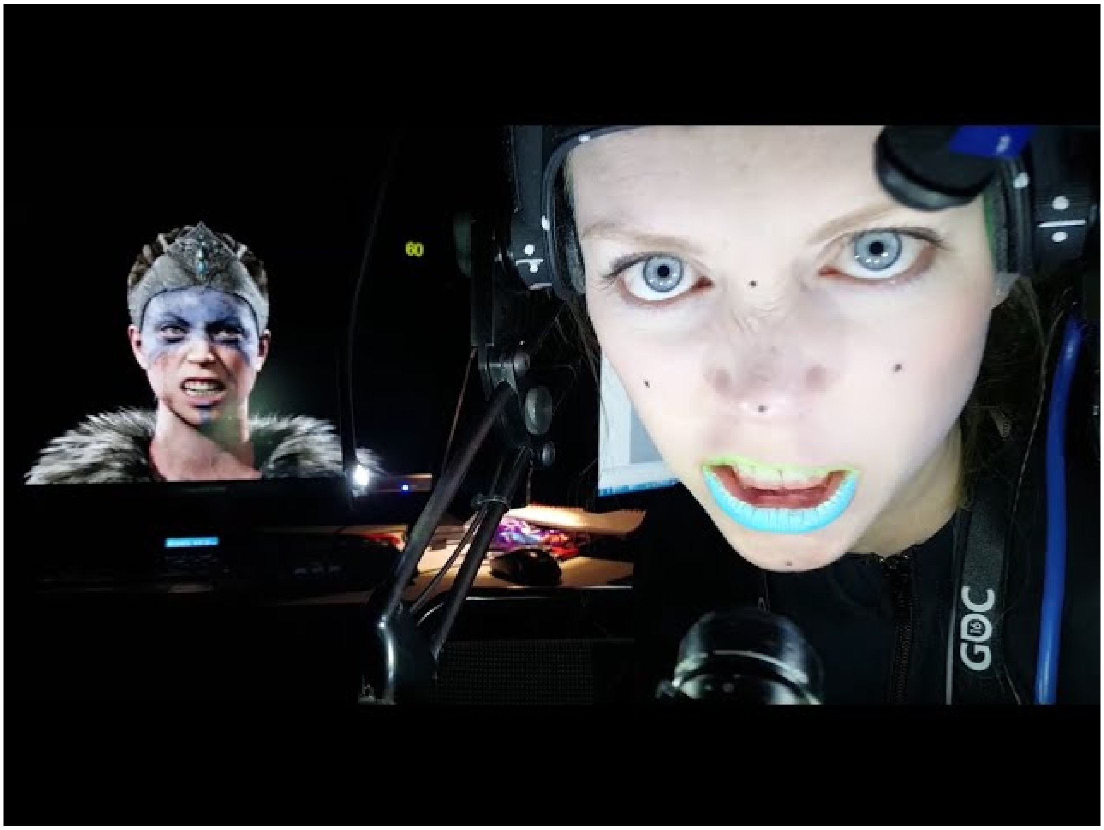
award winner Hellblade: Senua's Sacrifice demonstrated the immense potential of real-time motion capture when it is coupled with high quality graphics (Figure 4.5a) [2]. On the other hand, vision-based markerless approaches such as Kinect and Apple's Motion demonstrate the future direction of this technology (Figure 4.5b) [122].

Although it is best known to fame by its successful use in movie industry, exercise physiology is a field that's second to none when it comes to capturing and analyzing human movement [160]. Scholars of this field consistently used motion capture systems to better understand biomechanics of human movement and its clinical applications [160]. The majority of studies rely on marker or computer-vision based approaches for gait and posture analysis [122, 138]. Individuals with physical disabilities heavily depend on prostheses developed in accordance with motion capture technology [101]. Wearable systems based on inertial measurement units are gaining popularity due to their high level of portability [186]. In cycling, these systems are frequently used for achieving optimal bike fit and minimizing the possibility of overuse injuries [31]. Researchers track hand position to analyze its effects on pelvic motion according to gender and pedaling power

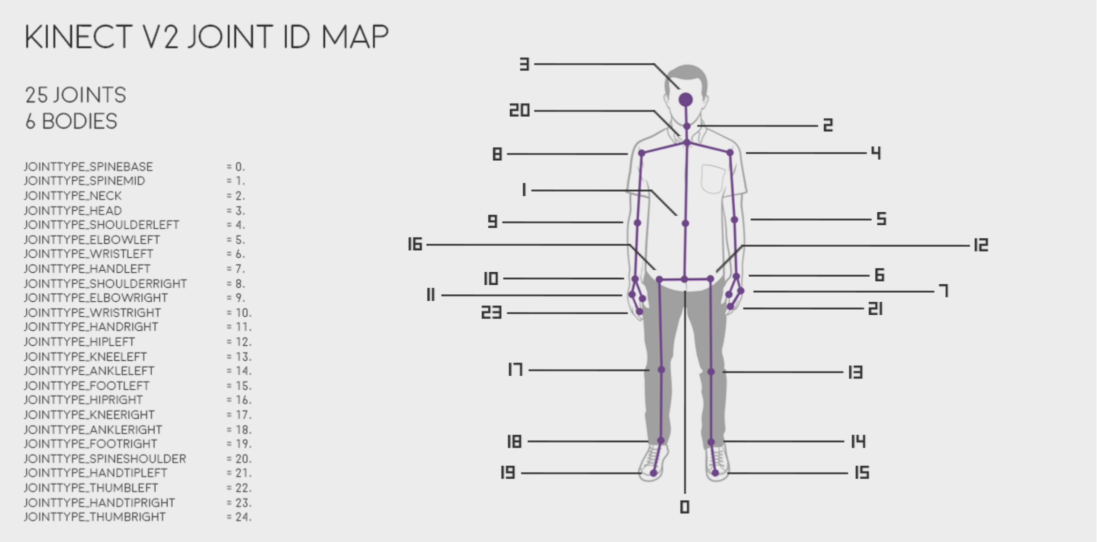
[148]. As a result, it is obvious that motion capture has an important role in understanding biomechanics of human movement to eradicate overuse injuries associated with risk factors in exercise.

4.2. Understanding Knee Movement in Cycling

The high recurrence rate of knee overuse injuries was clearly a pressing concern, which I realized as a result of the interviews I conducted during my previous study [96]. Most cyclists indicated the excessive amount of time they spent on small adjustments to achieve a satisfactory position on their bicycles. They placed a great effort on these adjustments mainly for two reasons; minimizing aerodynamic drag, and reducing the pain associated with overuse injuries. Amateur and professional cyclists acknowledged knee as the most labor intensive joint in terms of analysis and assessment, which is a widely recognized fact in research community [38, 39]. Participants often cited fundamental problems such as the lack of a cost-effective and effortless approach in support of these tasks. Moreover, they demonstrated a mediocre confidence in existing assessment procedures due to their indoor only and stationary structure. Professional cyclists pointed out the significant role center of mass and its shift plays in physics of cycling. Although current indoor only methods offer practical and highly accurate solutions, cyclists expressed displeasure due to the substantial deviation from the physics and biomechanics of outdoor cycling. They anticipated a considerable change in mathematical models used to explain cycling motion and associated movement analysis when outdoor environments were also taken into consideration. Majority of participants favored the idea of outdoor knee tracking despite the lack of research-based evidence in support of their opinions. Therefore, I consider the need for an affordable procedure to support indoor-outdoor tracking of knee movement in cycling prior to receiving a professional intervention. I aim to encourage self-assessments and further elaborate our biomechanical knowledge on knee movement in cycling to reduce the likelihood of overuse injuries.



(a) SIGGRAPH 2016: Hellblade, live performance and real-time animation [2].



JOINTTYPE_SPINEBASE = 0.
JOINTTYPE_SPINEMID = 1.
JOINTTYPE_NECK = 2.
JOINTTYPE_HEAD = 3.
JOINTTYPE_SHOULDERLEFT = 4.
JOINTTYPE_ELBOWLEFT = 5.
JOINTTYPE_WRISTLEFT = 6.
JOINTTYPE_HANDLEFT = 7.
JOINTTYPE_SHOULDERRIGHT = 8.
JOINTTYPE_ELBOWRIGHT = 9.
JOINTTYPE_WRISTRIGHT = 10.
JOINTTYPE_HANDRIGHT = 11.
JOINTTYPE_HIPLEFT = 12.
JOINTTYPE_KNEELEFT = 13.
JOINTTYPE_ANKLELEFT = 14.
JOINTTYPE_FOOTLEFT = 15.
JOINTTYPE_HIPRIGHT = 16.
JOINTTYPE_KNEERIGHT = 17.
JOINTTYPE_ANKLERIGHT = 18.
JOINTTYPE_FOOTRIGHT = 19.
JOINTTYPE_SPINESHOULDER = 20.
JOINTTYPE_HANDTIPLEFT = 21.
JOINTTYPE_THUMBLEFT = 22.
JOINTTYPE_HANDTIPRIGHT = 23.
JOINTTYPE_THUMBRIGHT = 24.

(b) Joint locations that can be tracked with a Kinect v2 [122].

Figure 4.5: Modern motion capture approaches.

Table 4.1: Exercise routine I followed throughout the experiments.

Duration	**Exercise Type**	**Cadence**	**Repetition**
300 sec	Warm-up	90 ∼ 100 rpm	x 2
60 sec	Rest	70 rpm	
180 sec	Seated 3-min	90 ∼ 100 rpm	x 2
60 sec	Rest	70 rpm	
10 sec	Maximal	Max rpm	x 3
20 sec	Rest	70 rpm	
20 sec	Standing	70 rpm	x 3
10 sec	Rest	70 rpm	

4.2.1 Initial Study

Although research commonly cites the deviation of knee joint from its intended path as a leading cause in cycling-related overuse injuries, the associated movement patterns and analysis methods continue to be ill defined [38]. Therefore, I examined the knee movement of amateur and professional cyclists with an indoor scenario to familiarize myself with frequently encountered problems and better understand user requirements for development. I replicated the current de facto standard used to capture knee movement data in cycling, and orally interviewed the participants to consider a user-centric approach for clarifying consistently encountered obstacles.

4.2.2 System Design

I utilized a highly customizable cycle ergometer which easily allowed me to achieve personalized bike fit for each participant. Since this device was incapable of tracking knee movement, I coupled it with an optical motion capture setup. I selected this approach due to its high accuracy and my expertise with a system of this type. Since optical motion capture is a marker based approach, I attached multiple passive reflective markers to knees and heels of participants. Additionally, I attached markers to pedals for calculating their planes of movement, and used this information as ground truth while calculating angular deviation of knee movement according to following procedure (Figure 4.6):

1. Accumulate marker data for one second.
2. Calculate movement plane of pedals.
3. Use principle component analysis (PCA) on accumulated knee marker data and select the eigenvector with biggest eigenvalue for extracting dominant movement direction.
4. Calculate the angular difference between pedal plane and selected eigenvector.
5. Repeat steps 1 $\sim$ 4 until all data has been processed.

4.2.3 Experiment Procedure

I captured the knee movement of seventeen amateur and nine professional cyclists. I collected informed consent and physical measurements before each experiment. Additionally, I followed orthodox bike fitting techniques to optimize cyclist position and minimize the potential effects of fit related arguments [33].

Each experiment session consisted of four phases; subject preparation, training, analysis, and oral discussion. I administered a warm-up session before actual training to prepare participant's body for strenuous physical activity. I controlled the training load based on participant's experience level and body weight as it is common practice in cycling training. Thereafter, I post-processed the motion capture data to fill gaps and reject erroneous reflections. I used the resulting data to calculate angular difference between pedal planes and dominant knee movement direction. Finally, I had an oral discussion session with participant to acquire subjective comments and opinions.

4.2.4 Apparatus

I made use of a Wattbike Trainer, a cycle ergometer, due to its exceedingly customizable architecture, and its capability to replicate the feeling of a real bicycle (Figure 4.7). I used six Optitrack Flex:V100R2 to accurately capture knee

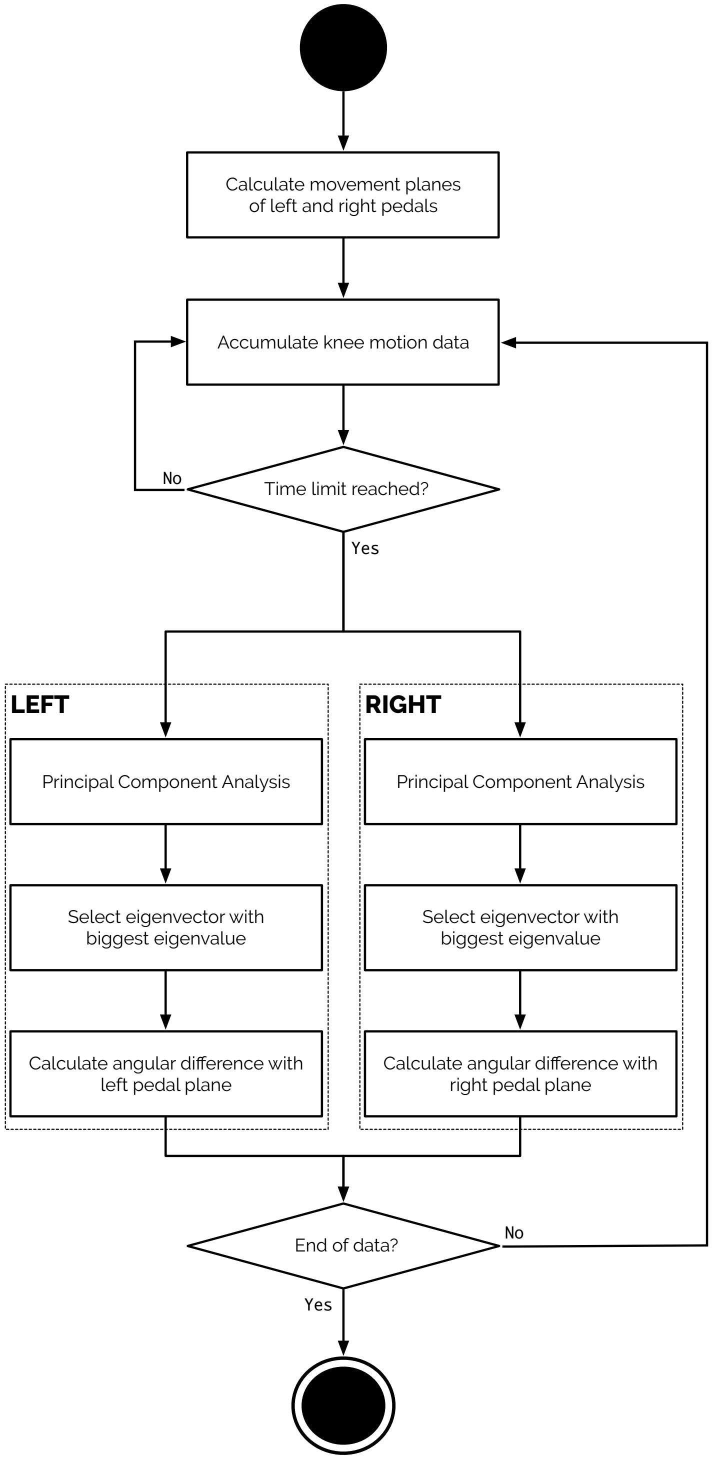


Figure 4.6: Angular deviation calculation process.

Figure 4.7: Experiment setup and the Wattbike I used during my study.

movement. I placed six passive reflective markers on subject's lower extremities; two on knees, two on heels, and two on toes. I placed an additional marker to each pedal for extracting their movement planes and used them as references to calculate angular deviation in knee trajectories. I also attached three markers to Wattbike for locating it in the capture space.

4.2.5 Results

I observed no significant agreement between lateral movement patterns of participants as I anticipated. Professional cyclists had a more left-right balanced movement compared to amateurs (Figure 4.8). Yet, I have rarely observed knee motion perfectly parallel to the calculated pedal planes between all participants. I observed no gender based difference. Left knee of a professional cyclist demonstrated an unusual movement pattern where I observed a significant shaking while transitioning from pull to push phase. The peculiar nature of this movement was self-evident in video-based visualization of passive reflective marker trajectories, which is a typical method used by optical motion applications. This discovery was carried to a specialist by the participant in discussion and associated with muscle

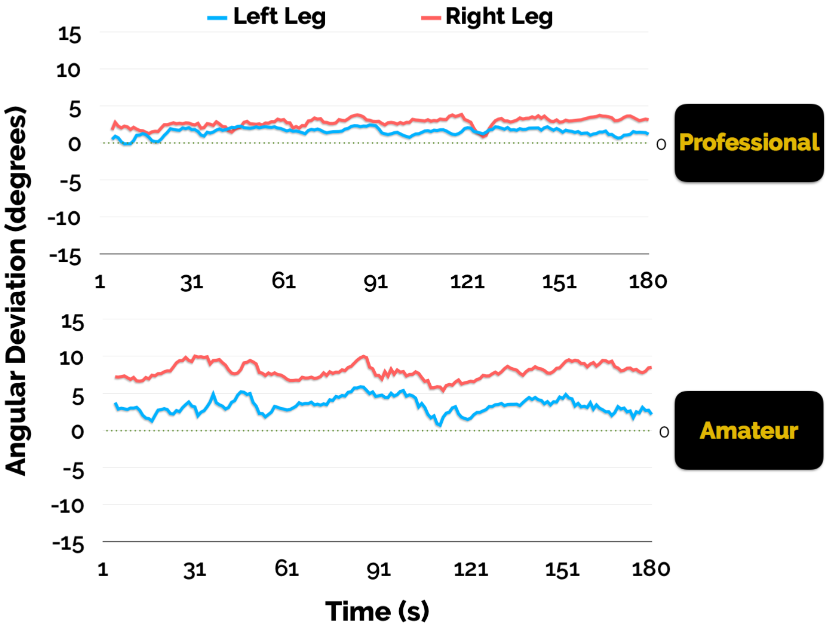


Figure 4.8: Lateral deviation in knee movement of a professional and an amateur level cyclist. Positive angles correspond to outward trajectories and vice versa.

imbalances as a result of physical examination. Additionally, participants had a significant interest on video-based visualizations of marker trajectories (Figure 4.9) compared to common visualization methods such as data plots.

4.3. Discussion

My results are in agreement with previous work on individual characteristics of knee movement in cycling. Moreover, trying to determine a generalized pattern attributed to knee overuse injuries is an ill-defined effort with current tracking approaches in cycling due to highly individualistic nature and indoor only structure. As I reported earlier, I observed a significant interest towards video-based visualizations of marker trajectories (Figure 4.9). Although I did not conduct any further analysis, this has significant implications on personal preferences and importance of subjective information to support qualitative monitoring. Building upon this interest, I consider visualizations for qualitative monitoring important to address risk inducing factors in addition to cost-effective indoor-outdoor

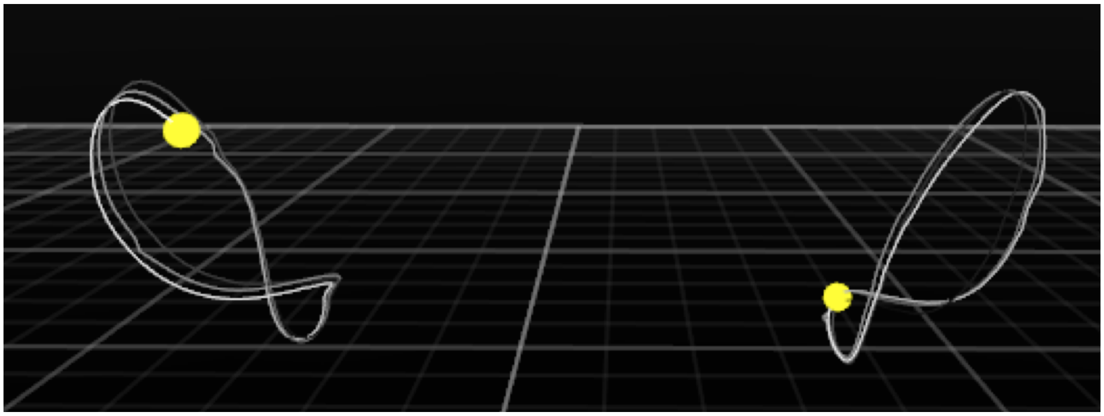


Figure 4.9: Single frame taken from a video where passive-reflective marker trajectories of both knees are visualized in 3D. This visualization attracted significant interest and it was favored by most professional cyclists during my studies.

tracking of knee movement in cycling. Accordingly, I consider a framework with two components for cycling; unobtrusive robust indoor-outdoor tracking of knee joint, and visualization of knee movement for enabling quantitative and qualitative monitoring (Figure 4.10).

4.3.1 Indoor-outdoor Knee Tracking in Cycling

Understanding the underlying factors of lower-extremity injuries in cycling requires carefully designed indoor-outdoor studies with sufficient sample sizes. Yet, research efforts frequently suffer from mediocre attention given to environmental settings and insufficient amount of data [124], resulting in failure to detect existing cause-effect associations. I partly associate this outcome with shortcomings of current tracking technologies for providing a cost-effective medium to collecting data from indoor-outdoor cycling scenarios. Predominant procedures focus on accuracy and individual rather than outdoor and whole; leading to highly accurate but brief and costly observations of injury associated movements. Therefore, I recognize a need for adequate means to acquire indoor-outdoor knee movement data in cycling through robust and unobtrusive tracking practices.

Consequently, I consider the applicability of an existing deep learning toolbox titled DeepLabCut for robust and unobtrusive markerless tracking of knee joint

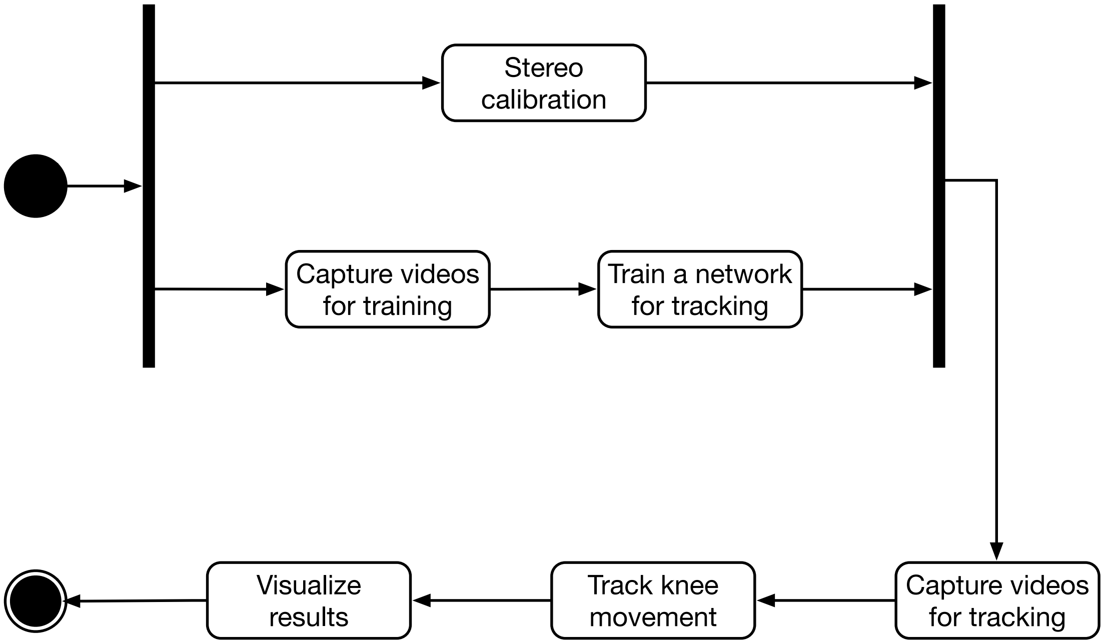


Figure 4.10: Framework overview.

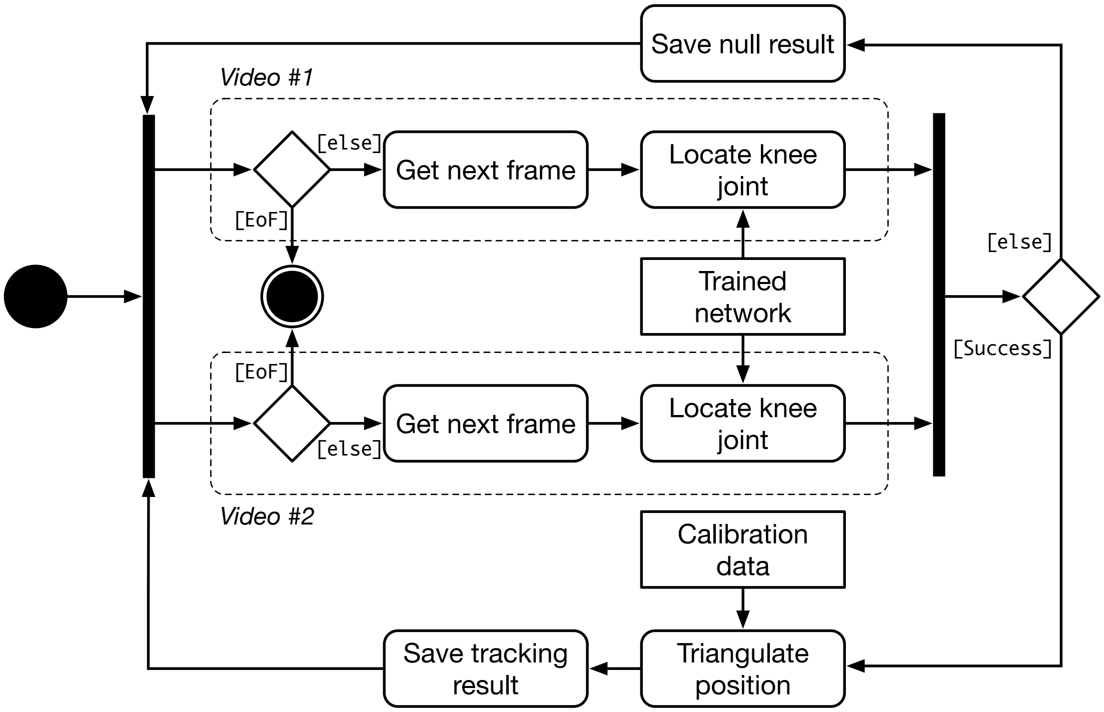


Figure 4.11: Video-based indoor-outdoor tracking of a single knee joint in cycling.

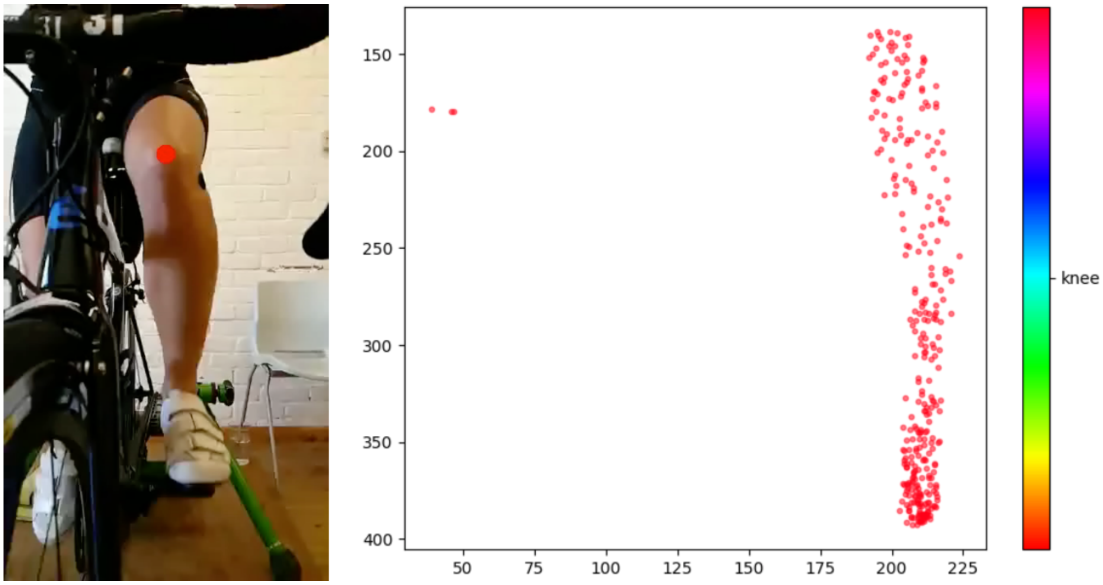


Figure 4.12: One of the tracking results I obtained after using DeepLabCut [117] with the videos I downloaded. The outliers on the left belong to erroneous detection of right knee instead of left.

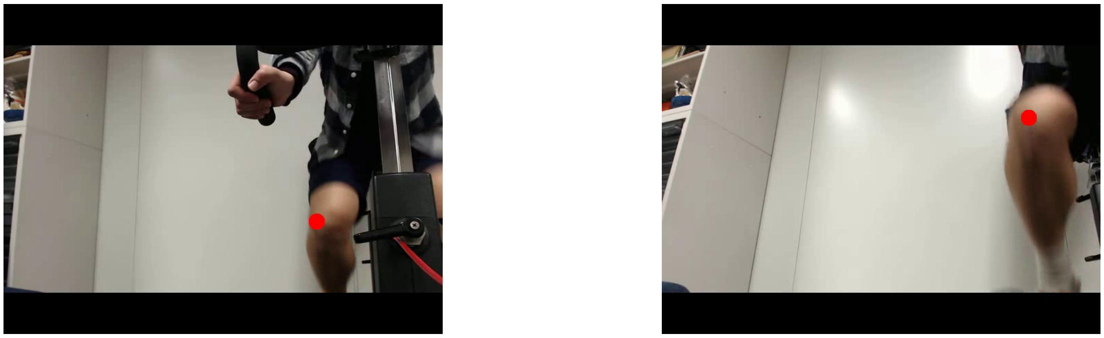
in cycling to promote indoor-outdoor movement assessments.Subsequently, I have conducted two preliminary studies to assess the applicability of this toolbox to knee tracking in cycling. I utilize a naive visual evaluation in both studies. I downloaded several videos that was shot through a single camera for the first study. I labeled 80% of each video to train a network and used the remaining 20% for visually confirming the tracking accuracy. The second study, however, followed a more detailed three staged process using several videos I captured with a calibrated stereo camera rig of my own. First stage included the stereo calibration of two cameras (Dual Logitech c920r) I used to track knee movement. I used the standard functions provided in OpenCV library for stereo calibration. Afterwards, I captured multiple videos via the same camera rig and and equally divided them into training and test groups. I used the videos from first group with DeepLabCut [117] to train a network capable of unobtrusive and robust markerless tracking of knee joint in cycling. I trained my network according to the training procedure described by Nath et al. [125]. I extracted 64 images from four 60-seconds long training videos using k-means clustering. I used these images to train my network for around 1,000,000 iterations (≈ a day with Nvidia GeForce Titan X). Finally, I used this network with videos from test group to locate knee joint location in video frames. I used the resulting tracking information with calibration parameters to triangulate knee joint location(Figure 4.11).

The tracking results I obtained in both trials are promising and comparable to human accuracy. Although my assessments up to this point were merely visual, I consider this toolbox suitable for realizing a robust and unobtrusive approach to markerless tracking of knee joint in indoor-outdoor cycling. I experienced no problem with detection, but observed several tracking errors during first trial when both knees were visible (Figure 4.12). Network tracked a single knee at all times as I trained it to do so, and could not distinguish between left and right which led to a few outliers in tracking results. This is due to the simplicity of labels I used to train my network and the associated problems can be easily solved by retraining it to detect both knees at the same time, or by ensuring a single knee is visible in each video feed as I did during my second study (Figure 4.13). This approach resulted in improved accuracy by eliminating the outliers which confirmed my expectations.

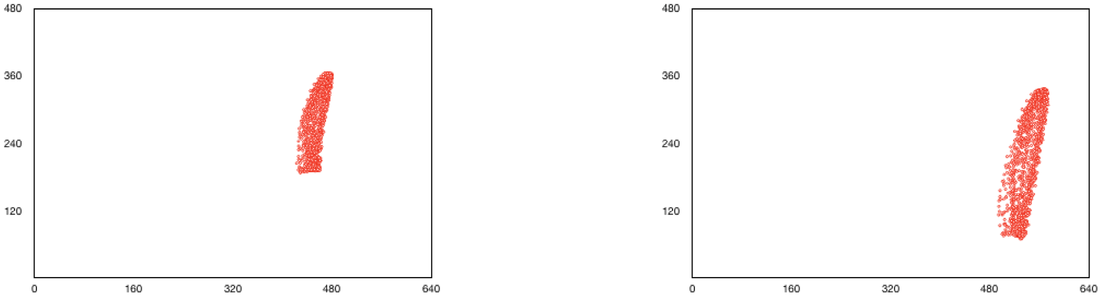
4.3.2 Visualizing Trajectories of Knee Movement

The majority of participants were taken by surprise when their movement perception differed from the actual results. General agreement when I questioned them before the experiments was to observe a straight movement pattern. Yet, I consistently observed lateral deviation among all participants regardless of their self-reported lower-extremity injury history. This has serious implications on significance of subjective movement monitoring, which is a consistently overlooked subject in common approaches to knee movement visualization in cycling. Presumably, I argue that video-based visualizations may provide new insights to exercising individuals, coaches, or health practitioners by presenting a perspective that has not explored in its entirety. Therefore, I consider connecting data graphs representing tracking results from DeepLabCut to input videos for realizing simultaneous quantitative and qualitative monitoring.

Combining several visualizations of quantitative and qualitative data as a form of intuitive modality is not a new idea within the augmented reality (AR) com-



(a) Frame from the first camera. (b) Frame from the second camera.



(c) Results of the first camera. (d) Results of the second camera.

Figure 4.13: An example tracking result I obtained during my second study.

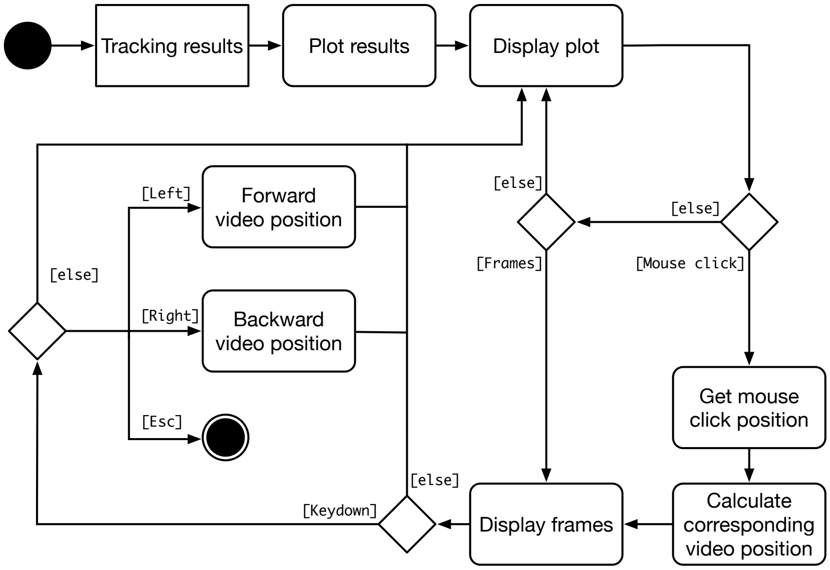
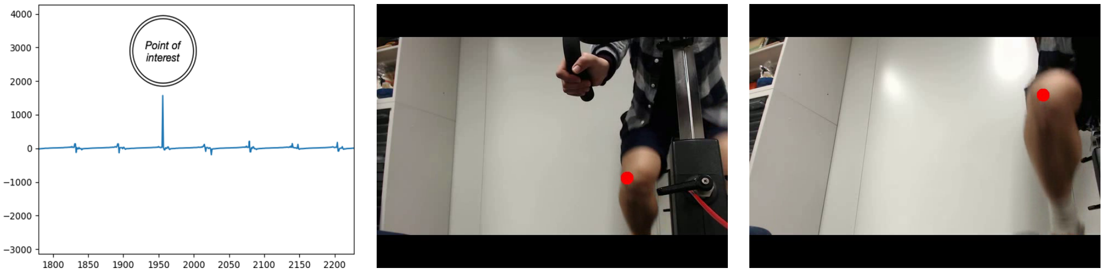


Figure 4.14: Visualization process.

munity. White and Feiner introduced the term *situated visualization* for referring to a visualization which is related to its environment [191]. They designed a system to support urban planners, designers, and architects via visualizing quantitative data in the context of its physical site. Their approach intended to aid professionals in pattern finding and decision making by combining qualitative aspects of an environment with a quantitative data visualization. Takeuchi and Perlin illustrated a visualization concept utilizing free form transformations to address problems associated with information bubble trend in AR applications [175]. They focused on enhancing the details and importance of physical world by reducing the attention placed upon visualizations. Kalkofen et al. designed interactive visualizations to emphasize the spatial relationship between real and virtual objects in AR applications [94]. They explored the perception of user considering focus and context when scene clutter density is significantly high. Zollman et al. augmented users view with a flight management interface designed for micro aerial vehicles [200]. They provided spatial information about the environment to support cognition and introduced visualization techniques to provide additional depth cues for controlling flying objects. However, the research work I mentioned above do not consider the physically and mentally demanding nature of sports and exercise. Naive situated visualization approaches significantly increase the likelihood of inducing information overload by not taking the resource limitation of exercising individuals into consideration [95] as I introduced in Chapter 3. Therefore, although I acknowledge the potential of situated approaches, I consider a visualization approach based on visual information-seeking mantra [158] to support autonomy as well as qualitative and quantitative monitoring.

Accordingly, I used the videos I captured and the tracking results I obtained from DeepLabCut in conjunction to demonstrate my visualization approach. I used Matplotlib to create data graphs of knee movement and connected them to videos with an event listener. I displayed the video frames corresponding to a data in graph to provide qualitative monitoring when user clicks a point of interest. I also displayed the detected knee joint location to visually validate tracking results 4.15. I anticipate a visualization of this design to introduce new perspectives on knee movement in cycling, and minimize the likelihood of knee overuse injuries which is connected to one's risk perception. On the other hand,



(a) x-plot of 3d knee movement over time.

(b) First frame corresponding to PoI.

(c) Second frame corresponding to PoI

Figure 4.15: Visualization concept based on visual information-seeking mantra [158]. a) The overview and zoom-and-filter are implemented with data plots. b&c) Clicking a point of interest (PoI) such as a sudden spike displays the corresponding frames for extracting details.

video-based visualizations can provide a new evaluation mechanism to support staff such as coaches and physical therapists; which remains uncharted in annals of knee movement analysis in cycling.

4.4. Future Work

I acknowledge the need for an in-depth analysis and evaluation of my framework while considering several directions for future research. First and foremost, although I consider the application of my visualization framework to indoor-outdoor cycling, I only carried out indoor trials until the present. I am planning to address this by modifying my video capture approach by attaching dual micro cameras to a bicycle's down tube where a single knee joint is visible at all times. This opens up indoor-outdoor tracking and visualization of knee movement in cycling, and makes an effective comparison possible between the two. I also consider the potential of this comparison in initiating new investigations from sports science point of view by providing an original perspective. However, I consider a comparison between indoor and outdoor tracking before anything else to demonstrate its evidence-based necessity rather than intuition or subjective comments alone.

Moreover, I consider replacing the raw video feed approach with a model-based VR visualization of knee to reduce the possibility of information overload.

Figure 4.16: My situated visualization concept to tracking knee movement in cycling. Visualizing the movement trajectories of knee joints on videos has a potential to promote subjective and objective monitoring simultaneously.

This approach, however, might remove access to certain qualitative factors by discarding background information which may serve an essential role in outdoor cycling. Therefore, it is vital to specify its use-case prior to development, and my current suggestion involves indoor-only training scenarios.

Finally, I retain my point of view on situated visualizations and acknowledge their value for promoting qualitative and quantitative monitoring in cycling. Yet, I still find its application to sports and exercise difficult due to problems associated with resource limitations and resulting information overload (Chapter 3). Therefore, I recognize affordable and realistic means to deal with these problems essential towards success before pursuing this direction.

4.5. Chapter Summary

In this chapter, I focused on risk perception and illustrated how it is associated with injuries in physical exercise. I studied cycling as an intricate case and introduced frequently encountered overuse injuries in this type of exercise. I reviewed the common approaches used to capture movement and briefly described their development over the past decades to provide a historical perspective. I investigated knee overuse injuries in cycling by tracking movement and gathered subjective opinions of both professional and amateur cyclists. Finally, I introduced a framework with two different components and discussed about the philosophy behind my efforts until the present.

CHAPTER 5

Conclusion

In this thesis I investigated human factors in computer-aided system design for physical exercise. I introduced the gravity of problems associated with sedentary behavior, and discussed a human-computer interaction perspective for realizing long-lasting solutions based on an existing psychological theory. I conducted three case studies to investigate its three central constructs which are the initiators of motivation for achieving positive health behavior change among sedentary individuals. First, I focused self-efficacy in computer-aided physical exercise and introduced a role for age in exergame difficulty adjustment methods. Second, I addressed outcome expectancy through a situated visualization approach in exercise and introduced their capabilities in supporting both subjective and objective monitoring. Lastly, I studied knee overuse in cycling as a form of exercise-related injury and described my efforts on providing adequate means to better understand the underlying risk factors and promote self-awareness.

5.1. Contributions

I designed, developed, and evaluated multiple computer-aided systems for physical exercise throughout the case studies I introduced in this thesis. I briefly explain the contribution of each study I have conducted and how they are related to three pillars I introduced in Chapter 1.

5.1.1 Pillar I: Self-efficacy

Self-efficacy refers to one's belief in his or her abilities to achieve certain goals and it plays a very important role in achieving health behavior change among sedentary individuals. It is significantly affected by positive or negative experiences from the past with optimal task difficulty settings. Therefore, achieving an ongoing equilibrium between presented challenge and skill of individuals becomes an important factor in successful physical exercise practices. I have investigated the same factor using a simple exergame where I compared four frequent approaches to difficulty adjustments while taking player age into consideration. My results indicate a role for age in exergame difficulty adjustments for achieving optimal experiences and enable designers to make informed decisions in health behavior change approaches.

5.1.2 Pillar II: Outcome Expectancy

Outcome expectancy is about a person's estimate that a given behavior will lead to certain results depending on performance. These often manifest at a later stage after initiating exercise due to the properties of human physiology, such as loosing weight after a period of three months. Therefore, performance evaluations and feedback provision becomes significantly important elements for satisfying one's outcome expectancy and achieving desirable goals. Although both subjective and objective monitoring play an important role in this process, current approaches mainly consider objective assessments while disregarding the significance of subjective. To address this issue, I have studied a situated visualization approach to indoor cycling training using a computer-aided system of my design. I utilized an in-situ approach to pedaling training in cycling for providing both qualitative and quantitative information to exercising individuals or their trainers alike. The results of my studies with professional cyclists demonstrated their interest in my approach and how it can lead to better training regimes. Additionally, I introduced several future research direction to address its shortcomings and how solving the associated problems may better promote different aspects pf outcome expectancy in exercise settings.

5.1.3 Pillar III: Risk Perception

Risk perception refers to the subjective judgments that individuals make about the severity of any situation with effects of danger or loosing something of value. It plays a crucial role in health behavior change due to perceived negative outcomes of physical activity such as exercise-related injuries. Therefore, reducing the likelihood of experiencing an injury is expected to significantly increase the chances of achieving success in health promotion programs. Unfortunately, many exercise-related injuries lack research-based evidence that can help in better understanding the underlying risk factors for reducing their occurrences. To address this issue and lay the groundwork for future research efforts, I have targeted knee overuse injuries in cycling due to their high recurrence rate and clinical importance. I demonstrated the shortcomings of current computer-aided systems used to gather data on knee movement and considered a video-based tracking approach for as a promising solution to the associated problems. Additionally, I described my recommendations in two different directions. First, I introduced the capabilities of an existing deep learning framework for robust and unobtrusive tracking of knee joint in cycling. Second, I have described a video-based visualization approach to promote qualitative and quantitative monitoring of knee movement. I consider both directions substantial for reducing the perceived risk in cycling training by achieving generalized solutions to consistently encountered injury-related problems.

5.2. Lessons Learned

I list some of my findings and the valuable lessons I have learned to expand our understanding with further insight into future systems.

5.2.1 Taking a General Look Back

- **Different Target Populations**
  I studied three human factors by conducting experiments with people from various age groups over the past five years; including juniors, seniors, and elderly. Thanks to this, I have frequently observed individual differences in human factors and had to come up with different strategies to cope with them. This experience allowed me to grow both personally and professionally, and gave me a profound understanding on intricate nature of humanity. I often encountered great variation due to tiny differences in human factors, which caused a significant effect on end results. Therefore, I support the idea that the characteristics of a target population must be taken into consideration while coming up with computer-aided approaches.

- **Understanding Collaborative Research**
  Despite the universal nature of existing information and knowledge, it is beyond the bounds of possibility for an individual to acquire it all within a single lifetime. Therefore, research is undertaken as a collaborative effort between scientists from various fields. Yet, means or goals of research tend to differ substantially between each field and this leads to subtle differences in evaluation strategies used to assess success. This simple fact lays the groundwork for numerous administrative problems when one is involved with collaborative research, which I have also experienced my fair share. It is important for me to point out that there is no useless but inadequately used information, such as valuable in one field whereas without value in another. Subsequently I consider universally agreed approaches and evaluation metrics necessary in case of collaborative research work done by scholars for the promotion and advancement of science. Furthermore, establishing a new science field that I may refer as ”sports informatics” or ”sports information science” might play a critical role in understanding the nature of exercise and the problems we are facing today.

5.2.2 Age and Difficulty Adjustment Methods in Exergames

- **Role of Age in Exergame Difficulty Adjustments**
  Designers of exergames must take age into consideration while using or developing their own difficulty adjustment techniques for exergames. It is important to achieve optimal task difficulty for promoting self-efficacy and motivational aspects of physical exercise. The results of my study with young and old individuals support this idea and correlate well with previous studies done in this area.

- **Player Characteristics**
  Despite the above findings, optimal exergame experience do not have to be solely associated with difficulty adjustment methods. Player characteristics and gaming perception can also be regarded as valid components for adequate exergame experiences.

- **Supporting Proprioception**
  I frequently observed changes in movement where they deviated from the intended path. While gaming perception might be an important factor for achieving optimal experiences, supporting proprioception for correct physical exercise execution can also be regarded as essential in computer-aided system design for physical exercise.

- **Perceived Social Interaction**
  Systems designed to promote physical exercise often use perceived social interaction for motiving individuals to performance regular exercise. Identifying the nature of collaborative and competitive social interaction in exergame difficulty adjustments deserves to be taken into account for motivating people to perform regular physical exercise.

5.2.3 In-situ Visualization of Pedaling Forces

- **Combining Physical with Digital**
  Current visualization approaches dominantly focus on activity results and often disregard the underlying physical factor. Situated visualizations present a new dimension by supporting bodily awareness in computer-aided systems

designed for physical exercise. Although performance in sports is defined according to obtained results, understanding bodily movement has a significant potential for achieving goals and promoting exercise.

- **Information Overload**
  Situated visualizations significantly increase the amount of output compared to graph-based approaches by adding meaning to background. This challenges user's cognitive processing capacity which is already being exposed to exercise related physical and mental load. It is important to have a profound understanding on this aspect of physical exercise for determining most suitable approaches to information visualization in physical exercise. Supporting bodily movement to promote outcome expectancy should not come at a high price, therefore visualization approaches must be carefully modeled while considering human factors in computer-aided system design.

- **Real-time Support**
  The current trend of using motion capture in physical exercise mainly focuses on indoor scenarios and offline evaluations. Lack of real-time support on bodily movement was a consistently recognized issue of current approaches. Vision-based tracking techniques offer a promising direction for capturing and visualization in real-time, yet significant technical challenges remain to be solved for achieving required sub-millimeter level accuracy.

5.2.4 Understanding Knee Movement in Cycling

- **Peculiar Nature of Knee Motion**
  The articular structure and mechanics of knee make it one of the most complex joints in the human body. Its movement pattern is affected by numerous factors including genetics and muscle tissue quality. Therefore, evaluating injuries from the single perspective of movement might not produce satisfactory results for furthering our understanding on underlying injury causes. Similar to situated visualizations, integrating multiple sources of information is a valid approach which might provide a more adequate solution to problems associated with knee overuse injuries in cycling exercise.

- **Importance of Self-assessments**
  Most participants subjective opinions on their perceived motion differed from the actual results I captured. This has serious implications on importance of perceived motion and proprioceptive neuromuscular facilitation. Focusing on improving our joint position sense, research supports the potential benefits of this practice for increasing range of motion and athletic performance. Although many research work on computer-aided systems refer to human-centered guidelines, proprioception remains as a neglected study area in computer-aided system design.

- **Indoor-outdoor Tracking**
  There is an ongoing transition from indoor to outdoor in terms tracking bodily movement. Yet, current trend in capturing knee movement in cycling still continues to rely only indoor-only practices. Consistently utilized approaches place significant importance on accuracy and mainly rely on stationary indoor setups. This methodology overlooks several factors that may play a significant role in understanding the underlying causes of knee overuse injuries. Although indoor-outdoor tracking of knee movement in cycling seems logical by intuition, there is no body of knowledge in existence to provide evidence-based strategies. Therefore, I consider a robust and obtrusive tracking approach necessary to promote better assessment practices and lay the groundwork for outdoor tracking of knee joint in cycling. Current advancements in deep learning approaches are enabling promising directions, but they are still far from being perfect and require additional effort of scholars for achieving further improvements.

5.3. Future Work

Potential future work directions and suggestions to further improve my efforts include:

1. **Professionally developed games:** Studies on exergames often fail to confirm existing relationships due to poor game design. Although my game conformed to guidelines published by other researchers, it still lacks certain

game elements such as a strong narrative. Utilizing exergames acknowledged by gamer communities can provide more insights into evaluation of age-related changes in difficulty adjustments.

2. **Factors on difficulty adjustments:** Additional elements that might have a strong correlation with self-efficacy and motivation require careful consideration in exergame difficulty adjustment methods. Aside from the factors discussed in Chapter 2, assessing player characteristics plays an important role in difficulty adjustments. Additional methods to measure player's understanding or expectations from exergames can be helpful for furthering our understanding on optimal exergame experience. I particularly recommend using a wide variety of neurological or psychiatric measurements such as eye tracking or galvanic skin response to further elaborate my findings.

3. **Interface improvements:** I utilized rather simple game interface design during my first and second work. Professionally designed interfaces can substantially improve the quality of results and user satisfaction in both research. Additionally, I only considered single side view in this work. Further qualitative investigations into versatile situated visualizations are required for improving our understanding.

4. **Outdoor support for capturing knee motion:** The approaches I used to track knee joint considered indoor scenarios only. As I discussed in Chapter 4, an unobtrusive and robust tracking approach is important for considering both indoor and outdoor environments under similar conditions, and may have a significant impact on our understanding and risk perception regarding knee overuse injuries. Unfortunately, I could not study knee movement with outdoor scenarios due to time limitations placed on me. Therefore, I recommend future work to build on top of mine and consider improved tracking technologies to support outdoor scenarios.

Publication List

Journal Articles

1. **Oral Kaplan**, Goshiro Yamamoto, Takafumi Taketomi, Alexander Plopski, Christian Sandor, and Hirokazu Kato. *Exergame experience of young and old individuals under different difficulty adjustment methods.* MDPI Computers: Special Issue on Computer Technologies for Human-centered Cyber World, 7(4), no 59, pp. 1–20, November 2018.

Peer-Reviewed Conference Publications

1. **Oral Kaplan**, Goshiro Yamamoto, Yasuhide Yoshitake, Takafumi Taketomi, Christian Sandor, and Hirokazu Kato. *In-situ visualization of pedaling forces on cycling training videos.* Proceedings of IEEE Systems, Man, and Cybernetics, pp. 994–999, October 2016.

2. **Oral Kaplan**, Goshiro Yamamoto, Takafumi Taketomi, Yasuhide Yoshitake, Alexander Plopski, Christian Sandor, and Hirokazu Kato. *Promoting short-term gains in physical exercise through digital media creation.* Proceedings of Advances in Computer Entertainment Technology, pp. 272–277, December 2017.

3. **Oral Kaplan**, Goshiro Yamamoto, Takafumi Taketomi, Yasuhide Yoshitake, Alexander Plopski, Christian Sandor, and Hirokazu Kato. *Towards situated knee trajectory visualization for self-analysis in cycling.* Proceedings of IEEE Virtual Reality and 3D User Interfaces, pp. 595–596, March 2018.

Other Conference and Workshop Publications or Presentations

1. **Oral Kaplan**, Takafumi Taketomi, Goshiro Yamamoto, Alexander Plopski, Christian Sandor, Hirokazu Kato, and Yasuhide Yoshitake. *Overthrowing monotonous strength exercise methods : Further improvements in sustainability rate and wellness.* Proceedings of SICE System Integration Division Annual Conference, pp. 1991–1994, December 2016.

Acknowledgements

First and foremost, my appreciation and thanks to all individuals who advised me during this journey. I would like to express my utmost gratitudes to Professor Hirokazu Kato for accepting me to his laboratory and allowing me to grow personally and professionally. I appreciate all his contributions of time and ideas to make my Ph.D. experience a successful one. I thank Affiliate Associate Professor Goshiro Yamamoto for making it possible for me to study in Japan. I am forever in his debt, for he returned a sincere reply to my first email to him which was written in remarkably broken Japanese. I would also like to thank Dr. Takafumi Taketomi for his continued support of my studies.

I would like to thank the rest of my thesis committee: Professor Tsukasa Ogasawara and Professor Yasuhide Yoshitake, for their insightful questions and comments. Without them, I could not widen my research from various perspectives or conduct the studies I have disclosed in this thesis. My sincere thanks also goes to Associate Professor Christian Sandor and Assistant Professor Alexander Plopski for refining my research topic and my presentations.

Last but not the least, I would like to thank all Interactive Media Design Laboratory members and my whole family; especially my beloved parents Aysel and Fethi Kaplan. I could not have achieved anything in life without you. I am also grateful to my mother for her endless supply of premium quality almonds from my homeland, which kept my energy and motivation levels high at all times.

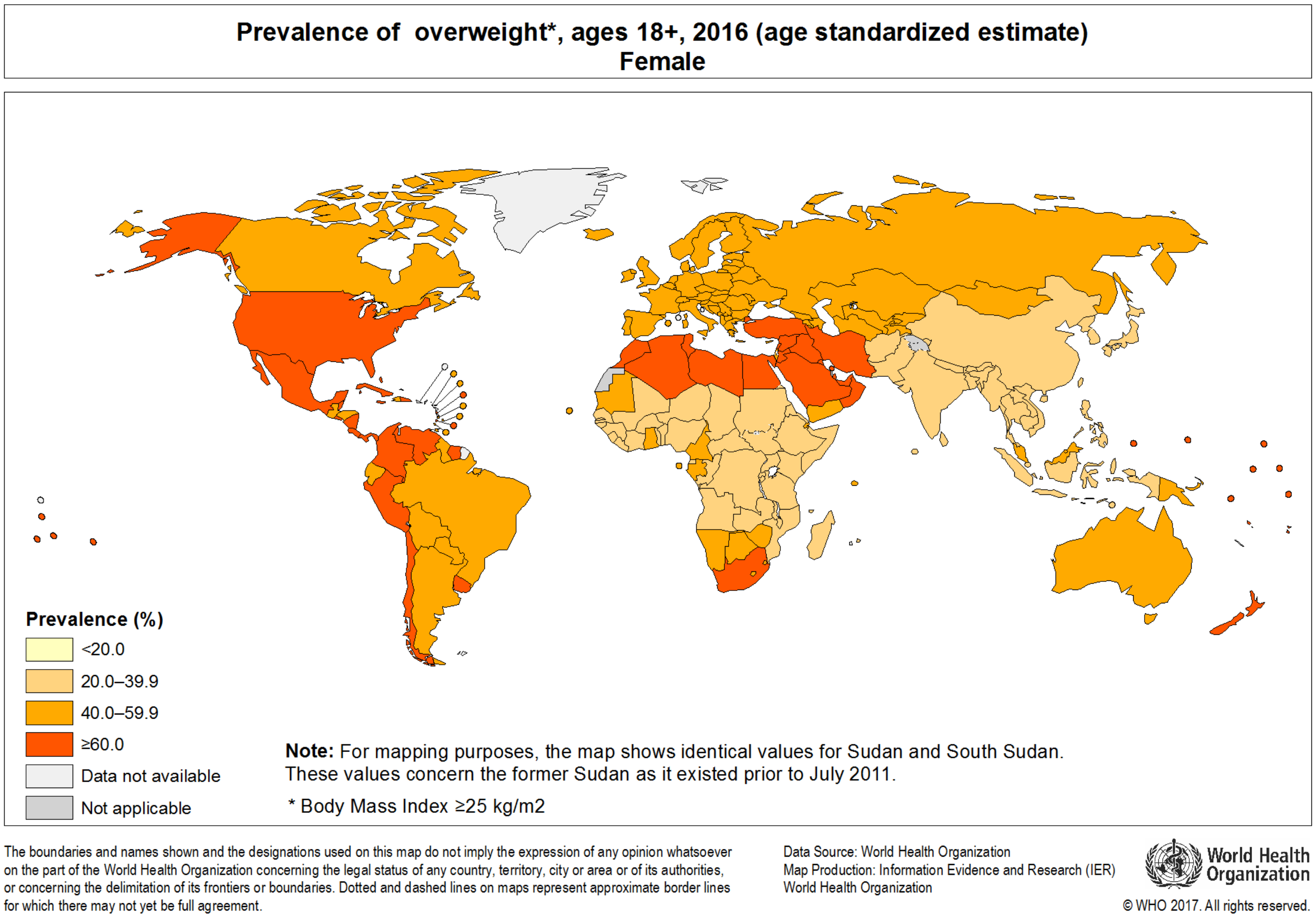
Appendix

A. Global Health Observatory Data

Noncommunicable diseases (NCDs) attributed to physical inactivity such as stroke, cancer, or diabetes are the leading mortality causes around the globe(Table A.1). According to World Health Organization, 39% of women and 39% of men aged 18 and over were overweight in 2016 [197]. More than 70% of the 56 million global deaths in 2015 were due to NCDs [197]. 48% of NCD deaths in low-and middle income countries in 2015 occurred before the age of 70 [197].

Table A.1: Prevalence of insufficient physical activity among adults.

WHO Region	**Insufficiently Active**		
	Both Sexes	*Male*	*Female*
Africa	22.6 [13.3 - 42.9]	19.3 [11-41]	25.9 [14.6 - 46.8]
Americas	31.4 [21.7 - 47.2]	26.3 [16.8 - 43.8]	36.6 [25.2 - 53.1]
South-East Asia	15.9 [14.2 - 17.8]	12.7 [10.3 - 15.6]	19 [16.7 - 21.7]
Europe	22.6 [10.5 - 44.5]	19.9 [9.2 - 43.5]	25.3 [11.4 - 47.4]
Eastern Mediterranean	33.2 [23.1 - 50.5]	27.5 [18.5 - 46.1]	38.7 [26.6 - 56.8]
Western Pasific	25 [19.7 - 33]	23.1 [17.5 - 32.2]	27 [20.3 - 36.2]



Prevalence of overweight*, ages 18+, 2016 (age standardized estimate)
Female

Note: For mapping purposes, the map shows identical values for Sudan and South Sudan. These values concern the former Sudan as it existed prior to July 2011.

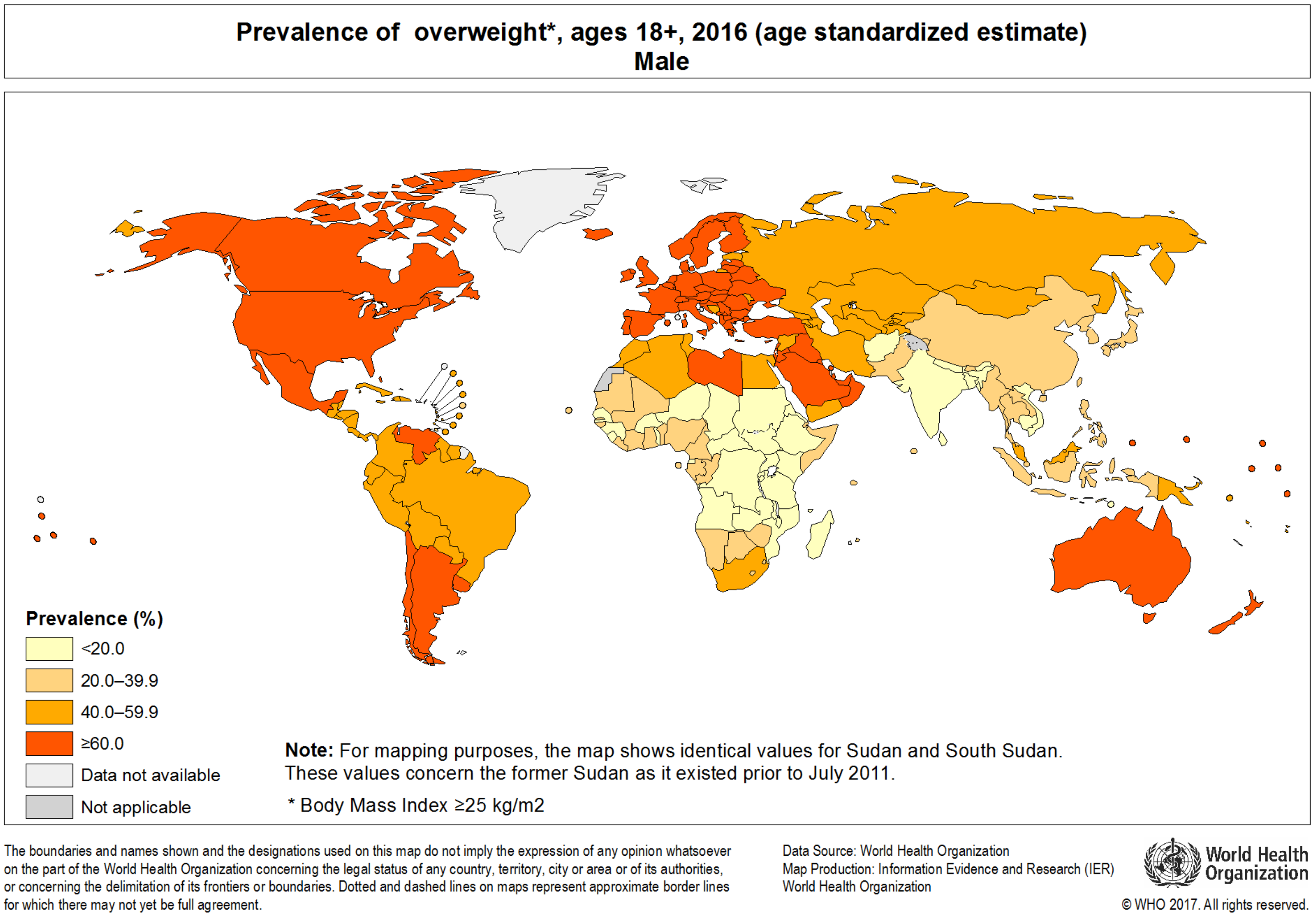
* Body Mass Index ≥25 kg/m2

The boundaries and names shown and the designations used on this map do not imply the expression of any opinion whatsoever on the part of the World Health Organization concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. Dotted and dashed lines on maps represent approximate border lines for which there may not yet be full agreement.

Data Source: World Health Organization
Map Production: Information Evidence and Research (IER)
World Health Organization

World Health Organization

Figure A.1: 2016 Global Health Observatory data on overweight female individuals [197]



Note: For mapping purposes, the map shows identical values for Sudan and South Sudan. These values concern the former Sudan as it existed prior to July 2011.

* Body Mass Index ≥25 kg/m2

The boundaries and names shown and the designations used on this map do not imply the expression of any opinion whatsoever on the part of the World Health Organization concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. Dotted and dashed lines on maps represent approximate border lines for which there may not yet be full agreement.

Data Source: World Health Organization
Map Production: Information Evidence and Research (IER)
World Health Organization

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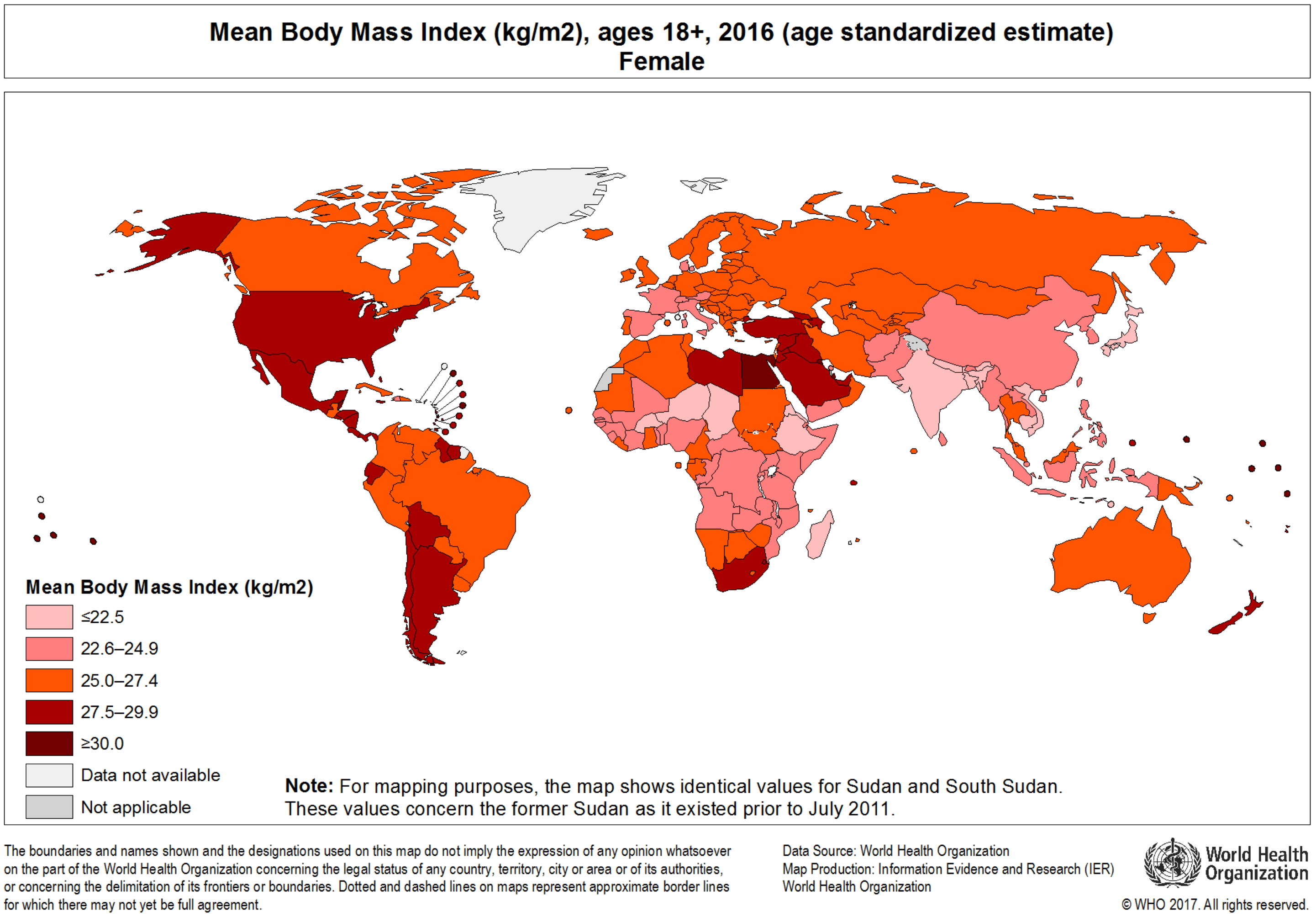
Figure A.2: 2016 Global Health Observatory data on overweight male individuals [197]

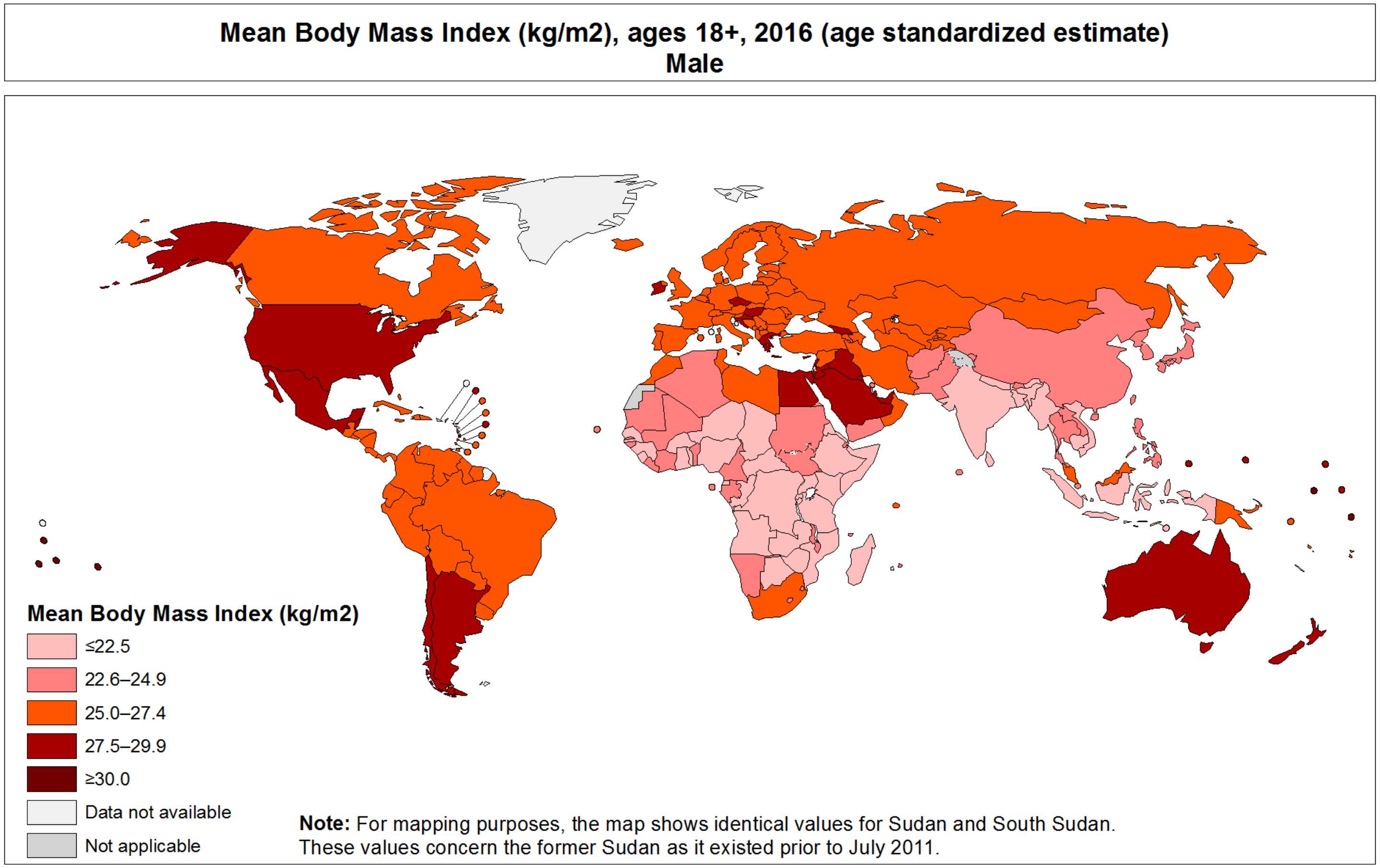


Note: For mapping purposes, the map shows identical values for Sudan and South Sudan. These values concern the former Sudan as it existed prior to July 2011.

The boundaries and names shown and the designations used on this map do not imply the expression of any opinion whatsoever on the part of the World Health Organization concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. Dotted and dashed lines on maps represent approximate border lines for which there may not yet be full agreement.

Data Source: World Health Organization
Map Production: Information Evidence and Research (IER)
World Health Organization

Figure A.3: 2016 Global Health Observatory data on mean mass body index of female individuals [197]



Note: For mapping purposes, the map shows identical values for Sudan and South Sudan. These values concern the former Sudan as it existed prior to July 2011.

The boundaries and names shown and the designations used on this map do not imply the expression of any opinion whatsoever on the part of the World Health Organization concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. Dotted and dashed lines on maps represent approximate border lines for which there may not yet be full agreement.

Data Source: World Health Organization
Map Production: Information Evidence and Research (IER)
World Health Organization

World Health Organization

Figure A.4: 2016 Global Health Observatory data on mean mass body index of male individuals [197]

B. Measured Data and Difficulty Adjustments

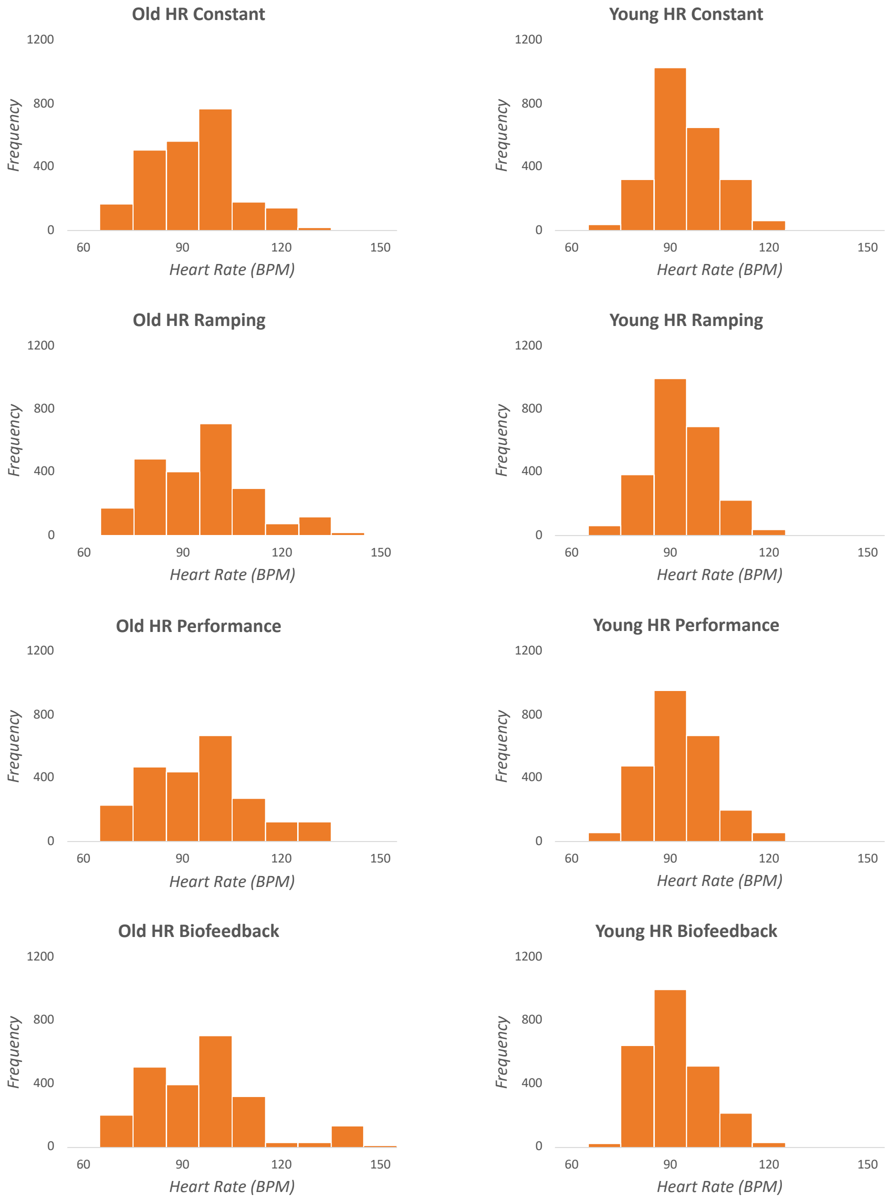


Figure A.5: Histograms of the heart rate (HR) data I captured throughout the experiments with all participants. The data is separated into age groups and divided according to difficulty adjustment methods.

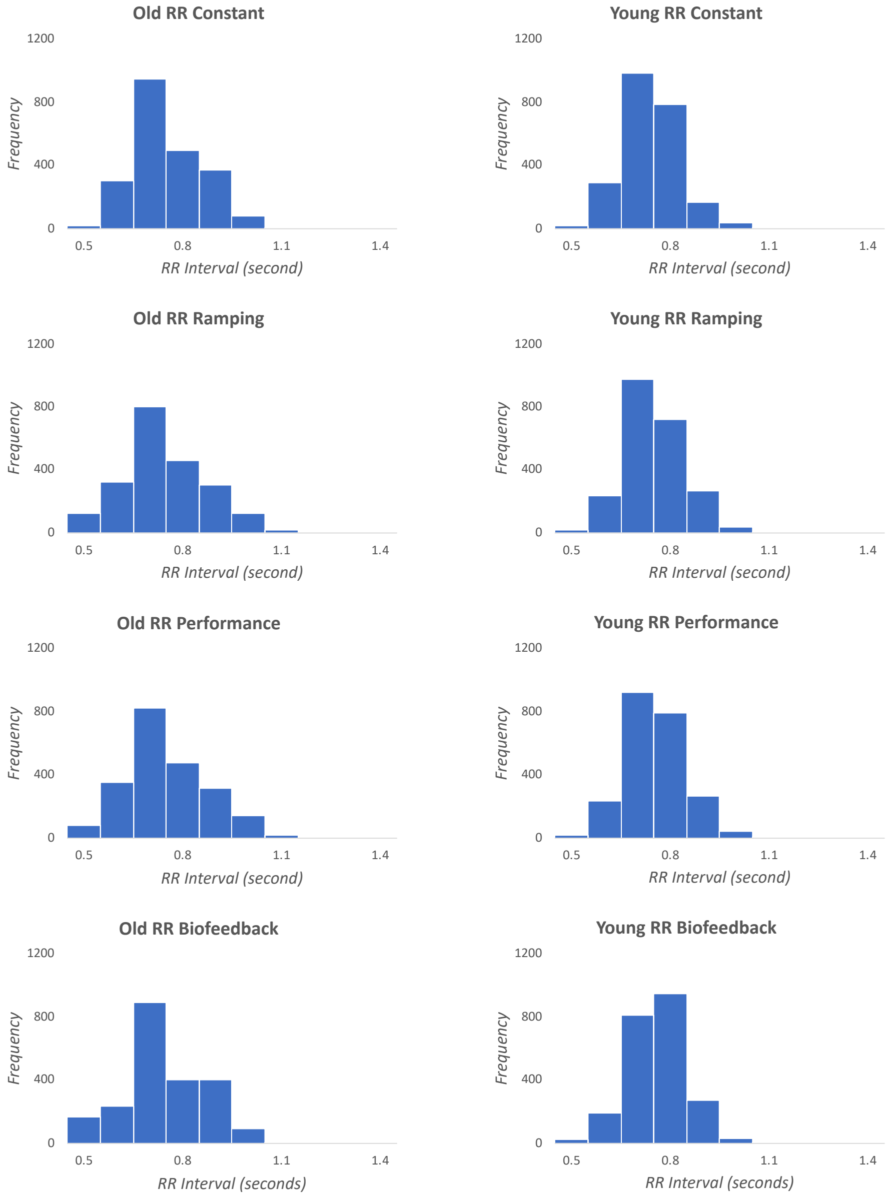


Figure A.6: Histograms of the inter-beat interval (RR) data I captured throughout the experiments with all participants. The data is separated into age groups and divided according to difficulty adjustment methods.

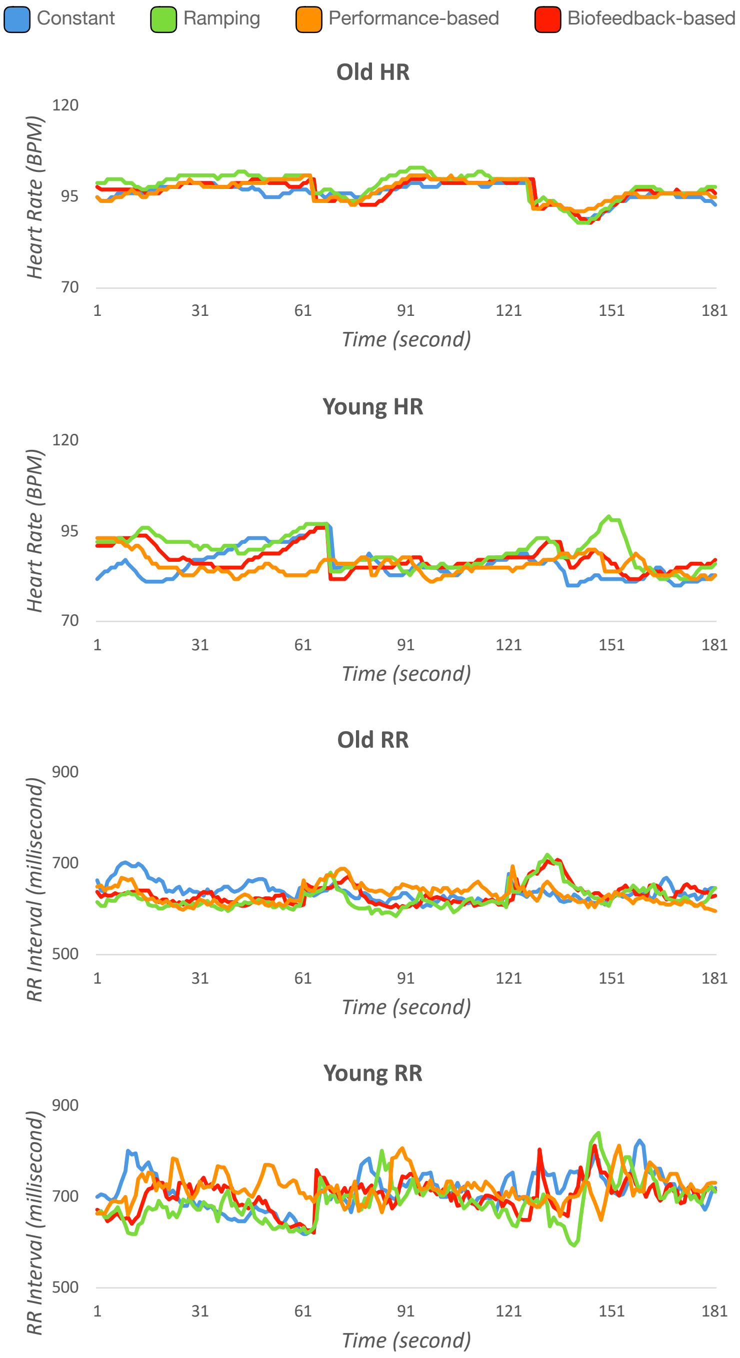


Figure A.7: The raw heart rate (HR) and inter-beat interval (RR) data I obtained from two randomly chosen individuals. The data includes all three trails for each difficulty adjustment methods; constant, ramping, performance-based, and biofeedback-based.

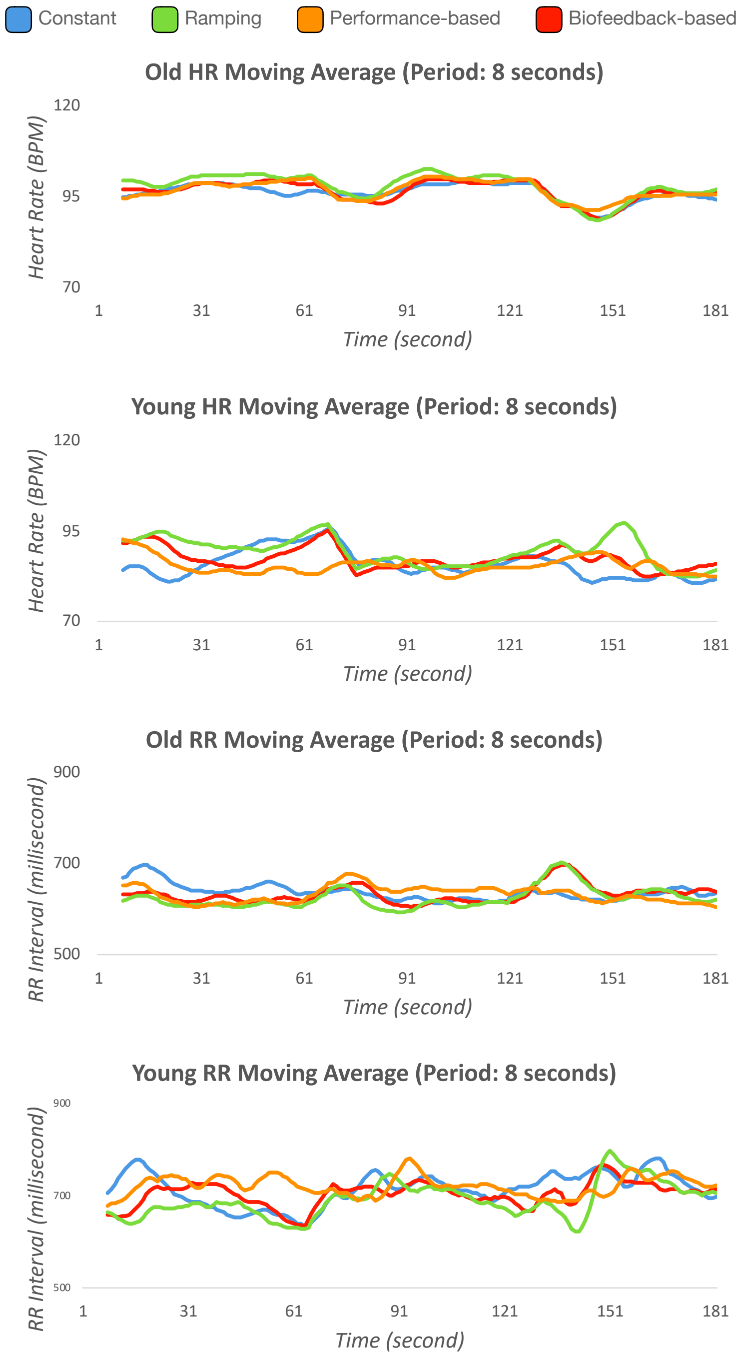


Figure A.8: 8-second moving average of the raw heart rate *(HR)* and inter-beat interval *(RR)* data I obtained from the same participants in Figure A.7. The data includes all three trails for each difficulty adjustment methods; constant, ramping, performance-based, and biofeedback-based.

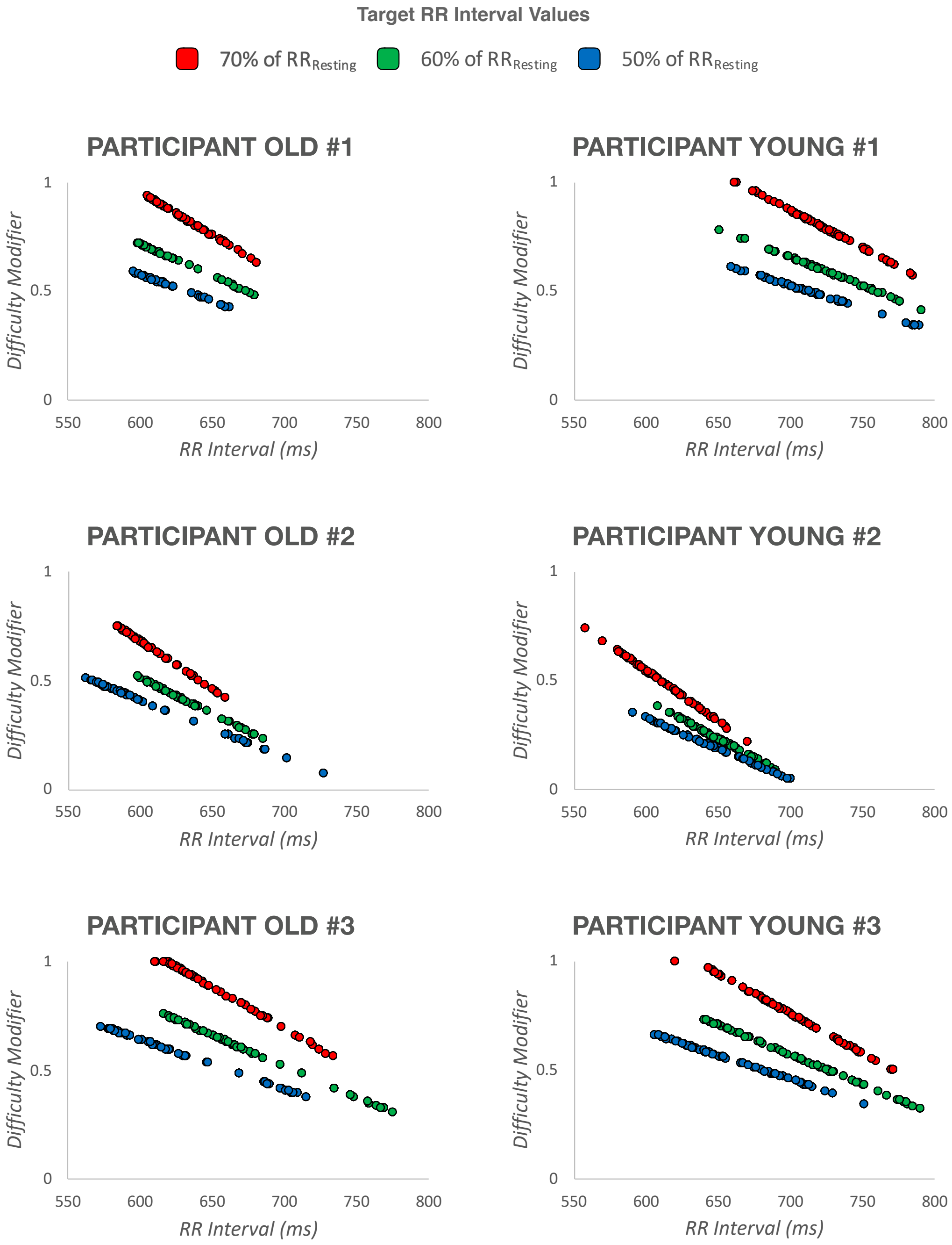


Figure A.9: Scatter plots of randomly chosen participants, representing the RR interval measurements and the corresponding difficulty modifiers calculated by the system. I utilized these values during biofeedback-based difficulty adjustments to consistently modify the distance between rings in real-time.

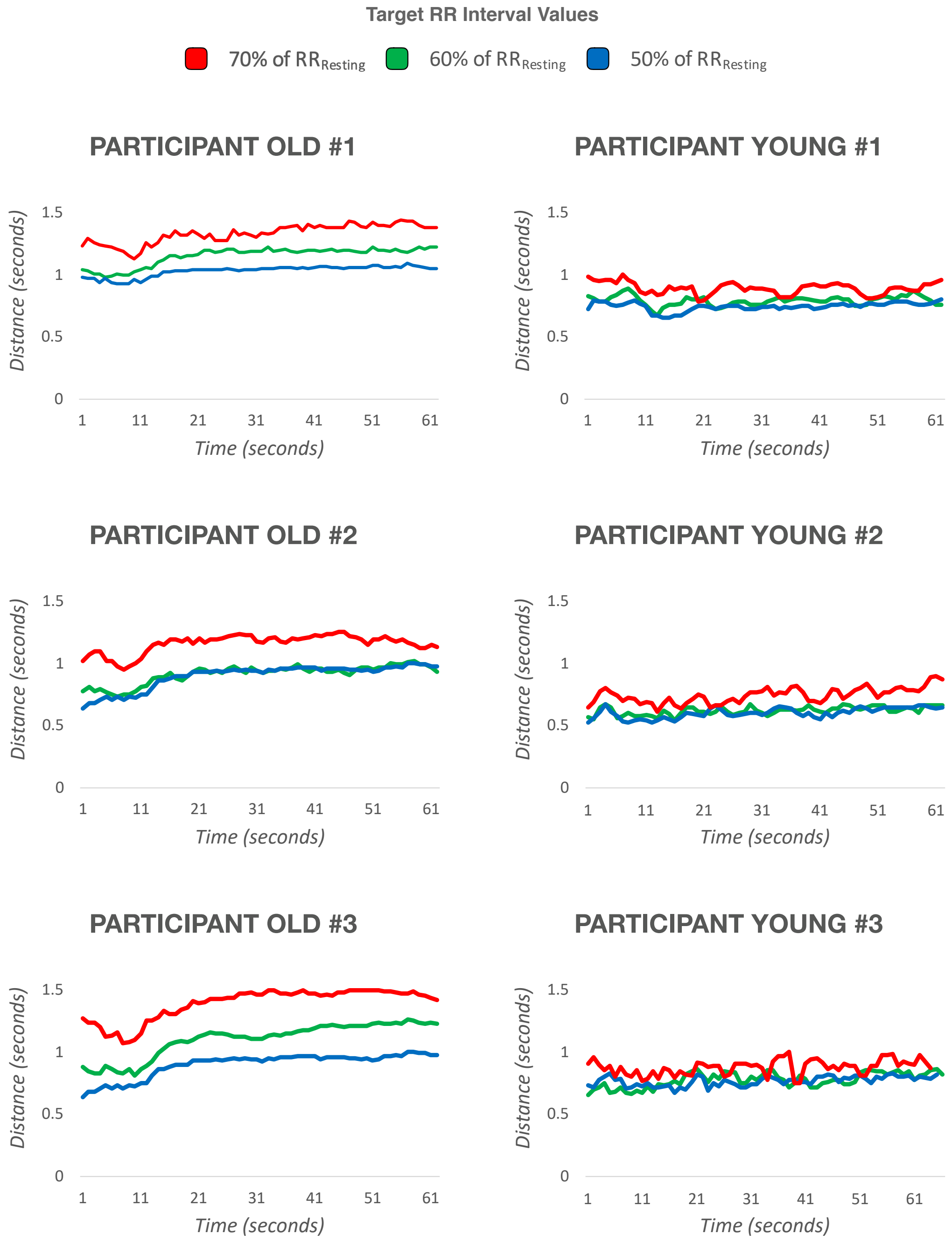
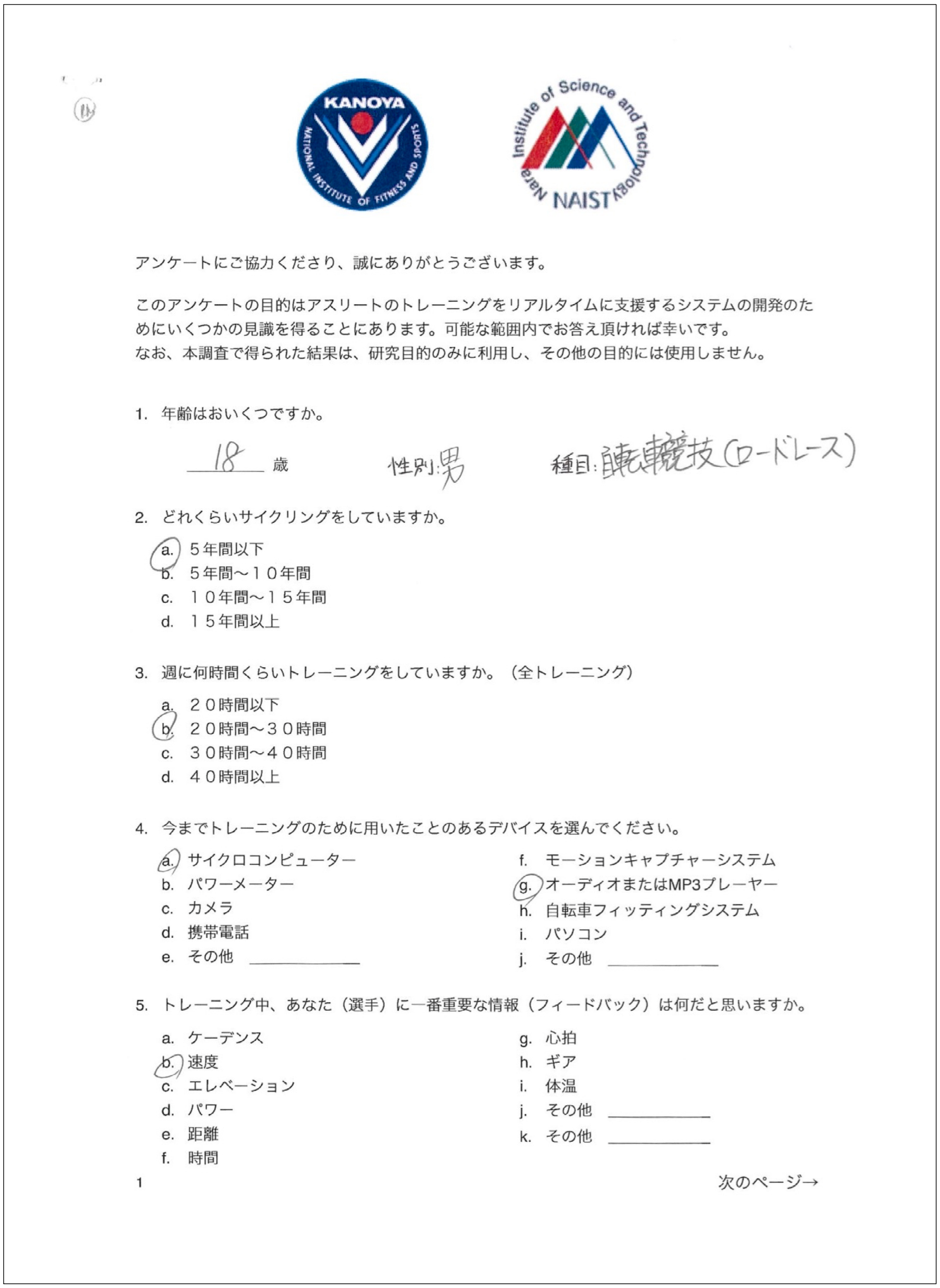


Figure A.10: Line graphs of difficulty adjustments belonging to the same participants (Figure A.9). The distance represented in seconds refers to time it takes for airplane to move from one ring to another. The modification interval was set to 0.5”-1.0” for young and 0.5”-1.5” for old to compensate for age related differences.

C. Survey Used with Professional Cyclists



アンケートにご協力くださり、誠にありがとうございます。

このアンケートの目的はアスリートのトレーニングをリアルタイムに支援するシステムの開発のためにいくつかの見識を得ることにあります。可能な範囲内でお答え頂ければ幸いです。
なお、本調査で得られた結果は、研究目的のみに利用し、その他の目的には使用しません。

1. 年齢はおいくつですか。

18 歳　性別:男　種目:自転車競技（ロードレース）

2. どれくらいサイクリングをしていますか。

[✓ a.] ５年間以下
b. ５年間～１０年間
c. １０年間～１５年間
d. １５年間以上

3. 週に何時間くらいトレーニングをしていますか。（全トレーニング）

a. ２０時間以下
[✓ b.] ２０時間～３０時間
c. ３０時間～４０時間
d. ４０時間以上

4. 今までトレーニングのために用いたことのあるデバイスを選んでください。

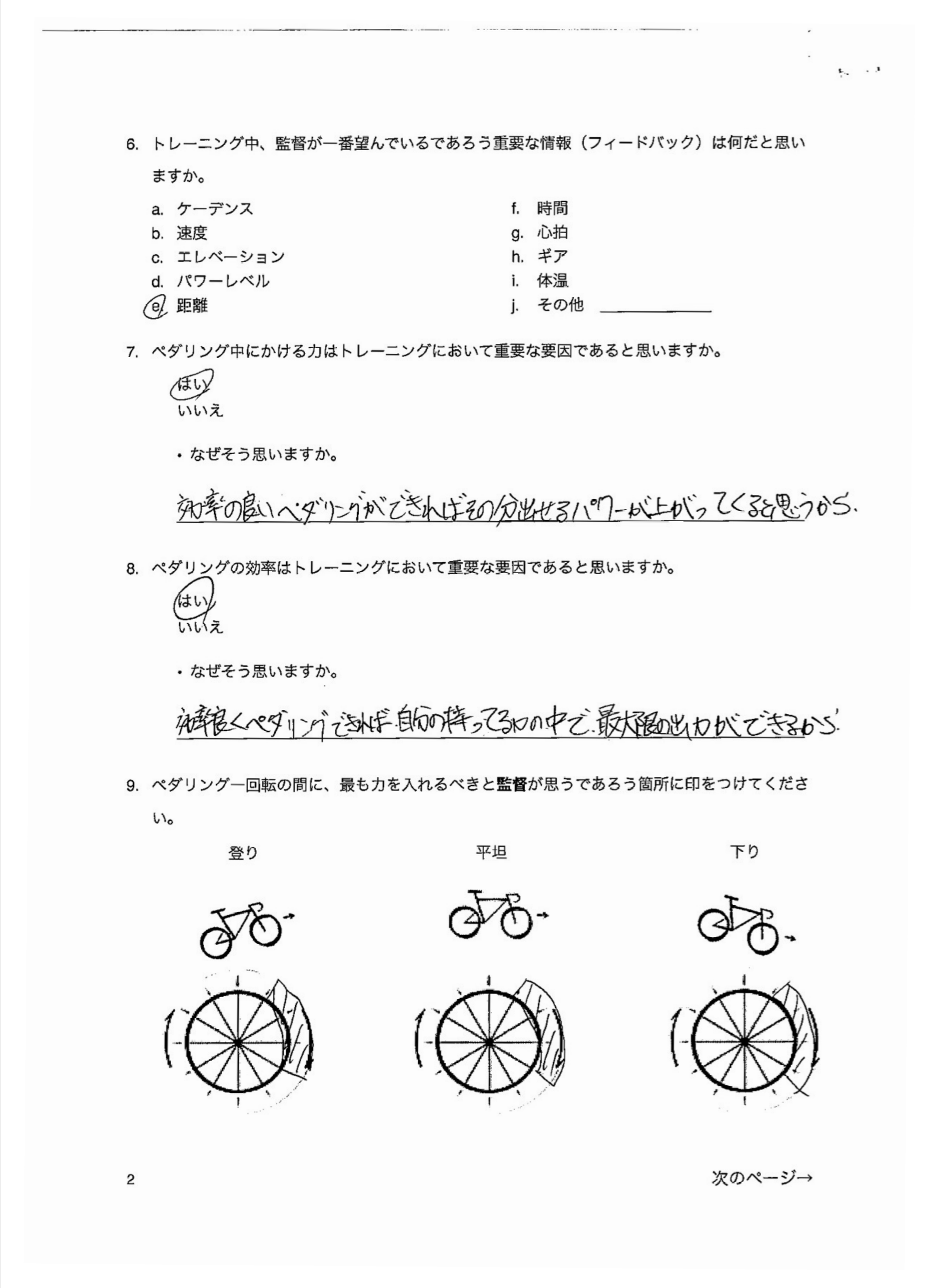
[✓ a.] サイクロコンピューター
b. パワーメーター
c. カメラ
d. 携帯電話
e. その他 ____________
f. モーションキャプチャーシステム
[✓ g.] オーディオまたはMP3プレーヤー
h. 自転車フィッティングシステム
i. パソコン
j. その他 ____________

5. トレーニング中、あなた（選手）に一番重要な情報（フィードバック）は何だと思いますか。

a. ケーデンス
[✓ b.] 速度
c. エレベーション
d. パワー
e. 距離
f. 時間
g. 心拍
h. ギア
i. 体温
j. その他 ____________
k. その他 ____________

1　次のページ→

Figure A.11: Two incompatible set of answers given to my survey (Page 1.1)



6. トレーニング中、監督が一番望んでいるであろう重要な情報（フィードバック）は何だと思いますか。

a. ケーデンス
b. 速度
c. エレベーション
d. パワーレベル
[✓ e.] 距離
f. 時間
g. 心拍
h. ギア
i. 体温
j. その他 ________

7. ペダリング中にかける力はトレーニングにおいて重要な要因であると思いますか。

[✓ はい]
いいえ

- なぜそう思いますか。

効率の良いペダリングができればその分出せるパワーが上がってくると思うから.

8. ペダリングの効率はトレーニングにおいて重要な要因であると思いますか。

[✓ はい]
いいえ

- なぜそう思いますか。

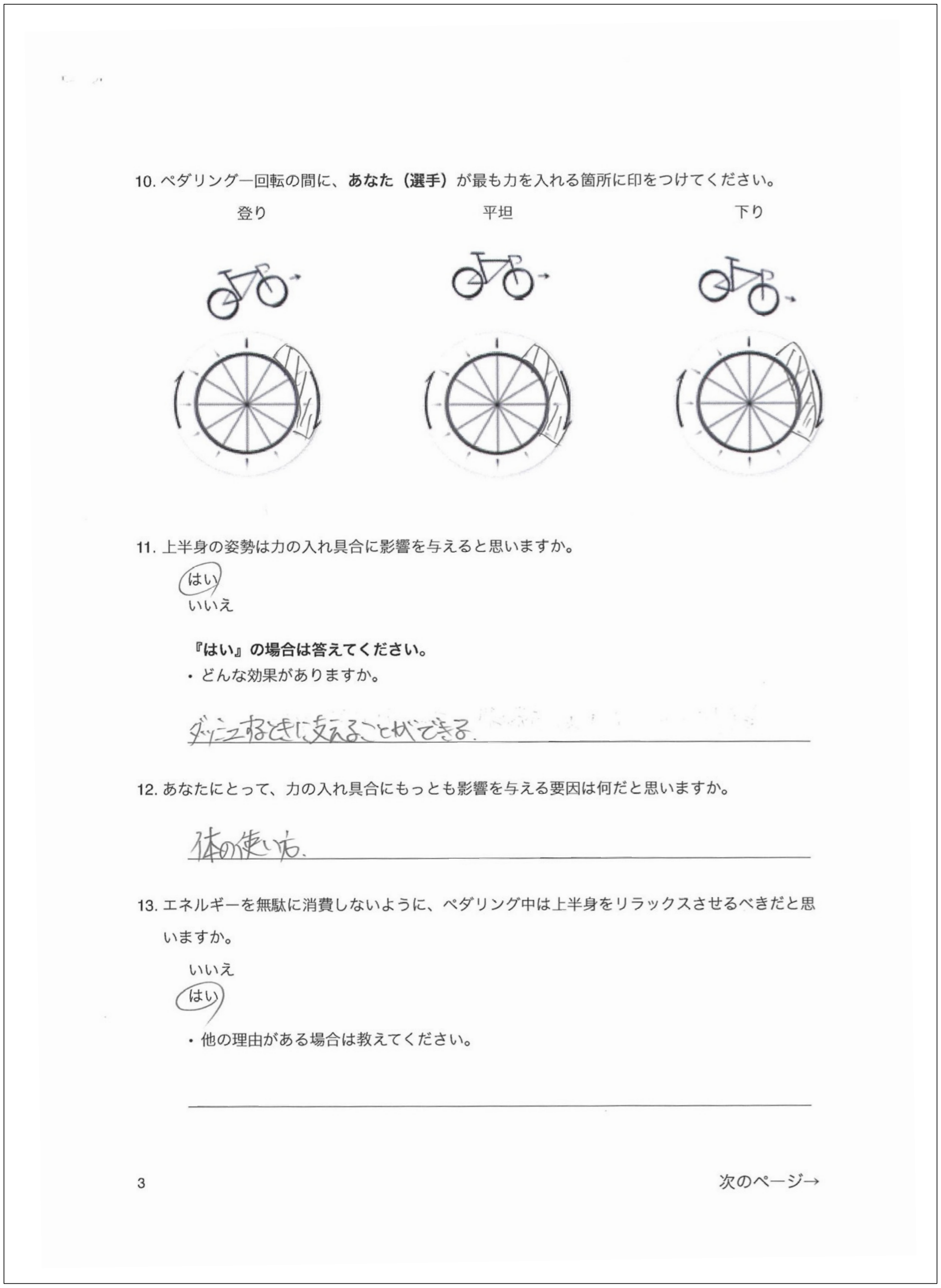
効率良くペダリングできれば.自分の持ってる力の中で.最大限の出力ができるから.

9. ペダリング一回転の間に、最も力を入れるべきと**監督**が思うであろう箇所に印をつけてください。

登り　平坦　下り

2　次のページ→

Figure A.11: Two incompatible set of answers given to my survey (Page 1.2)



10. ペダリング一回転の間に、**あなた（選手）**が最も力を入れる箇所に印をつけてください。

11. 上半身の姿勢は力の入れ具合に影響を与えると思いますか。

[✓ はい]
いいえ

『はい』の場合は答えてください。

- どんな効果がありますか。

ダッシュするときに支えることができる.

12. あなたにとって、力の入れ具合にもっとも影響を与える要因は何だと思いますか。

体の使い方.

13. エネルギーを無駄に消費しないように、ペダリング中は上半身をリラックスさせるべきだと思いますか。

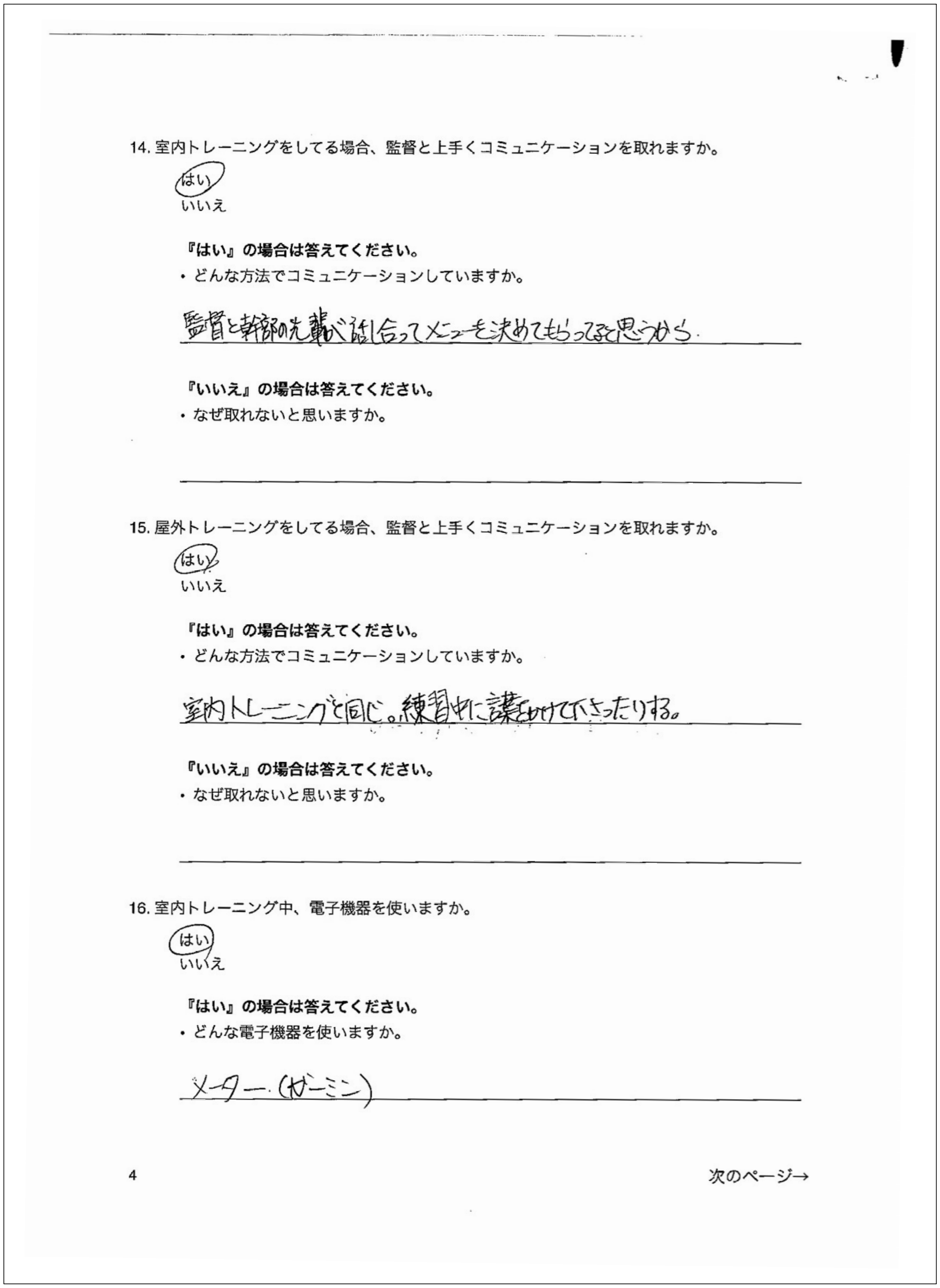
いいえ
[✓ はい]

- 他の理由がある場合は教えてください。

3

次のページ→

Figure A.11: Two incompatible set of answers given to my survey (Page 1.3)



14. 室内トレーニングをしてる場合、監督と上手くコミュニケーションを取れますか。

[✓ はい]
いいえ

『はい』の場合は答えてください。

- どんな方法でコミュニケーションしていますか。

監督と幹部の先輩が話し合ってメニューを決めてもらってると思うから.

『いいえ』の場合は答えてください。

- なぜ取れないと思いますか。

15. 屋外トレーニングをしてる場合、監督と上手くコミュニケーションを取れますか。

[✓ はい]
いいえ

『はい』の場合は答えてください。

- どんな方法でコミュニケーションしていますか。

室内トレーニングと同じ。練習中に言葉をかけてくださったりする。

『いいえ』の場合は答えてください。

- なぜ取れないと思いますか。

16. 室内トレーニング中、電子機器を使いますか。

[✓ はい]
いいえ

『はい』の場合は答えてください。

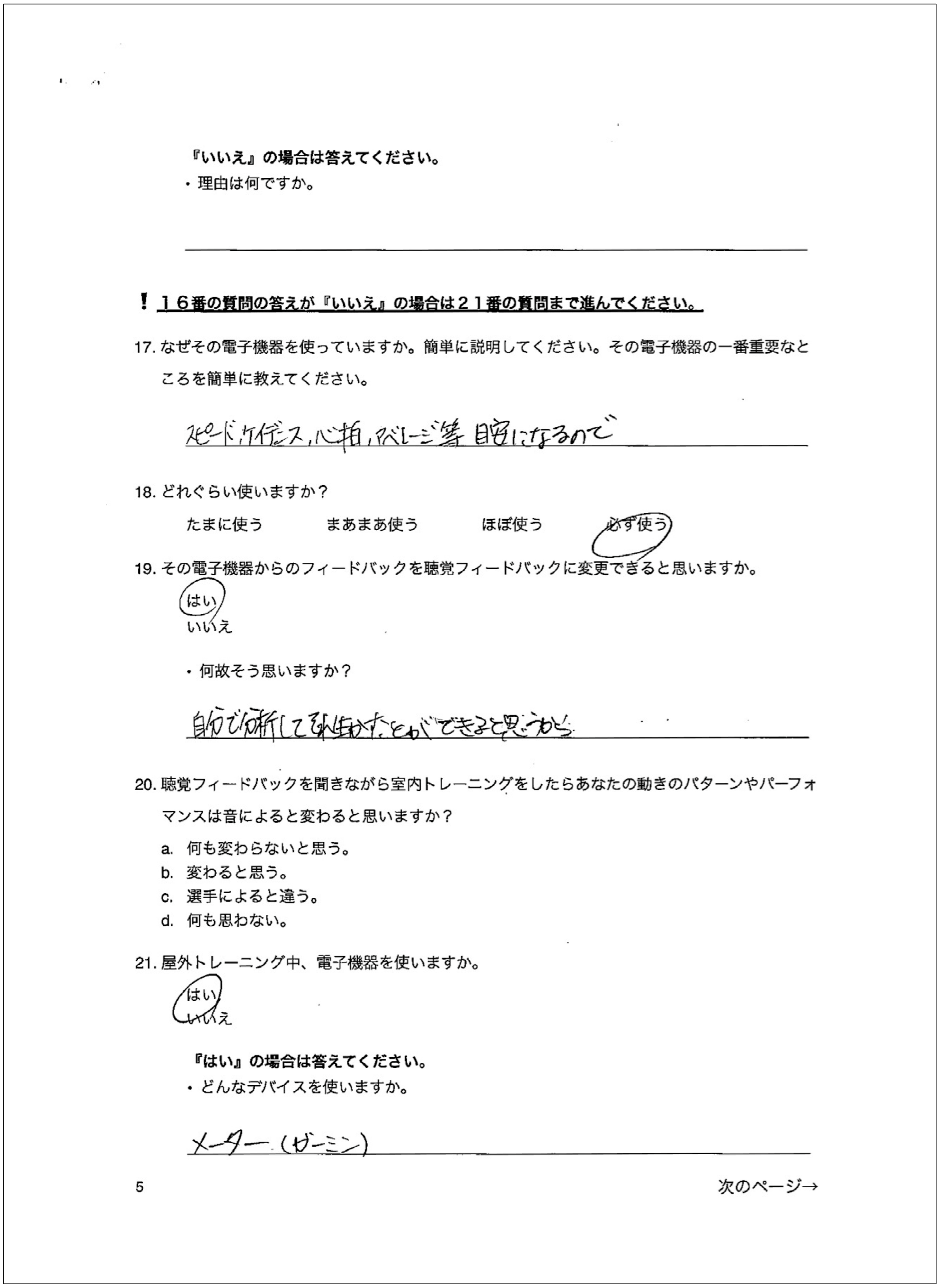
- どんな電子機器を使いますか。

メーター.（ガーミン）

4

次のページ→

Figure A.11: Two incompatible set of answers given to my survey (Page 1.4)



『いいえ』の場合は答えてください。

・理由は何ですか。

! １６番の質問の答えが『いいえ』の場合は２１番の質問まで進んでください。

17. なぜその電子機器を使っていますか。簡単に説明してください。その電子機器の一番重要なところを簡単に教えてください。

スピード，ケイデンス，心拍，アベレージ等 目安になるので

18. どれぐらい使いますか？

たまに使う　まあまあ使う　ほぼ使う　[✓ 必ず使う]

19. その電子機器からのフィードバックを聴覚フィードバックに変更できると思いますか。

[✓ はい]
いいえ

・何故そう思いますか？

自分で分析してそれを生かすことができると思うから

20. 聴覚フィードバックを聞きながら室内トレーニングをしたらあなたの動きのパターンやパーフォマンスは音によると変わると思いますか？

a. 何も変わらないと思う。
b. 変わると思う。
c. 選手によると違う。
d. 何も思わない。

21. 屋外トレーニング中、電子機器を使いますか。

[✓ はい]
いいえ

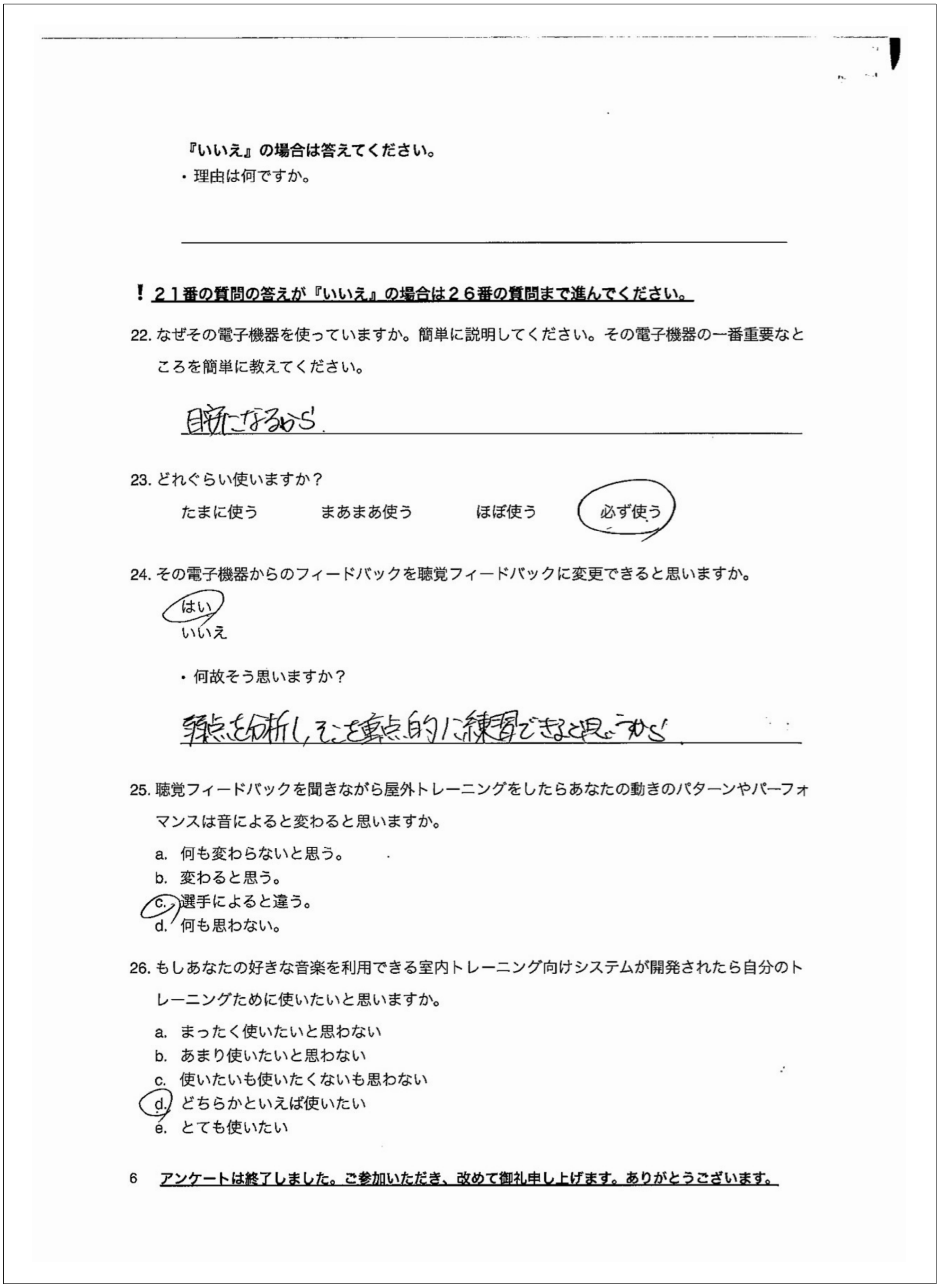
『はい』の場合は答えてください。

・どんなデバイスを使いますか。

メーター（ガーミン）

5　次のページ→

Figure A.11: Two incompatible set of answers given to my survey (Page 1.5)



『いいえ』の場合は答えてください。

- 理由は何ですか。

____

！ ２１番の質問の答えが『いいえ』の場合は２６番の質問まで進んでください。

22. なぜその電子機器を使っていますか。簡単に説明してください。その電子機器の一番重要なところを簡単に教えてください。

目安になるから.

23. どれぐらい使いますか？

たまに使う　まあまあ使う　ほぼ使う　[✓ 必ず使う]

24. その電子機器からのフィードバックを聴覚フィードバックに変更できると思いますか。

[✓ はい]
いいえ

- 何故そう思いますか？

弱点を分析し,そこを重点的に練習できると思うから

25. 聴覚フィードバックを聞きながら屋外トレーニングをしたらあなたの動きのパターンやパーフォマンスは音によると変わると思いますか。

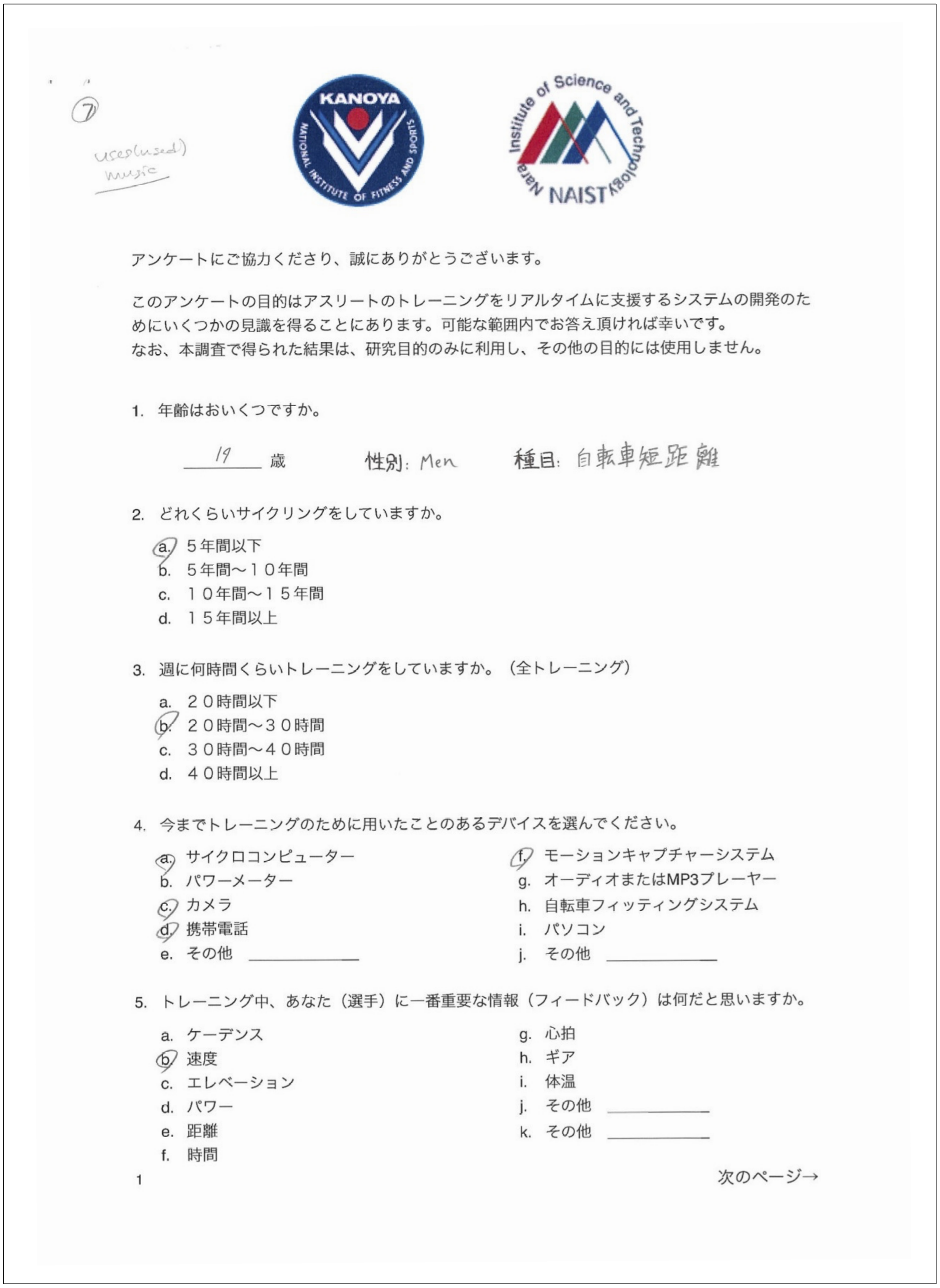
a. 何も変わらないと思う。
b. 変わると思う。
[✓ c.] 選手によると違う。
d. 何も思わない。

26. もしあなたの好きな音楽を利用できる室内トレーニング向けシステムが開発されたら自分のトレーニングために使いたいと思いますか。

a. まったく使いたいと思わない
b. あまり使いたいと思わない
c. 使いたいも使いたくないも思わない
[✓ d.] どちらかといえば使いたい
e. とても使いたい

6　**アンケートは終了しました。ご参加いただき、改めて御礼申し上げます。ありがとうございます。**

Figure A.11: Two incompatible set of answers given to my survey (Page 1.6)



⑦

used(used) music

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なお、本調査で得られた結果は、研究目的のみに利用し、その他の目的には使用しません。

1. 年齢はおいくつですか。

19 歳　　性別: Men　　種目: 自転車短距離

2. どれくらいサイクリングをしていますか。

[✓ a.] ５年間以下
b. ５年間～１０年間
c. １０年間～１５年間
d. １５年間以上

3. 週に何時間くらいトレーニングをしていますか。（全トレーニング）

a. ２０時間以下
[✓ b.] ２０時間～３０時間
c. ３０時間～４０時間
d. ４０時間以上

4. 今までトレーニングのために用いたことのあるデバイスを選んでください。

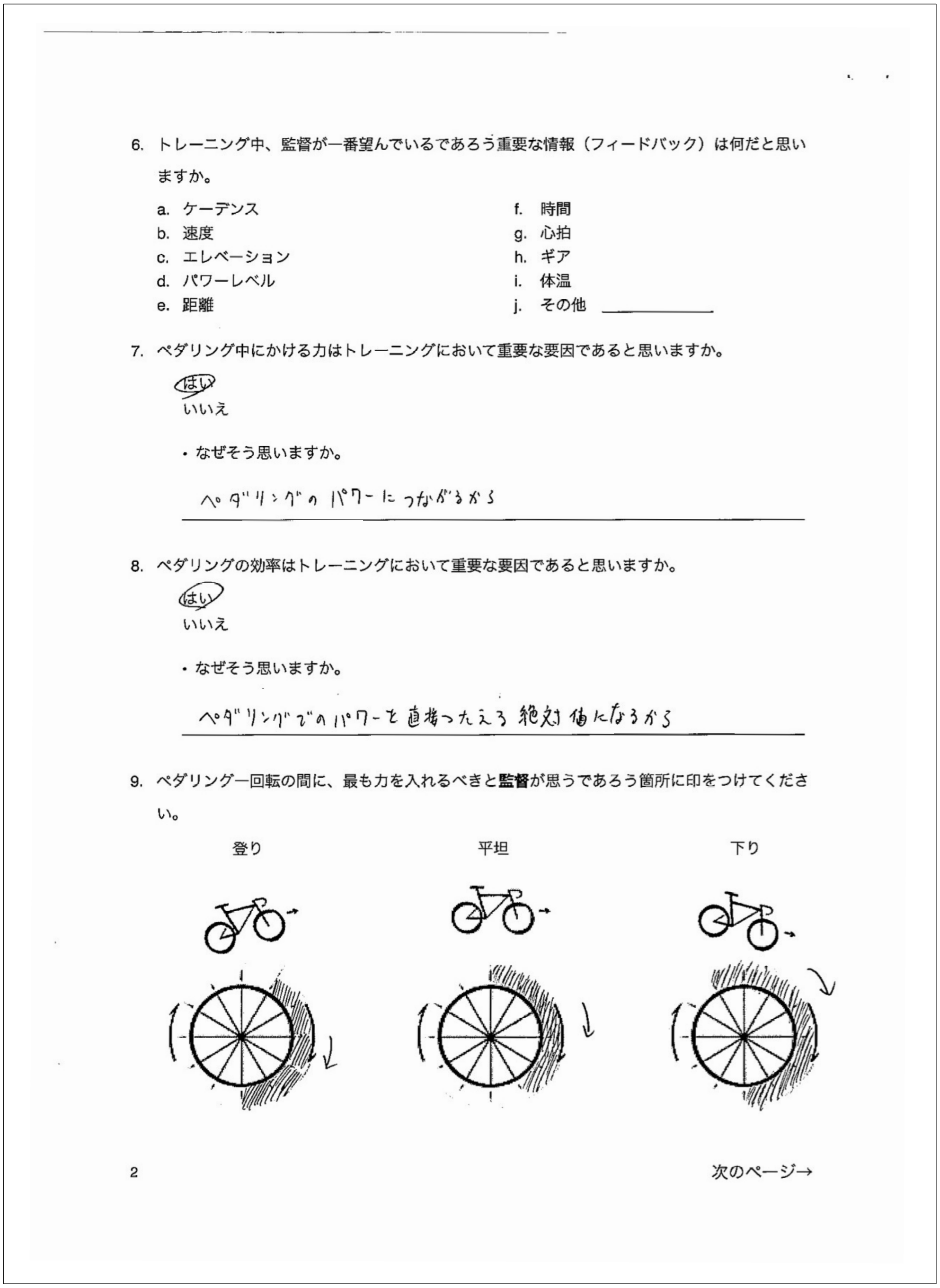
[✓ a.] サイクロコンピューター
b. パワーメーター
[✓ c.] カメラ
[✓ d.] 携帯電話
e. その他 ________
[✓ f.] モーションキャプチャーシステム
g. オーディオまたはMP3プレーヤー
h. 自転車フィッティングシステム
i. パソコン
j. その他 ________

5. トレーニング中、あなた（選手）に一番重要な情報（フィードバック）は何だと思いますか。

a. ケーデンス
[✓ b.] 速度
c. エレベーション
d. パワー
e. 距離
f. 時間
g. 心拍
h. ギア
i. 体温
j. その他 ________
k. その他 ________

1　　次のページ→

Figure A.11: Two incompatible set of answers given to my survey (Page 2.1)



6. トレーニング中、監督が一番望んでいるであろう重要な情報（フィードバック）は何だと思いますか。
   - a. ケーデンス
   - b. 速度
   - c. エレベーション
   - d. パワーレベル
   - e. 距離
   - f. 時間
   - g. 心拍
   - h. ギア
   - i. 体温
   - j. その他 ＿＿＿＿＿＿

7. ペダリング中にかける力はトレーニングにおいて重要な要因であると思いますか。

   [✓ はい]
   いいえ

   - なぜそう思いますか。

   ペダリングのパワーにつながるから

8. ペダリングの効率はトレーニングにおいて重要な要因であると思いますか。

   [✓ はい]
   いいえ

   - なぜそう思いますか。

   ペダリングでのパワーを直接つたえる絶対値になるから

9. ペダリング一回転の間に、最も力を入れるべきと**監督**が思うであろう箇所に印をつけてください。

登り　平坦　下り

2　次のページ→

Figure A.11: Two incompatible set of answers given to my survey (Page 2.2)

10. ペダリング一回転の間に、**あなた（選手）**が最も力を入れる箇所に印をつけてください。

登り　平坦　下り

11. 上半身の姿勢は力の入れ具合に影響を与えると思いますか。

[✓ はい]
いいえ

『はい』の場合は答えてください。

- どんな効果がありますか。

エンデュランス、スプリント、斜度、スピードによって上半身を固定させる、させないをしっかりしないといけないから

12. あなたにとって、力の入れ具合にもっとも影響を与える要因は何だと思いますか。

ペダリングと上半身の支持力

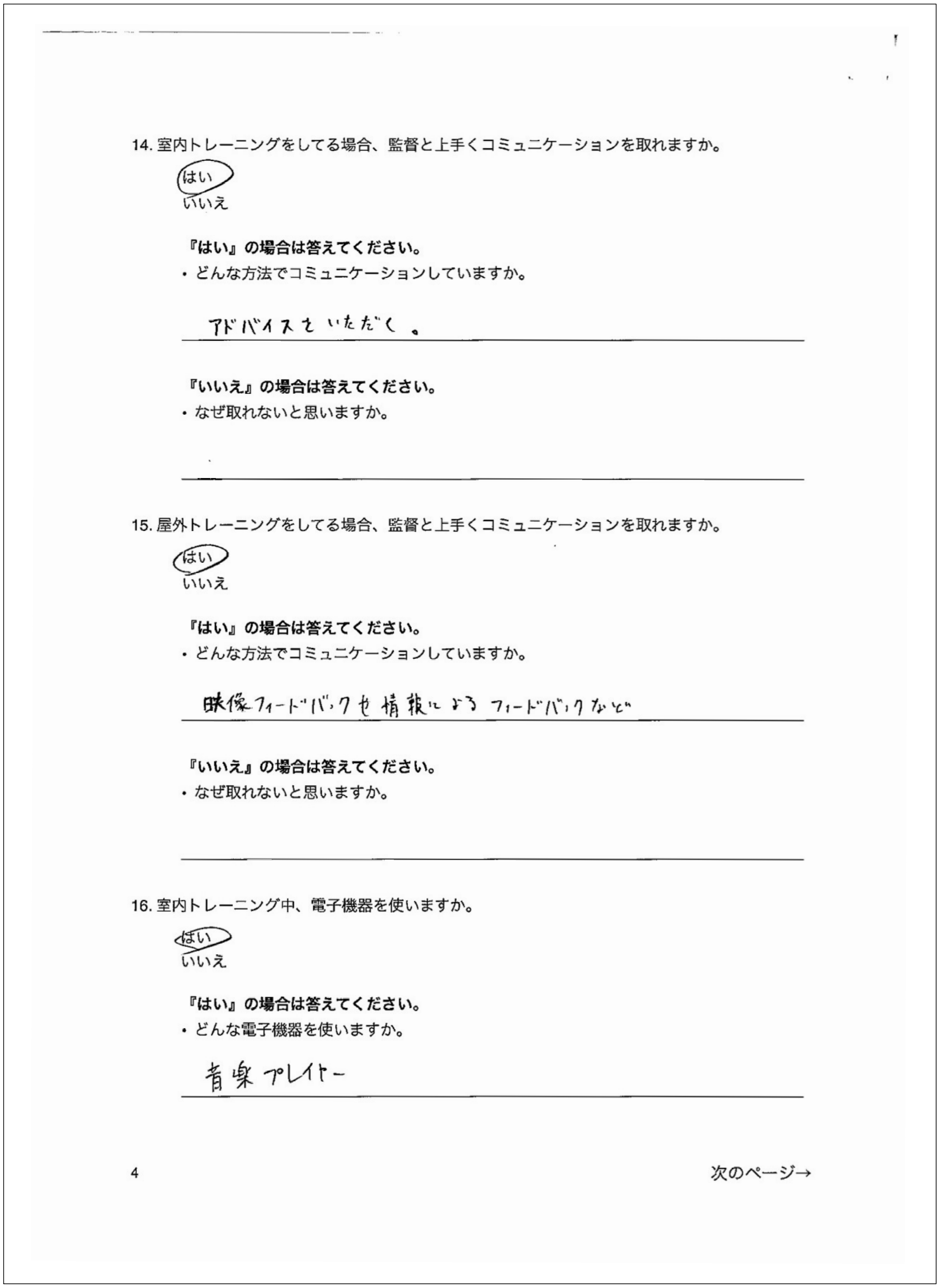
13. エネルギーを無駄に消費しないように、ペダリング中は上半身をリラックスさせるべきだと思いますか。

いいえ
[✓ はい]

- 他の理由がある場合は教えてください。

3　次のページ→

Figure A.11: Two incompatible set of answers given to my survey (Page 2.3)



14. 室内トレーニングをしてる場合、監督と上手くコミュニケーションを取れますか。

[✓ はい]
いいえ

『はい』の場合は答えてください。

- どんな方法でコミュニケーションしていますか。

アドバイスをいただく。

『いいえ』の場合は答えてください。

- なぜ取れないと思いますか。

15. 屋外トレーニングをしてる場合、監督と上手くコミュニケーションを取れますか。

[✓ はい]
いいえ

『はい』の場合は答えてください。

- どんな方法でコミュニケーションしていますか。

映像フィードバックや情報によるフィードバックなど

『いいえ』の場合は答えてください。

- なぜ取れないと思いますか。

16. 室内トレーニング中、電子機器を使いますか。

[✓ はい]
いいえ

『はい』の場合は答えてください。

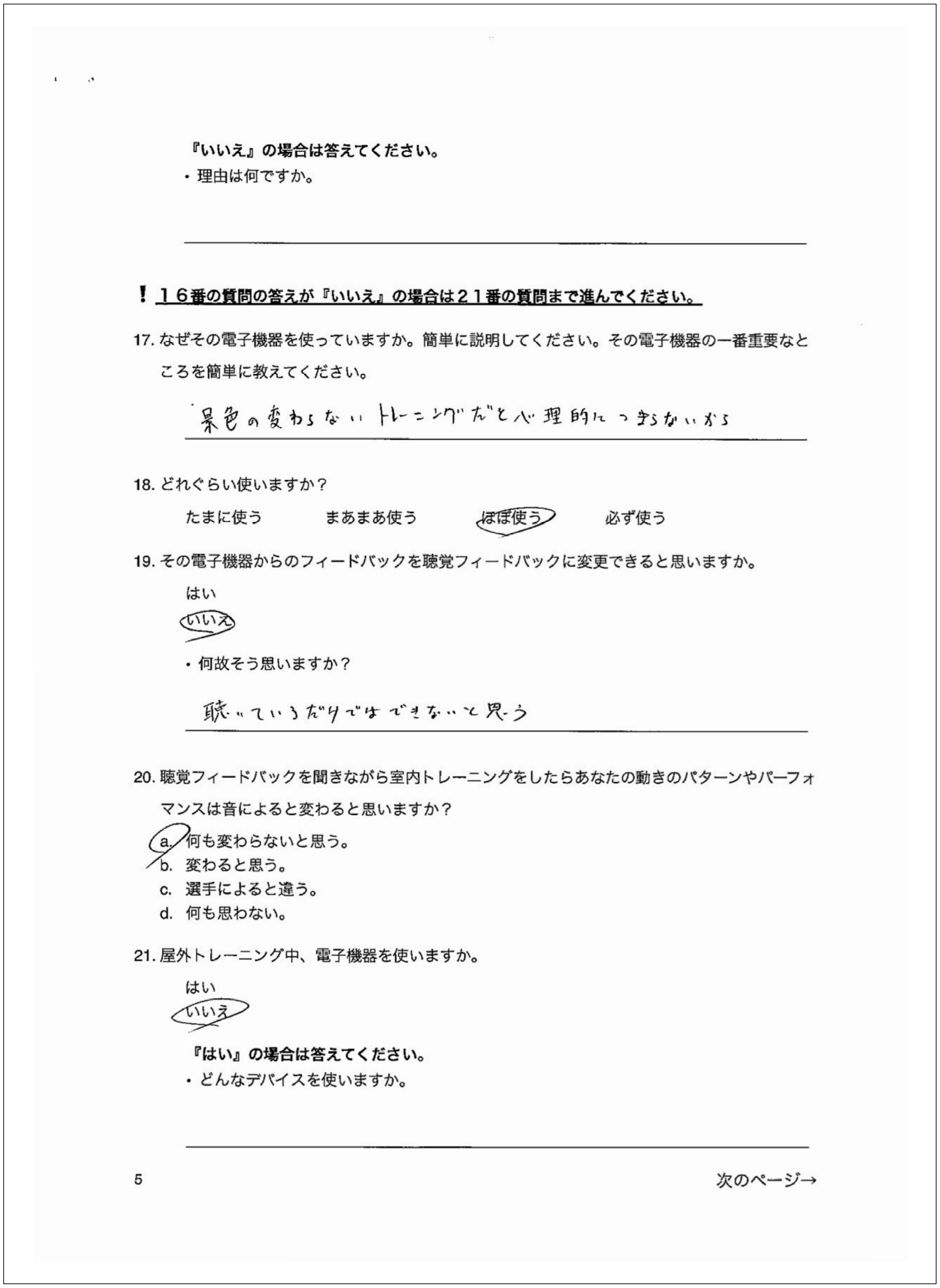
- どんな電子機器を使いますか。

音楽プレイヤー

4

次のページ→

Figure A.11: Two incompatible set of answers given to my survey (Page 2.4)



『いいえ』の場合は答えてください。

- 理由は何ですか。

！１６番の質問の答えが『いいえ』の場合は２１番の質問まで進んでください。

17. なぜその電子機器を使っていますか。簡単に説明してください。その電子機器の一番重要なところを簡単に教えてください。

景色の変わらないトレーニングだと心理的につまらないから

18. どれぐらい使いますか？

たまに使う　まあまあ使う　[✓ ほぼ使う]　必ず使う

19. その電子機器からのフィードバックを聴覚フィードバックに変更できると思いますか。

はい
[✓ いいえ]

- 何故そう思いますか？

聴いているだけではできないと思う

20. 聴覚フィードバックを聞きながら室内トレーニングをしたらあなたの動きのパターンやパフォーマンスは音によると変わると思いますか？

[✓ a. 何も変わらないと思う。]
b. 変わると思う。
c. 選手によると違う。
d. 何も思わない。

21. 屋外トレーニング中、電子機器を使いますか。

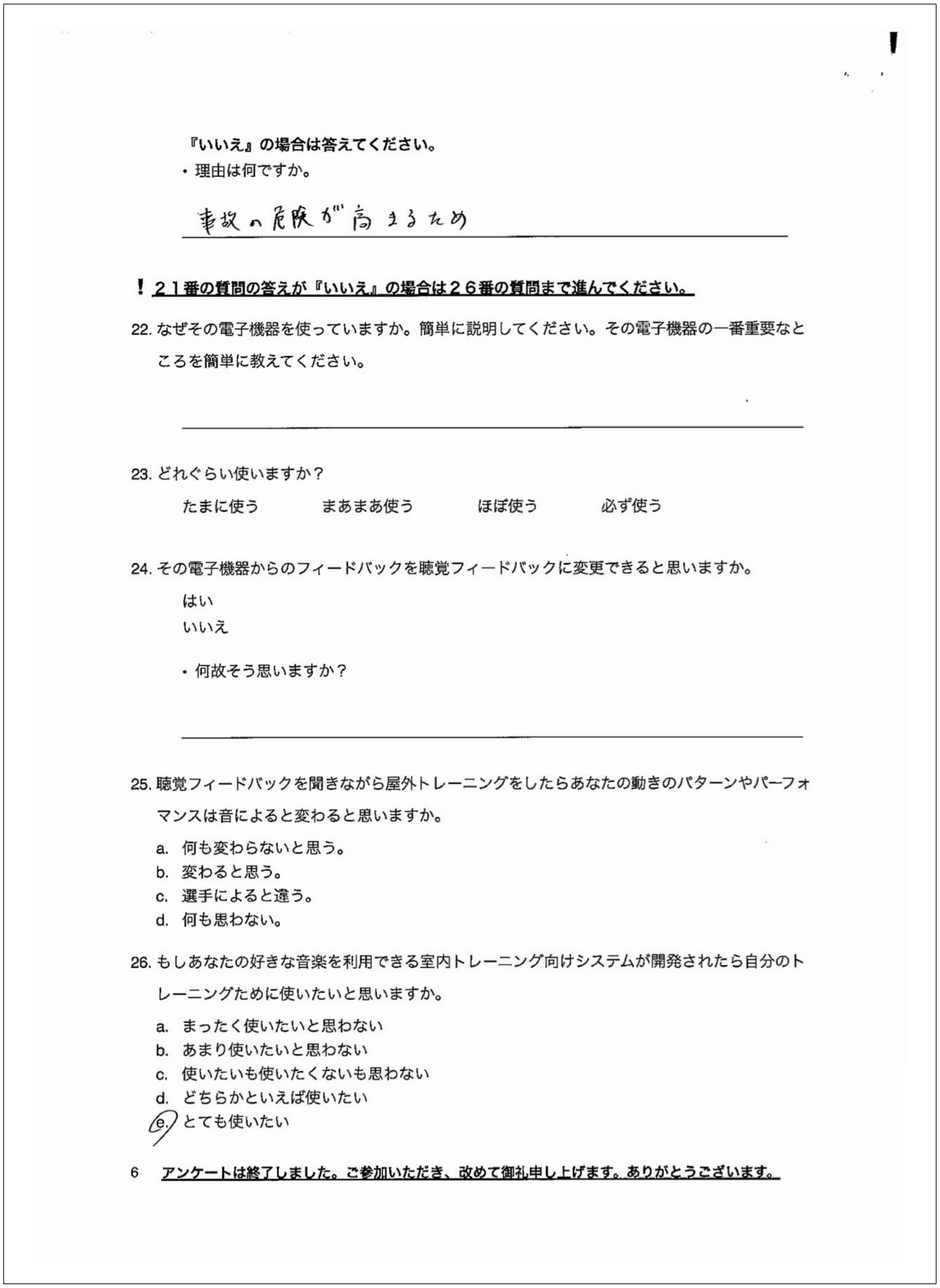
はい
[✓ いいえ]

『はい』の場合は答えてください。

- どんなデバイスを使いますか。

5　次のページ→

Figure A.11: Two incompatible set of answers given to my survey (Page 2.5)



『いいえ』の場合は答えてください。

- 理由は何ですか。

事故の危険が高まるため

! ２１番の質問の答えが『いいえ』の場合は２６番の質問まで進んでください。

22. なぜその電子機器を使っていますか。簡単に説明してください。その電子機器の一番重要なところを簡単に教えてください。

23. どれぐらい使いますか？

たまに使う　まあまあ使う　ほぼ使う　必ず使う

24. その電子機器からのフィードバックを聴覚フィードバックに変更できると思いますか。

はい
いいえ

- 何故そう思いますか？

25. 聴覚フィードバックを聞きながら屋外トレーニングをしたらあなたの動きのパターンやパーフォマンスは音によると変わると思いますか。

a. 何も変わらないと思う。
b. 変わると思う。
c. 選手によると違う。
d. 何も思わない。

26. もしあなたの好きな音楽を利用できる室内トレーニング向けシステムが開発されたら自分のトレーニングために使いたいと思いますか。

a. まったく使いたいと思わない
b. あまり使いたいと思わない
c. 使いたいも使いたくないも思わない
d. どちらかといえば使いたい
[✓ e.] とても使いたい

6　**アンケートは終了しました。ご参加いただき、改めて御礼申し上げます。ありがとうございます。**

Figure A.11: Two incompatible set of answers given to my survey (Page 2.6)

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