Training and Evaluating Champions: A Skills Acquisition Training Tool in Badminton

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Statement of Authorship

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I dedicate this dissertation to my parents, who have always been there for me and will forever be a continued source of inspiration

Hung Huynh & Lan Huynh
Summary

The aim of this research was to examine if a visual based training method could improve badminton players’ decision making and in game performance. This research comprises a collection of research problems relating to visual based training, digital learning and general tau theory in relation to badminton. Firstly (Chapter 1), the limitations of the traditional method of training are discussed, specifically dealing with the lack of cognitive training. A visual based training (VBT) is introduced to be integrated into the traditional method of training. This novel approach aims to improve not only the standard physical aspects of training, but also the cognitive components of decision making and awareness. Following this, both traditional and current theories of skill acquisition are discussed (Chapter 3) in relation to movement and skill development in sport. Chapter 4 details the methods used to complete this research, as well as describing the statistical procedures that are utilised for analysing the results of this dissertation. The subsequent chapters (5 – 8) discuss the various experiments that were conducted using this novel program as well as examining if a visual based approach is effective in training badminton players. Specifically, the research conducted revealed significant results using the VBT program. Participants were able to improve their performance both on the program and badminton court. These findings provide a new method of training badminton players. Future research could consider expanding upon the model presented, and include the analysis of individual strokes and doubles play.
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Glossary

Shuttlecock  A high-drag projectile which players hit to one another during a game of badminton.

Racket  The object players use to hit the shuttlecock with.

Smash shot  This shot is used to hit the shuttle down hard and fast. It is generally a way to end the point quickly. This shot is hit high in the air and you snap your wrist as soon as your racket makes contact with the shuttle.

Drive shot  This shot is an attacking shot that is usually played from the sides of the court when the shuttle has fallen too low for it to be returned with a smash. The shuttle should be between your shoulder and knee height.

Drop shot  This shot lands in your opponent’s frontcourt area, as close to the net as possible. It is intended to move your opponent to the frontcourt creating space in their midcourt and backcourt for you to exploit.

Clear shot  Generally, this shot is used to move your opponent to the backcourt. It will create space in the frontcourt for you to exploit. The optimal hitting zone is located somewhere above the central area of your racket.

Net shot  These shots are played from around the net area back to your opponent’s net area. The objective is to force your opponent to hit a weak lift or hit that could not clear the net.
Push shot This shot is generally executed with little force, played by gliding the shuttle with little wrist motion. It is usually hit from your net or midcourt to the opponent’s midcourt.

Motor learning A relatively permanent change, resulting from practice or a novel experience, in the capability for responding.

Motor skill A learned sequence of movements that combine to produce a smooth, efficient action in order to master a particular task.
# List of Abbreviations

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<td>ANCOVA</td>
<td>Analysis of Covariance</td>
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<td>ANOVA</td>
<td>Analysis of Variance</td>
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<td>BA</td>
<td>Badminton Australia</td>
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<td>BMI</td>
<td>Body Mass Index</td>
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<td>BWF</td>
<td>Badminton World Federation</td>
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<td>CNS</td>
<td>Central Nervous System</td>
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<td>DA</td>
<td>Discriminant Analysis</td>
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<td>df</td>
<td>Degrees of Freedom</td>
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<td>DST</td>
<td>Dynamical Systems Theory</td>
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<td>GMP</td>
<td>Generalised Motor Program</td>
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<td>IBF</td>
<td>International Badminton Federation</td>
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<td>KMT</td>
<td>Knowledge Measures Test</td>
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<td>MANOVA</td>
<td>Multivariate Analysis of Variance</td>
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<td>MLP</td>
<td>Multilayer Perceptron</td>
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<td>NN</td>
<td>Neural Network</td>
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<td>SATB</td>
<td>Skills Acquisition Trainer for Badminton</td>
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<td>VBT</td>
<td>Visual Based Training</td>
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<tr>
<td>VRL</td>
<td>Video Rally Selector</td>
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<td>WBA</td>
<td>World Badminton Association</td>
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Chapter 1

Introduction

The ability to develop the skills necessary to complete daily tasks and activities is crucial to survival in any environment. The acquisition of skill is of particular importance in sport, where the difference between victory and defeat is most often decided by the level of skill or the effectiveness of techniques utilised by the athletes. Therefore, the nature in which athletes acquire the skills for mastering various techniques in their respective sports is critical. This raises BIG questions for sports scientists to answer: ‘How do athletes acquire the skills necessary to become experts in their respective fields?’ and ‘Is there an ideal training method coaches/educators can utilise for reducing the time required to train their athletes into experts?’ The many facets of skill acquisition now bridges many related disciplines, including psychology, motor learning, physical education and therapy, biology, sports statistics and motor impairment. In attempting to answer how experts acquire their skills, we introduce a novel program that was designed using both statistical analyses and programming.

Badminton is the world’s fastest racket sport, with a top speed of 421km/h. Because it is such a fast paced sport, the skill of swift decision making has become imperative for top levelled badminton players, and the need for athletes to train and improve their ability to
instantaneously determine the best course of action to make is essential. In recent years, extensive research has been carried out to analyse the physiological and biomechanical factors that characterise racket sport athletes (Manrique and González-Badillo, 2003), especially with tennis and squash players. There is, however, limited data to assess which factors are desirable in competitive badminton (Manrique and González-Badillo, 2003; Huynh and Bedford, 2010). Despite its inclusion as an official sport at the 25th Olympic Games in Barcelona, research in the field of performance optimisation, mental and visual training, and skill acquisition for badminton remains scarce (Blomqvist, Luhtanen and Laakso, 2001; Huynh and Bedford, 2010; Manrique and González-Badillo, 2003).

The primary aim of this research is to examine the various methods by which a badminton player can be taught the skills and techniques necessary to become an expert player. In addition, this research also aims to improve the current skill level of badminton players via a novel training method. Currently, the majority of training methods that coaches and trainers utilise to train their athletes focus on developing a player’s physical capabilities. It is assumed that athletes who are fit, healthy and physically well built will become the star players in any game. Throughout this dissertation, a number of questions relating to the physical aspects of training are asked. Is there a better method for training badminton players? Why does the literature not mention an integrated training regime that allows for cognitive growth in conjunction with physical training? How long will it take novices to become experts with this current training method? Ultimately, it was my goal to: (1) expose the weaknesses and limitations of the traditional method (for training badminton players) and (2) introduce a new regime that will revolutionise training by developing a novel visual based system that trains the cognitive functions of decision making and awareness in badminton players.
1.1 Why badminton?

In Australia, the sport of badminton is not popular. It would be rare to view a match of badminton on Australian television during the either the Commonwealth or Olympic Games. This is unfortunate however when you consider the following (taken from Badminton Information, 2006):

- Badminton first made its Olympic debut during the 25th Olympic Games held in Barcelona, with 1.1 billion people tuning in to watch these matches.

- During the 2004 Athens Olympic Games, a report released by the Olympic Programme Commission revealed that badminton was ranked as the 11th (out of 28) most watched sport broadcasted worldwide.

- In Indonesia and Malaysia approximately 15,000 spectators fill the stands to watch the finals for each tournament.

- It is estimated that approximately 200 million people participate in badminton worldwide, with age groups ranging from as young as 2 to as old as 89 years of age.

Despite these facts, badminton remains fairly unknown in many parts of the world, particularly in America and Australia. In fact, the number of people who play badminton in Australia constitutes only 0.3% (approximately 41,000 players) of our population. This number seems minuscule when compared to the 615,549 registered AFL players (Australian Institute of Sport, 2010). There are over ten times more AFL players than badminton players in Australia, despite badminton’s status as an official Olympic event. When we look at other countries dominated by the indigenous sport (e.g. USA and baseball), we find similar participation rates. Despite being the fastest racket sport, we have to ask: ‘why is badminton so underrepresented in our country?’

The simple answer may be that badminton is a fairly unknown sport. And unfortunately, little is being done to change the way most of us view this sport. The success of a game may
vary based upon its popularity within the community. Despite being a dominant sport in Asia and some parts of Europe, badminton simply isn’t popular in other parts of the world, including Australia. This could explain (partially) our lack of success in the sport. Within the last 12 years, Australia has only ever won two medals in Badminton (the 1998 Commonwealth Games in Kuala Lumpur and the 2010 Commonwealth Games in Delhi). Whereas, if we consider a sport where Australia dominates and wins medals continuously (e.g. swimming), we will find that the popularity of and participation rate for that sport is exceptionally large compared to badminton. Therefore, a first step towards increasing the popularity of badminton in Australia could be a focus to improving current players’ skill levels and performance, with the objective of winning more medals at the Commonwealth and Olympic Games.

This research came into existence when we were approached by the Badminton Olympic team, seeking our assistance to improve the team’s performance during matches. I have always been curious as to why some players learn techniques, and become proficient in them, faster than others. I often questioned some player’s decisions during a match and frequently believed there were better options to make. Therefore, the idea that I would be conducting research on a sport I was familiar and comfortable with, in conjunction with the understanding that I would be improving my own skills as well as those of my participants, was a great incentive for me.

1.2 Literature Review

This section will discuss previous research in the field of sport statistics with a specific focus on visual based instructions, discriminating expertise, digital learning and visual based integration. Compared to other racket sports (e.g. tennis, squash, and table tennis) there has
not been as much research conducted for badminton. As such, some of the research referenced in this dissertation will be in relation to a variety of racket sports.

1.2.1 Visual based instructions

In any fast paced sport, the outcome of a match may be decided by the ability to make decisions quickly and accurately (Blomqvist, Luhtanen and Laakso, 2000). Considering the importance of swift decision making, it has become imperative that athletes train and improve their ability to instantaneously determine the best course of action to take. However, improving an individual’s capacity for decision making is more complex and detailed (Macquet and Fleurance, 2007) than improving physical abilities such as strength or agility. Currently, coaches and trainers attempt to maximise athletes’ physical skills and competencies (Chin, Wong, So, Siu, Steininger and Lo, 1995; Fahlstrom, Lorentzon and Alfredson, 2002), rather than their decision making capabilities. In attempting to optimise an athlete’s competency, the development of a training program that incorporates the improvement of reaction time and awareness in juxtaposition with physical performance would be ideal.

Currently, the majority of training methods in badminton focus on improving a badminton player’s physical capabilities (Blomqvist, Luhtanen and Laakso, 2001). There has been little research into the use of other training methods (Blomqvist, Luhtanen and Laakso, 2001), such as creative problem solving and visual based methods, in badminton, despite numerous studies suggesting that visual based training (VBT) methods can improve perceptual skills in athletes (e.g., Abernethy, Woods and Parks, 1999; Christina, Barresi and Shaffner, 1990; Farrow, Chivers, Hardingham and Sachse, 1998; Starkes and Lindley, 1994). The small number of training programs that do attempt to improve decision making and
awareness in badminton players are limited (Macquet and Fleurance, 2007), and may not provide athletes with the necessary improvements needed to optimise their in-game performance.

In their classic study, Blomqvist et al. (2001) compared the effectiveness of two types of training for a group of young badminton players: (1) the traditional method and (2) a strategy-oriented method (combining a visual based method with some aspects of the traditional training method). The researchers found that both groups were able to improve their serving skill through direct teaching of techniques, whereas the cognitive aspects of game performance improved only for the strategy-orientated group. While it is essential that athletes continuously train and improve their physical capabilities (Chin, Wong, So, Siu, Steininger and Lo, 1995; Fahlstrom, Lorentzon and Alfredson, 2002), it seems evident that the cognitive components of badminton must not be underemphasised when training athletes (Blomqvist et al., 2001). In developing and improving decision making, the ideal strategy would be to expose the athlete to all possible situations and scenarios that they may face. With the traditional training method, it is sometimes extremely difficult to expose athletes to all possible situations and scenarios they may face as they acquire a regular standard of play from training with the same athletes and coaches. As such, VBT methods expose players to an abundance of different scenarios and situations, preparing them for in-game utilisation (Blomqvist, Luhtanen and Laakso, 2001).

Elite sport is big business, full of pressures from conflicting sources. Currently, the majority of training methods coaches utilise to train their athletes are focused heavily on physical training. Athletes who appear physically strong are generally better received than smaller athletes. For this reason, the primary goal of this research is to create a training system that incorporates a visual based program that operates in conjunction with the traditional method, which emphasises physical fitness. By introducing a visual based training
program we will be exposing players to all the various situations and scenarios that they may encounter during any given match, without the necessity of being on a physical court. In doing this we will be able to statistically examine the influence of the physiological (agility, strength, etc) and psychological (decision making, awareness) factors which we can then quantify into an interpretable model of skill acquisition.

1.2.2 Discriminating expertise

A key component of this dissertation will be the ability to discriminate experts from novices using the VBT method. Previous research involving VBT has shown that the ability to detect and utilise advanced visual cues allows players to predict their opponent’s actions more accurately. A classic example of this can be found in Abernethy and Russell’s (1987) study regarding the differences between the ability of experts and novices to discriminate visual cues. Their research suggested that novice badminton players were less successful (compared to experts) in detecting advance cue sources, which is the ability that provides experts with superior anticipatory skills. Specifically, the researchers stated that experts would utilise the visual cues from both their opponent’s racket and arm placement to predict stroke direction and speed, whereas, novices were only capable of extracting advance information from the racket itself.

In a more recent study, Blomqvist, Luhtanen and Laakso (2000) utilised a visual based test to examine the differences in skill, game performance and game understanding between expert and novice badminton players. The game understanding component of this study involved participants viewing different video simulations of offensive and defensive situations. With every sequence, participants were presented with a tactical problem to solve, such as predicting the next shot type that will be made. Overall, the research suggested that
experts exhibited significantly more sport skill, played more effective shots and understood the game situations better than novices, who were unable to select the appropriate actions due to their underdeveloped procedural knowledge base. This study demonstrated how VBT methods were effective in discriminating expertise among badminton players. Research regarding VBT and detecting visual cues for other sports has also shown similar results.

Renshaw and Fairweather (2000) utilised a visual based method to examine expertise among cricket players by assessing verbal discrimination when faced with five different types of bowling deliveries. They showed that expert batters were more successful than novices in identifying different types of deliveries made by an expert wrist-spin bowler. The overall detection rates in this study differed significantly between national, regional and club level cricket players. National players correctly identified 63% of deliveries, regional players identified 56% and club players correctly identified 48% of overall deliveries. However, when examining this discrimination capability for types of delivery, the authors found that batters were less able to discriminate between same deliveries that were similar in nature, regardless of expertise. Renshaw and Fairweather (2000) explained this poor discrimination ability as being due to the fact that deliveries such as topspin and backspin closely resembled a legspin delivery. Similarly, in badminton many different shot types used appear similar in execution and may generally only be differentiated during the last few milliseconds prior to the racket making contact with the shuttle.

In squash, the utilisation of VBT methods has also shown significant results for improving anticipatory skills. Abernethy, Wood and Parks (1999) demonstrated how perceptual training can be used to detect visual cues in squash players. In their study, participants received one of three training methods for four weeks of experimentation: (1) perceptual and motor practice training, (2) supervised and motor practice training, and (3) just motor practice training. The perceptual training consisted of a series of instructions,
video sequences and simulated practice. The supervised training consisted of reading racket sport coaching manuals and watching videotape replays of top-level tennis matches. All three groups completed the same motor practice component. After the four weeks of training, participants were assessed on anticipatory skills, using the temporal occlusion task devised by the author in a previous study (Abernethy, 1990). Overall, the researchers suggested that novices are able to acquire expert-like anticipatory skills using a training program that incorporates perceptual training in conjunction with motor practice.

Finally, being the most popular racket sport, the game of tennis has seen the generation of an extensive literature on skill acquisition. In a recent study, Williams, Ward, Knowles and Smeeton (2002) used visual based methods to examine anticipation skills in tennis. The researchers utilised film simulations, movement-based response measures, and eye movement recording systems to analyse the anticipatory skills of 32 tennis players. The results of the study indicated that the participants who received the perceptual training improved their performance for both lab and field based testing compared to participants who did not receive perceptual training. Overall, the researchers suggest that anticipation skill in real-world tasks can be accurately measured in the laboratory with representative tasks that incorporated life-sized film displays; and realistic response measures.

These research studies lead us to suggest that utilising perceptual training early in an athlete’s skill development program will prove beneficial for their anticipatory skills in the long run. However, this is not to say that VBT methods would be more efficient or that they should replace the standard training regimens of physical training. Adapting a perceptual strategy which emulates an expert will not bring a novice to that level simply by use of the training (Abernethy, 1987). From a practical approach, these types of visual imagery training would be insufficient (Renshaw and Fairweather, 2000) unless coupled with a form of
physical practice. Ideally, it is the combination of both visual training and motor practice that will enhance overall perceptual performance.

1.2.3 Digital Learning

With the digital age constantly developing and the nature in which Gen-Z children are raised and taught through digital means (Mitchell, 2008; Tapscott, 2008; Howe and Strauss, 2008), the use of a VBT method to train athletes should prove not only effective but stimulating for the athletes of the future. The term Gen-Z refers to people born from the early 2000s through to the present (Jayson, 2008).

Research in the field of digital learning has shown positive outcomes (Musgrove and Musgrove, 2004; Yelland and Lloyd, 2001; Riel and Schwarz, 2002) with many studies suggesting such methods are beneficial and rewarding for children as young as five. Downes, Arthur and Beecher (2001) argue that the integration of digital learning in conjunction with traditional methods would provide a powerful framework for learning and development. Downes et al. (2001) reviewed the use of digital learning within a primary school environment for a group of students under eight years of age. They stated that a learning environment needs to be progressively layered so that children can actively investigate and satisfy their learning focus. Thus, the introduction of digital learning in early childhood allows for accurate interpretation of visual based imagery in other programs.

Similarly, Daniels (2001) examined the use of technology to improve the writing skills of elementary school students. The researcher showed that within the duration of one year, the use of digital technology increased the proficiency rating of fifth grade children from 16.7% to 54.3%. Daniels (2001) suggests that the improvement in writing skill was accredited to both digital learning and appropriate educator’s instructions. Despite the effectiveness of
technology and digital learning, human guidance and intelligence in terms of facilitating the learning process should not be rendered redundant too hastily (Blahous, Dybdahl and Shaw, 1997). In a similar sense, when training athletes using visual based methods, the instructions and training of coaches in the traditional manner must still be reinforced.

In a similar study to the previous, Nir-Gal and Klein (2004) examined the effect of digital learning on the cognitive performance of children aged 5 to 6. They indicated that children who engaged in adult-mediated computer activities improved the level of cognitive performance on measures of abstract thinking, planning ability, vocabulary, and visual-motor coordination. Additionally, the research revealed that children who were a part of the mediated group learned to use planning strategies more frequently than children in the control group (who alternatively relied on trial and error) to solve problems. Nir-Gal and Klein (2004) argued that by utilising planning strategies, the students in the computer learning group were able to obtain a higher number of correct answers on various cognitive and motor tests, compared to students who only received verbal instructions. Ultimately, the researchers concluded that the integration of digital learning devices improved the awareness and decision making capabilities of students, as well as providing them with insight into their own learning processes.

These research studies demonstrate the effectiveness of visual based training and learning methods, particularly with the younger generation. The utilisation of a VBT method to acquire skills and knowledge has shown to be both rewarding and stimulating. As such, the VBT program that forms part of the work in this dissertation was designed to incorporate the visual stimulants and ease of use that will appeal to the future generation of athletes.
1.2.4 Visual Based Integration

Thus far this dissertation has mentioned visual based literature relating to learning and discriminating expertise. The main focus of my research, however, was to develop a VBT program that incorporates both the cognitive and physical aspects of training. While visual based learning and visual based discriminating techniques have been studied extensively (Abernethy et al., 1993; Blomqvist et al., 2001; Renshaw and Fairweather, 2000; Thomas, 1994) little research has been carried out in terms of an actual VBT program. As it stands, the traditional method of training athletes (heavy focus on physical training) is unlikely to change unless sufficient research is presented to support the value of cognitive training.

The traditional approach to training badminton players follows a three step sequential process: perception, decision-making and movement execution training (Abernethy, 1996; Blomqvist et al., 2001). Initially players are taught the standard rules and concepts of the game; your basic “hit the shuttle over the net, not under” type of instructions. This covers a large component of their perception and decision making training. Following this, coaches and trainers will place heavy emphasis on the execution, movement and physical training of the athlete, with the cognitive processes of perception and decision making being left to develop on their own. This is unfortunate, however, considering the quality of decision-making in a game situation is often as important as the execution of the motor skills (Blomqvist, Luhtanen and Laakso, 2001; Thomas, 1994).

This is not to say that the physiological aspects of training should be ignored. Abernethy (1987) argues that adapting a perceptual strategy to emulate an expert will not bring a novice to the same level unless they have experienced similar (in game) situations. It takes a combination of both physical and cognitive training to become an expert in the desired field. A VBT program doesn’t transform a novice into an expert; rather it ideally accelerates their
training and makes the transition into an expert a less difficult process. Therefore, the VBT introduced should be integrated into (rather than replacing) a coaching program when used to train badminton players.

In building the VBT program itself (refer to the method section for a detailed account of the program’s construction), various models from past research have been integrated into its structure. Specifically, the program was based upon the following works:

1. Abernethy’s (1987) classic study which utilised visual techniques to identify experts. The idea for a visual program began when I read this paper. The author used visual based methods to identify visual cues which led me to believe that I could introduce a VBT method for training athletes.

2. Renshaw and Fairweather’s (2000) study on discriminating expertise among novice and expert cricket players. In order for my program to be successful it had to be able to accurately identify expert badminton players from novice badminton players. Therefore, many of the key ideas that Renshaw and Fairweather discuss in their paper have been integrated into my program.

3. Blomqvist, Luhtanen and Laakso’s (2001) paper which examined the effectiveness of visual based instructions for a group of badminton players. This research provided participants with different tasks/problems to solve, which became a key component in the design of my program.

4. Jorgensen, Garde, Laurens and Jensen’s (2002) paper regarding digital learning strategies when the subject is placed under time pressure. The equation I used in
building my program was a variant of the constant the researchers introduced in their paper.

5. Hammond and Smith’s (2006) paper on using low compression balls to train tennis players. The researchers stated that: “if new methods and ideas can be determined to improve player performance, they will change coaching practices and processes.” This one sentence encouraged me to reconsider the traditional method of training badminton players and consider a new (VBT) regime.

In this dissertation I build upon and integrate the works of several researchers to introduce a new model of training badminton players. This system which has been named the Skills Acquisition Trainer for Badminton (SATB), will hopefully demonstrate to coaches the importance of visual and perceptual training.

1.3 Research Questions and Publications

In organising the research questions posed by this dissertation into a clear, precise manner, each question forms the foundation for a separate chapter or section. The sections that follow in the subsequent chapters have been published (or are accepted for publication) in a journal article or fully refereed conference proceeding. Note that the numbers and titles of the research questions correspond to the respective chapters in this dissertation.
1.3.1 Research Questions and Hypotheses

Chapter 5  Visual Based Training

(i) Do athletes who utilise VBT methods perform better in a game compared to athletes who follow the traditional method of training?
   Specifically, it was hypothesised that an athlete who utilises a VBT will perform better in a game than an athlete who utilises the traditional method of training.

(ii) Do athletes who utilise VBT methods develop better decision making capabilities compared to athletes who follow the traditional method of training?
    Specifically, it was hypothesised that an athlete who utilises a VBT will develop better decision making skills than an athlete who utilises the traditional method of training.

(iii) Can we improve an athlete’s reaction time and awareness using VBT methods?
    It was hypothesised that we can improve an athlete’s reaction time and awareness using a VBT method.

Chapter 6  Discriminating Expertise

(i) Can we correctly identify experts from novices using a VBT method?
    It was hypothesised that we can correctly identify experts from novices utilising a VBT method.

(ii) Which statistical method, neural networks or discriminant analysis, is more effective in identifying our athletes into their correct skill groups?
It was hypothesised that neural networks would be more effective in identifying skill level for badminton players compared to discriminant analysis.

Chapter 7  A Tau Theory for Training

(i) Can we introduce general tau theory to explain skill acquisition for badminton players?

It was hypothesised that general tau theory can explain the skill acquisition process of badminton players.

(ii) Using time-to-contact, can we design a model to predict movement and velocity in badminton players?

It was hypothesised that time-to-contact theory can used to predict movement and velocity in badminton players.

1.3.2 Publications

Chapter 5 Visual Based Training

Chapter 6 Discriminating Expertise


Chapter 7 A Tau Theory for Training

Chapter 2

Skill Acquisition

This chapter details the many different theories and models of skill acquisition. In Section 2.1, a brief introduction regarding skill acquisition is provided. Sections 2.1.1 provides the definitions of a few key words that are mentioned frequently in this chapter. Section 2.2 – Section 2.5 detail a number of traditional theories of skill acquisition. Section 2.6 covers the dynamical systems theory of skills acquisition. Finally, Section 2.7 covers the general tau theory of perceptual learning. Please note that full definitions of the colloquial terms in this chapter are provided in the glossary.

2.1 Introduction

The nature in which humans learn how to control and coordinate their movements has received much attention over the last century (Davids, Button and Bennett, 2008), with scientists proposing various different theories and models regarding the issue. This chapter will begin by examining some of the traditional theories of skill acquisition and their applications to motor learning, with the arguments and criticisms for each theory provided. I will then examine the more recent theories of skill acquisition and how they have been
applied to motor learning and sport. Note that not all the traditional theories will be mentioned (e.g. neuromaturational theory). For additional reading on other traditional theories of skill acquisition please refer to Davids, Button and Bennett (2008).

2.1.1 Definitions

The definition of skill acquisition was initially quite broad with heavy emphasis on the cognitive aspects of learning. Traditionally, the theory revolved around how the brain handled information through the learning process, from conscious efforts to master a task to the point where decision making required to complete that task becomes automatic. Over time however, with the introduction of various models and designs, the definition became more explicit, with a focus on the dynamic interactions of the learner and his/her surroundings (which will be covered in more detail later in this chapter). Some of the key words defined in this section will be used frequently in this chapter.

In describing motor learning, Schmidt’s (1988) widely quoted definition suggests that: “Motor learning is a set of internal processes associated with practice or experience leading to a relatively permanent change in the capability for responding.” This type of learning often involves improving the smoothness and accuracy of movements. It is necessary for complicated movements such as speaking, playing the piano and climbing trees, but it is also important for calibrating simple movements like reflexes, as parameters of the body and environment change over time (Adams, 1971; Schmidt, 1975).

Motor control relates to the activities carried out by the central nervous system that organises the musculoskeletal system to create coordinated movements and skilled actions. Specifically, the study of motor control analyses how people and animals control movement, and the role of the nervous system in doing so.
2.2 The Power Law of Practice

Snoddy (1926) is generally attributed as being the first to propose a power law for human learning (Newell, Mayer-Kress, and Liu, 2006). He proposed that any form of learning can be described in a predictable manner using a mathematical logarithmic equation:

\[ \log C = \log B + n \log x \]  

(2.1)

where \( C \) is a measure of performance, \( x \) is the amount of practice, and \( B \) and \( n \) are constants. This **power law of practice** argues that performance simply improves with practice and can be predicted with a straight line relationship between the logarithmic functions of practice time and performance (Davids, Button and Bennett, 2008). The figure below provides an example of this relationship.

![Figure 2.1: The power law of practice predicting a logarithmic relationship between practice time and performance](image)

Figure 2.1: The power law of practice predicting a logarithmic relationship between practice time and performance
A well known example of Snoddy’s Power Law of Practice can be found in Crossman’s (1959) classic study regarding the reduction in cycle time in making 10,000,000 cigars over a 7 year period. Here, the researcher examined the production speed of several cigar making operators over an extended experimental period. Crossman (1959) stated in his study that “practice exerts a selective effect on the operator’s behaviour, favouring those patterns of action which are quickest at the expense of the others.” For each trial, the operator will adopt some particular combination of sensory, perceptual, and motor activities, partly from deliberate choice, partly from habit, and partly by chance. In successive cycles the operator will use either the same or more or less of different combinations, based on the efficacy of previous actions. This research supports Snoddy’s power model and suggests that performance time can improve with practice.

There were, however, a number of limitations and the model failed to gain universal acceptance as a suitable theory for motor learning and skill acquisition. Specifically, the major criticism of Snoddy’s model related to the dimensions of decrements in performance, and the failure to account for decreases in skill level and performance over time. Additionally, the model does not take into consideration the nature of learning and the way it is often characterised by sudden jumps and rapid improvements.

### 2.3 Association Theory

Association theory stems from a Behaviourist school of thought and states that concepts are learned by simple, reinforced connections between a stimulus and a desired response. Early researchers in this field (e.g. Skinner, 1938; Thorndike, 1927; Woodworth, 1899) employed repetitive movements or reflexes to test this association between stimulus and action. For example, Skinner (1938) introduced a starving rat into an experimental box
(commonly known as a Skinner box) which contained a series of lights and one or more levers. When the rat pressed on the lever, a small pellet of food would be dropped into the box. In his experiment Skinner demonstrated that the rat learnt that pressing the lever would result in a reward of food. Additionally, Skinner demonstrated that the rat learnt to discriminate between light and dark by only reinforcing the action (of pressing the lever) when the light was turned on. His findings demonstrated the importance of feedback to the reinforcement of learning.

However, association theories have been heavily criticised for assuming that animal models are relevant for studying motor skill acquisition in people (Davids et al. 2008). Humans are able to choose when and how to moderate their actions, with sensory feedback not always essential for the execution of some movements. Furthermore, reinforcement of particular predetermined behaviours sometimes interferes with maximal learning and performance over the long run. For example, athletes could consistently perform at a level where they complete the minimum amount of training required to receive the reinforcement, instead of being challenged to excel.

### 2.4 Fitts and Posner’s Stage Theory

The stage theory of motor learning argues that, when humans learn new skills, they gain a sense of progressing through distinct stages (Rosenbaum, 1991). Fitts and Posner (1967) suggested that there are three principal stages of skill acquisition: (1) the verbal-cognitive stage, (2) the associative stage and (3) the autonomous stage.

During the initial stage of the model (refer to the Figure below), the learner is introduced to basic procedures and verbal instructions in order to acquire a basic understanding of the task. Throughout this stage it is not uncommon for learners to talk to
themselves while experimenting with different movement configurations to learn the movement. At this stage, the movement is full of errors, with the learner requiring a considerable amount of attention to achieve the necessary improvements needed to advance to the next stage. As an example we will consider a badminton player learning to execute the jump smash. To perform a successful jump smash the player must: (1) estimate the shuttle trajectory, (2) move to the correct position, (3) align their body with the correct pose, (4) determine when to lift off the ground and (5) strike the shuttle with the appropriate force and angle. During the first stage of the model, the player will execute the jump smash with minimal success – perhaps due to misjudging the shuttle trajectory, or jumping with incorrect timing, or hitting the shuttle improperly. Advancing to the next stage will require a large amount of training/practice, with the player constantly questioning their movement patterns in executing the jump smash.

Figure 2.3: Fitts and Posner’s Stage Theory suggests learning as a continuous process
During the second stage, the associative stage, movement patterns are refined, and more consistent with the goal task. This stage represents a transition from the learner’s reliance on their verbal, conscious control to a more automated control of the movement. The required periods of practice and training may vary in duration depending upon the complexity of the task. When attempting the movement, the learner varies task components and associates them with success or failure. Here, the learner will preserve the actions that contribute to success and eliminate those that contribute to failure. Johnson (1984) emphasises the importance of feedback during this stage. Using the example above, we will continue to examine the jump smash scenario during the second stage of Fitts’ model. At this point, the learner performs the jump smash with more consistency – refining their movements to associate environmental cues with their actions. They are able to detect and correct errors (e.g. jumping too early) for future jump smash executions. Similarly, they will recognise when they perform the action successfully and utilise similar movement patterns in follow up jump smashes.

In the third stage, the autonomous stage, the learner is able to execute the movement quickly and consistently with few errors and little conscious involvement. Decision making required to complete the task has become automatic, and the necessity for continual feedback redundant. Additionally, the performer is able to execute this movement successfully while concurrently performing other tasks. To return to the jump smash scenario: the player is able to determine the shuttle trajectory almost instantaneously, executing the movement with few errors; with almost no conscious association (they perform the jump smash with a near habitual reflex). While performing the jump smash, the player is confident enough to also perform other tasks, such as examining their opponent’s location to determine the optimal place to execute the action (e.g. hit the shuttle as far away from them as possible).
2.5 Information Processing Theory

The Information processing theory is a popular theory that posits that perceptual-motor information can be represented within the central nervous system (CNS). These representations are acquired through the learning process, storing a set of motor commands that control movement behaviours within the CNS. Keele (1968) first described this set of stored movement commands as a motor program. The basic assumption is that the brain functions like a computer to process information and produce outputs in behaviour (refer to the figure below). Here, information-processing occurs through a series of discrete cognitive stages involving perception, decision making, and response execution (Davids, Button and Bennett, 2008).

However, this initial form of information-processing theory provoked a series of criticisms, mainly revolving around the notion of storage space. Critics argued that if information was acquired and stored within the CNS, then there must be a limit to how much an individual can learn without unlimited storage capacity. A second argued criticism that the concept of motor program assumes that the existence of a homunculus-type agent or executive agent (or “the little man inside the brain”) was necessary to create and select the programs from with the CNS (Davids, Button and Bennett, 2008). A third criticism questions how an individual can perform an action for the first time without having the stored motor program within their CNS.

To address these concerns, Schmidt (1975) proposed a ‘schema theory’ of discrete motor skill learning. A ‘schema’ is a set of rules and instructions regarding the execution component of a motor response linked to feedback received both during and after the action. Schmidt’s schema theory builds upon Keele’s (1968) Motor Program theory of movement.
commands and suggests a generalised motor program (GMP). The GMP is an abstract representation that contains the general characteristics for a given class of movements, for example: all the actions of running, walking, skipping and jogging could be represented by the same GMP. Overall, schema theory suggests that variable practice conditions can facilitate the creation of robust schemas, which in turn can lead to the internalisation of enhanced skills.

Figure 2.4: A model of Information Processing that Occurs in the CNS.

2.6 Dynamical System Theory

This section will discuss the dynamical systems theory (DST) as an alternative framework to the traditional theories of skill acquisition as described in the previous sections. In Section 2.6.1 the definition of a complex system is provided. The following section then discusses how a complex system operates within the dynamical systems model. Finally, the subsequent sections will discuss the constraints of a complex system as well as briefly describing the human movement process within the DST.
2.6.1 Complex Systems

A major component of DST is that it argues the need to understand natural phenomena as a system with many interacting components (Davids, Button and Bennett, 2008), as opposed to a traditional theory such as information-processing theory, where the CNS dictates all our movements. Before we begin examining a DST however, we first need to define and explore the notion of a complex system. Clarke and Crossman (1985) state that

in studying human behaviour, a systems perspective is ideal because

“structures and configurations of things should be considered as a whole, rather than examined piece by piece. In a highly complex system like the human mind or human body all the parts affect each other in an intricate way, and studying them individually often disrupts their usual interactions so much that an isolated unit may behave quite differently from the way that it would behave in its normal context.” (Clarke and Crossman, 1985, p.15).

From a systems approach, the word complex refers to the notion of being interwoven and describes a network of related, interacting parts. As such, a complex system is a highly integrated system that is made up of many interacting parts, each of which is capable of affecting other parts (Davids, Button and Bennett, 2008). If we apply the concept of a complex system to a sporting team (e.g. basketball), we can then examine how every different player performs as an independent part of a much larger entity (i.e. the whole team).

If we use the basketball example above, then we can consider the team as a sporting system which includes many independent parts and degrees of freedom (df). In terms of
physical science, a df typically refers to the independent components of a system that can fit together in many different ways. Understanding how dfs operate is essential for explaining the coordination processes of human movement, which will be mentioned in Section 2.6.4. Finally, it is worth noting for a DST that behaviour is potentially nonlinear due to the different types of components and the various ways they can interact with one another.

2.6.2 Human Movement as a Complex and Dynamic System

When considering DST it is worth remembering that there are constant fluctuations and interactions within the microcomponents of a complex system. There is the potential for a large amount of disorder within the whole system due to the seemingly random interactions among the individual parts of the system. For example, consider worker bees within a bee hive, all serving for the greater good of the queen and the colony (here the hive itself would be the system and all the workers would be the microcomponents). These microcomponents could potentially interact in unpredictable ways and result in the collapse of the system, such as one individual bee deciding to revolt, assassinate the queen and take her place as the new monarch of the system. Fortunately, these situations are rare, with analyses at the macroscopic level revealing high ordered patterns of behaviour. Most importantly, these patterns of behaviour exhibit coordination tendencies, with individual components linking together to form synergies (Davids, Button and Bennett, 2008; Haken, 1996; Kelso and Engstrom, 2006).

In understanding the coordination process within a complex system, it is important to take note of the behaviour of these systems and how they function as a whole. DST attempts to explain the behaviour of complex systems by deriving nonlinear mathematical descriptions to characterise the order that emerges within said complex systems. Van Gelder and Port
(1995) define a dynamical system as “*any state-determined system with a numerical phase space and a rule of evolution specifying trajectories in this space.*” Here, a numerical phase space refers to all the hypothetical states of organisation into which a dynamic system can evolve. In humans and other biological systems, these states correspond to patterns of coordination.

Consider once again the bee hive scenario from above. In reality it would take more than one rogue bee to disrupt the balance of the system. Complex systems are, by nature, fairly stable and organised. It would, in fact, require an extremely large perturbing force to destabilise the order of that system (e.g. a large group of hornets entering the hive and devouring the majority of bees from that hive system). Now consider the human being as our complex system. By nature, our movements are guided by a series of coordinated tendencies which are roughly synonymous with functional coordination patterns in our repertoire of movement.

### 2.6.3 Constraints and Coordination Patterns

The previous section demonstrated that coordination patterns can be understood within a framework for goal directed behaviour. This framework is a combination of different types of variables that define the phase space of a complex system. Specifically, these variables are known as constraints, and act as boundaries that limit the motion of the minute parts of a system (Newell, 1986). Constraints are capable of both limiting and enabling the number of behavioural trajectories that a complex system can adopt. In order to allow functional patterns of behaviour to emerge, complex systems such as human beings are able to exploit the constraints that surround them to reach a goal-directed behaviour. According to Newell (1986), constraints can be classified into three different categories: (a) organismic
constraints, (b) environmental constraints, and (c) task constraints. It is these constraints that provide the framework for understanding human movement and coordination tendencies.

Organismic constraints refer to an individual’s personal characteristics. These may include the person’s height, weight, genetic makeup, cognitions, motivations, and emotions. In addition, a person’s thought patterns, levels of practice, or visual defects can shape the way they approach a particular performance goal when these patterns act as an organismic constraint (Davids, Button and Bennett, 2008).

Environmental constraints can be either a physical or social variable that exists in nature. An example of a physical constraint that exists in nature is gravity, which restricts all movement coordination tasks on Earth. A social constraint may include family support, peer groups, societal expectations, values, and cultural norms (Haywood and Getchell, 2005).

A task constraint is related to a specific goal or task that lies within a performance context. For example, a task constraint may include task goals, rules, activity-related tools, surfaces, ground areas and boundary markings. The reason motor behaviour may fluctuate is because task constraints may vary from performance to performance, in the same way that no two goals in soccer are ever the same – they may be similar in style, technique or strength, but each contains their own unique set of task constraint differences.

In reality, we find that it takes more than one constraint to complete most tasks, with the interaction of all three constraints being required to complete goal directed activities. When the organismic, environmental and task constraints interact on the neuromuscular system, the result is the emergence of different states of coordination, which become optimised with practice and experience (Davids, Button and Bennett, 2008). As an example, consider an Olympic runner competing in the 800m relay. Here, the athlete’s organismic constraints would be his genetic makeup, endurance, and stamina, with the track surface being considered the environmental constraint. Additionally, the finish line, or target goal
might be considered the task constraint. Now that we understand how the three constraints interact with one another, we can identify how a highly complex system, such as the human body, learns to coordinate and execute advanced motor performance tasks.

Russian physiologist Nikolai Bernstein (1967) suggested that the acquisition of skill and coordination can be viewed as “the process of mastering redundant degrees of freedom of the moving organ, in other words its conversion to a controllable system.” This became known as Bernstein’s degrees of freedom problem and is concerned with how an individual learns to employ and constrain a large number of relevant motor system dfs during complex actions.

According to Bernstein (1967), learners initially form specific functional muscle-joint linkages to manage the large number of dfs that are controlled in the human movement system. He suggested that through training and experience the learner discovers relevant couplings between limbs to cope with the abundance of dfs. In this sense, variations among performance tasks are constrained to control for the fluctuations among dfs (Mitra, Amazeen and Turvey, 1998). As an example, consider a snowboarder learning to maintain balance on his snowboard. At first, the learner’s coordination patterns begin as fixed, rigid linkages between body parts. The assembly of a functional coordination solution is beyond the learner’s capacity and so the problem of controlling the movement system is managed by “dysfunctionally, suboptimally or overly” (Broderick and Newell, 1999) constraining the available motor system dfs (Davids, Button and Bennett, 2008). Typically, as a result of extended training, the snowboarder’s rigid coupling of hip, knee, and ankle joints become loosened with practice. Eventually, there is greater reliance on only a few couplings (e.g. the knee joints) for producing the appropriate muscle torques to guide the snowboard and harness the energetic impulses from the mountains surface to create rapid transitions in the snow.
2.7 General Tau Theory

This section will examine general tau theory in its detail and explain how it can be used by badminton players for skill acquisition training. It is then mentioned again in Chapter 6 of this dissertation.

Being able to anticipate approaching objects, as well as when the object will reach a goal or target, is a crucial technique for surviving in any environment (Hancock and Manser, 2009). This skill is of particular importance in any fast paced sport, where movement has to be controlled by perceiving what is likely to occur next (Kayed and Van der Meer, 2009). Catching a cricket ball or striking a badminton shuttle requires precise prospective control of the interceptive action and one must be prepared in advance to allow the body time to organise. This theory of prospective control is commonly known as general tau theory and has been associated with various forms of development and anticipation.

The notion of tau is based on Gibson’s (1966) work on ecological invariants in visual flow fields. Because tau is a measure on any motion-gap of any dimension, it explains how a single type of temporal variable can account for controlling the closure of perceptual information from different dimensions of motion gaps. The concept of a motion gap can generally be described as changing the gap between a current state and a goal state in a given event (Lee, 2005).

Using badminton as an example, we can make a statement regarding the motion gap for a player during a badminton rally. When a player is reaching for the shuttlecock with his/her racket would be an example of closing a distance motion-gap. Here, the current state would be the position of the player’s racket, the effector would be the racket itself, and the goal state would be the shuttlecock. There are of course numerous other forms of motion-gaps in badminton. Changing your vision to examine a shuttlecock lobbed into the air is an example of an angular motion-gap between the current vision direction and the direction of the
shuttlecock. A jump in badminton is an example of a force motion-gap between the current force and the force required for a satisfactory jump.

By making use of tau and the knowledge of when an object is approaching a location, players can estimate when the shuttlecock will land at a location on the court. With practice and repetitive motions, the players will acquire the skills necessary to predict (with a certain degree of accuracy) where (and how fast) a shuttle will land. This provides us with another theoretical theory of perceptual skill acquisition. Much of the concepts of tau theory have been utilised to develop the SATB program described in this dissertation. The theory is discussed in relation to badminton in greater volume in Chapter 6.

2.8 Summary

Overall, this chapter discussed a number of theories related to skill acquisition. A central theme surrounds all the theories of skill acquisition; that human beings can improve their performance through practice and training. However, the weaknesses, or criticisms, are also quite similar. For example, the Power Law of Practice and Fitt’s Stage theory cannot account for the decrement of skill over time. Similarly, critics of association theory argue that reinforcement interferes with the maximal learning and performance over the long run. On the other hand, the dynamic systems model attempts to explain skill acquisition whilst taking into consideration these weaknesses.

Dynamic systems theory is the broadest and most encompassing of all the developmental theories because it attempts to contain all the possible factors that may be in operation at any given developmental moment (Miller, 2002). Because it considers all these different factors, e.g. development from many levels (from molecular to cultural) and time
scales (from milliseconds to years), the dynamic systems model provides us with the best option for explaining the acquisition of skill.

The remainder of this thesis will utilise these theories, specifically the dynamic systems model, to develop and explain a novel VBT program that aims to improve the skills of badminton players.
Chapter 3

Methods

3.1 Introduction

In this chapter, the methodology utilized in the subsequent chapters is described. Section 3.2, covers the computer programming component of this dissertation which is utilised in Chapters 4 and 5. In section 3.3, repeated measures analysis is discussed with the methodology being utilised in Chapter 4. Similarly, Section 3.3 covers neural network analysis which is covered in Chapter 5. Section 3.4 describes discriminant analysis which will also be incorporated into Chapter 5.

3.2 Computer Programming

This section covers the computer programming component of this dissertation. The subsequent chapters will describe a series of experiments that were conducted in relation to this dissertation. These experiments were executed using the Skills Acquisition Trainer for Badminton (SATB) and the Knowledge Measures Test (KMT) that are described in this section of the methodology. To begin, a brief rationale is provided regarding our decision to
build a VBT model. I will then introduce the SATB program in its detail; construction, functionality and difficulties encountered. Finally, I will discuss the KMT program in relation to how it was formed and how it operates.

3.2.1 Introduction

The dissertation first came into existence when we were approached by the head coach of Badminton Australia, Lasse Bundgaard, with a theory that an athlete’s body mass index (BMI) can affect their decision making capabilities. Specifically, the coach suggested that “an athlete with a larger BMI (e.g. a large, slow player) will have better decision making skills because they require a longer time to reach a desired target. On the other hand, players with a smaller BMI (e.g. thin and agile) have poorer decision making skills because they have the advantage of waiting for the shuttle to be hit – they don’t need to predict in advance where the shot will travel because they can react fast enough to reach the target when it does.” In order to test this theory, we decided to build a visual program that focused on analysing decision making and game knowledge, while taking participants’ BMI into consideration.

Unfortunately for us and the coach, the theory was not optimal, with BMI accounting for very little, if any, difference in terms of decision making. From a dynamic systems approach, game decisions are acquired through a multitude of training, environmental and bodily interactions, and mental strategising. A person’s weight or height should not affect the way in which they acquire the skills to make optimal decisions. Fortunately for us, we were disheartened with these results for only a short amount of time. We enquired as to the current method utilised to train the badminton players. He told us that it was purely physical, with a large emphasis on strength training (e.g. sprinting and jumping tests). We proposed to him a
new training method that would keep his original physical training intact, but also incorporate a cognitive based system to improve his athletes’ decision making abilities. That was the genesis of the SATB and KMT.

### 3.2.2 Building the Program

Our first task was to acquire video footage that would form the basis of the SATB. These were generously provided to us from Badminton Australia (BA) in the form of:

- Video recordings of live games collected from the BA team. These videos included rallies taken from the Badminton Australian Open 2009.

- DVDs of recorded games at a professional level (purchased from BadmintonDVD.com).

Please refer to Appendix 9.7 for details regarding these video sequences (e.g. players, tournaments, countries, etc).

The second task was to identify the footage, or rather, the rallies that would be integrated into the SATB program. Prior to selecting the footage however, we were required to identify the different shot types used during a game of badminton. The table below categorises the main shot types that we identified based upon a number of different studies (e.g. Macquet and Fleurance, 2007; Tong and Hong, 2000).
<table>
<thead>
<tr>
<th>Shot type</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Smash shot</td>
<td>This shot is used to hit the shuttle down hard and fast. It is generally a way to end the point quickly. This shot is hit high in the air and you snap your wrist as soon as your racket makes contact with the shuttle.</td>
</tr>
<tr>
<td>Clear Shot</td>
<td>Generally, this shot is used to move your opponent to the backcourt. It will create space in the frontcourt for you to exploit. The optimal hitting zone is located somewhere above the central area of your racket.</td>
</tr>
<tr>
<td>Drop Shot</td>
<td>This shot lands in your opponent’s front court area, as close to the net as possible. It is intended to move your opponent to the frontcourt creating space in their midcourt and backcourt for you to exploit.</td>
</tr>
<tr>
<td>Block Shot</td>
<td>This shot is a situational shot – used while you are in the front of the court to keep the shuttle on your opponent’s side of the net, instead of working towards it.</td>
</tr>
<tr>
<td>Drive Shot</td>
<td>This shot is an attacking shot that is usually played from the sides of the court when the shuttle has fallen too low for it to be returned with a smash. The shuttle should be between your shoulder and knee height.</td>
</tr>
<tr>
<td>Push Shot</td>
<td>This shot is generally executed with little force, played by gliding the shuttle with little wrist motion. It is usually hit from your net or midcourt to the opponent’s midcourt.</td>
</tr>
<tr>
<td>Net Shot</td>
<td>These shots are played from around the net area back to your opponent’s net area. The objective is to force your opponent to hit a weak lift or hit that could not clear the net.</td>
</tr>
</tbody>
</table>

Table 3.2: A description of the different shot types utilised in badminton

The next task was to select the appropriate footage to be used in our program. This task was completed by viewing our video footage and selecting rallies which would end with one
of the above shots being executed. We then highlighted and cropped these rallies (using the AVS video editor software) and stored them into a database. Videos stored in the database were called Video Rally Selectors (VRL). Each VRL consisted of two sequences: (1) the point at start of the rally to the point just before the player executes the winning shot, and (2) the rally played from start to finish – clearly showing the winning shot and the location it landed. We collected approximately 8 – 15 different VRLs for each different shot type, with a total of 104 VRLs. These were then shown to a number of coaches and experts to aid us in determining which VRLs would be ideal to include in our program. Video sequences were selected based on:

1. Shot types that can have multiple shot options based upon the position of the player (e.g. a player holding the racket in an over arm forehand position can choose to execute either a smash or a drive).

2. Shot types that can have multiple location options based upon the shot type (e.g. a player executing a net shot while standing in the top left of the court may decide to hit the shuttle to either the top middle or top right).

The reason we selected such ambiguous sequences for our program was because we wanted the participants to focus on various factors they wouldn’t normally take notice of during a game (e.g. a player holding the racket in an over arm forehand position can choose to execute either a smash or a drive but depending upon the angle of the racket, it would be impossible to execute certain smash shots given the location of the player).

Finally, we randomly distributed the VRLs into different sessions of the SATB program, with each session containing a maximum of two of the same shot types. The original version of the SATB consisted of 50 sequences over 5 weeks of experimentation (so a 10x5 model). We encountered a number of difficulties with this system however (refer to Chapter 5) and
changed the system to operate as a 5x10 system (5 questions per session over 10 weeks of experimentation).

### 3.2.3 The SATB’s Functions

When participants first use the program, they will open up an Excel spread sheet which prompts participants to click the start button to begin (refer to the Appendix for extra information). Responses for the program are sent to Sheet3 (hidden) of the excel file. Upon selecting the ‘click to start’ button, the description screen appears with information regarding the current version and model of the SATB.

![Image of SATB program](image)

Figure 3.2: The information screen of the SATB program

Upon clicking ‘start,’ the user detail screen appears (refer to Figure 3.3). Here, participants are asked to enter their name and gender. This is so we can keep track of their change in score over the experimental period. Note that this user form still asks participants to enter their height and weight as an optional entry. These were originally used to calculate the user’s BMI for our initial hypotheses. Although we decided to reject this idea (refer to
Section 3.2.1) we have kept the same user form (with height and weight) so that we may have data for a future study.

Figure 3.3: The user form to enter in the participant’s details on the SATB

After selecting ‘Next’ from the user form screen, participants are given some information regarding the session they are about to take (refer to Figure 3.4). For example, Session One explains to the participants that the sequences were taken from the 2007 World Series Final between Germany and Indonesia.

After the participant clicks ‘Start,’ the first sequence will start to play (refer to Figure 3.5) parallel to the excel file. After a few seconds, the sequence (of the badminton rally) will pause just as a player is about to return the shuttle. This image appears as a still frame for 1.45 seconds, before the screen turns black. Participants now have the option of answering the question (by selecting ‘Answer Q1’) or viewing the sequence once again (‘Watch Again’).
It isn’t mentioned on the information screen, but the researcher administering the session would explain to the participant that as soon as they select ‘Answer Q1,’ a timer will start. The timer keeps running until they enter in their selection for the first question. Participants are informed that each time they select the ‘Watch Again’ option they will incur a 5 second penalty which is added to their final time.

Figure 3.4: The screen displaying information regarding the current session

Figure 3.5: The sequence screen on the SATB
When they are ready to select an answer (by pressing ‘Answer Q1’) the answer screen appears:

![Answer Screen Screenshot](image)

**Figure 3.6: The answer selection screen on the SATB**

Here, the participants have to select the type of shot they think is about to take place as well as the location on the court they believe the shuttle will land. From this screen we can see seven possible selections for shot type: (i) smash shot, (ii) clear shot, (iii) drop shot, (iv) block shot, (v) drive shot, (vi) push shot, and (vii) net shot. As for the location selection, there are 13 possible options: (i) top left, (ii) top middle, (iii) top right, (iv) middle left, (v) middle middle, (vi) middle right, (vii) bottom left, (viii) bottom middle, (ix) bottom right, (x) left out, (xi) right out, (xii) bottom out and, (xiii) net.

Prior to experimentation, the participants are taught about the different shot types as well as how/when those shots are likely to occur. During the session, if participants forget or are unsure of what a certain shot type means, they are able to click on the question mark next to the shot answer for a description. Participants are advised that the timer will still run even after selecting the question mark. The following figures provide examples of the images
participants are shown when they click the selected question mark. For a detailed account of all the images shown, please refer to the Appendix.

Figure 3.7: The screen that appears when the help for smash shot is selected

Figure 3.8: The screen that appears when the help for drop shot is selected
Once participants have selected their answers for shot type and location placement, they would select ‘Next’ and reach the final form for this question.

![Answer Recorded](image)

**Figure 3.9: The answer screen for the SATB**

Here, participants are able to view the answer to the previous question as many times as they would like without a penalty to their time. Participants are advised that as soon as they click ‘Next’ on the Answer selection screen (Figure 3.6), the timer stops and won’t activate again until they select ‘Answer QX’ for the subsequent questions (where X is the successive question number). The program then repeats for the next four questions (Figure 3.5 – Figure 3.9). Upon completion of the final question (Q5), participants are shown their results for that session (Figure 3.10). Here, participants are shown:

- Their selection for shot type and location placement for each question.
- The correct response.
- The score they obtained for that question.
- The total score they obtained for the session.
- The total time they required for that session.
Finally, selecting the ‘End’ button exits the program, saves their results to a hidden Excel spreadsheet, and closes Excel.

### 3.2.4 How Scores Are Calculated on the SATB

Scores on the SATB were calculated with the assistance of expert coaches and trainers. The following table explains how the scoring system for the SATB operates.
Table 3.3: How scores are obtained on the SATB program

<table>
<thead>
<tr>
<th>Shot Type</th>
<th>Score obtained</th>
</tr>
</thead>
<tbody>
<tr>
<td>(a) When the correct shot type is selected</td>
<td>2</td>
</tr>
<tr>
<td>(b) When an incorrect but possible shot type is selected</td>
<td>1</td>
</tr>
<tr>
<td>(c) When an incorrect shot type is selected</td>
<td>0</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Location Placement</th>
<th>Score obtained</th>
</tr>
</thead>
<tbody>
<tr>
<td>(a) When the correct location placement is selected</td>
<td>2</td>
</tr>
<tr>
<td>(b) When an incorrect but possible location placement is selected</td>
<td>1</td>
</tr>
<tr>
<td>(c) When an incorrect location placement is selected</td>
<td>0</td>
</tr>
</tbody>
</table>

Points on the SATB were awarded on a 2-1-0 system. 2 points were awarded when the correct shot type or location placement was selected. For example: when the participant selects smash shot as an answer, and the correct answer is smash shot, then they would be awarded 2 points. This was considered outcome (a).

Outcome (b) occurs when an incorrect shot type/location placement is selected, but the answer selected may have occurred in a different situation. As an example, consider this situation: the participant selects smash shot because the sequence they are viewing has the player standing in an over arm forehand position. The player, however, executes a drive shot. In these situations, the participant would be awarded 1 point for having selected a possible outcome even though it didn’t occur this time around. These types of situations were decided with the assistance of three different experts who deemed certain questions plausible as having multiple plausible answers. Similarly, with assistance from the experts, some sequences were awarded 1 point even for incorrect location selections, as long as they fit certain criteria for that sequence. Where applicable, 1 point was awarded for a location
selection that was adjacent to the correct answer. For example (refer to Table 3.3) if the player selected TL (top left) and the correct answer was TM (top middle), then they would be awarded 1 point. This system didn’t occur for every question, only those deemed appropriate by the experts. 

Outcome (c) occurs when a participant selects an incorrect shot type/location placement and is awarded 0 points. This indicates that their answer has no relation to the correct response, hence not falling into the category for outcome (b). Finally, the participants score on the program is compared with their time according to the following formula.

\[
\text{SATB SCORE} = \frac{21.8}{\text{TIME}} \times \text{SCORE} \quad (4.18)
\]

Here, \(\text{TIME}\) is the combined time it took participants to answer all ten questions regarding shot type and shuttle location. The value of 21.8 was based on the Jorgensen, Garde, Laursens and Jensen (2002) study “Using mouse and keyboard under time pressure: preferences, strategies and learning” (a click response time = 1.1±0.08 s), in conjunction with the experts’ opinion that it would take two seconds to select both location and shot type. \(\text{SCORE}\) is the combined score of each correct response from the ten questions. Therefore the maximum score an individual can acquire on the SATB, assuming all questions are answered correctly, is 40.

### 3.2.5 Designing the Knowledge Measures Test

The majority of the experiments asked participants to place themselves into the skill level category of play they felt they belonged (beginner, intermediate or advanced). For the remaining experiments, where the researchers decided the group placement (or in the event
the participants were not sure of their group), the Knowledge Measures Test (KMT) was applied to determine skill level. The purpose of the KMT was to examine the participants’ knowledge and game understanding of badminton. It did not measure their actual in game performance (this was left to the video recordings for certain experiments). The KMT was based on a simplified version of McGee and Farrow’s (1987) book “Test questions for physical education activities.” This book provides a series of questions that students would answer (multiple choice) about a certain sport to determine their game understanding of that sport. The KMT was designed to test each participant’s knowledge and understanding of different shot types used in badminton. Participants were timed on how quickly they could; (a) match up a shot type with a description and (b) match up an image with a shot type. The following section will explain these components of the KMT in detail.

3.2.6 The KMT’s Functions

When participants initiate the program, they are prompted to click the start button presented in the center of the spread sheet. Responses for the program are sent to Sheet3 (hidden) of the excel file. Upon selecting the ‘click to start’ button, the description screen appears with information regarding the current version and model of the SATB.

![Knowledge Measures Test](image)

Figure 3.11: The information screen of the KMT program
Upon clicking ‘start,’ the user detail screen appears (refer to Figure 3.12). Here, participants are asked to enter their name and gender. This is so we can compare their results on the KMT with their results on the SATB.

![User form to enter participant's details on the KMT]

Figure 3.12: The user form to enter in the participant’s details on the KMT

Pressing ‘next’ initiates Section A of the KMT. The following figures provide an example of the type of questions asked on the KMT. For a detailed account of all the questions on the KMT, please refer to the Appendix 9.5.

![Sample question for Section A of the KMT]

Figure 3.13: A sample question for Section A of the KMT
For the experiments where we used the KMT as a measure to determine group allocation, the following scoring system was applied; participants were awarded 1 point for every correct answer, and 0 points for every incorrect answer. Time was not a component to base scores on the KMT. Participants who received a score from 0 – 7 were placed in the beginner group, participants who received a score of 8 – 11 where placed in the intermediate group, and participants who received a score greater than 12 were placed in the advanced group. Take note that these scores are simply a measure of participants’ knowledge and understanding of the game. Actual in game performance was measured using the SATB and video recordings.

### 3.3 Repeated Measures Analysis

This section covers the repeated measures analysis of this dissertation, which is used extensively in Chapter 4. To begin, additive and non additive models for a repeated measures analysis are discussed. This is followed by the various assumptions that must be satisfied in order to make inferences about the results of the analysis. Finally, the procedure for conducting a repeated measures ANOVA is described in relation to obtaining a treatment
effect. It should be noted that the methodology described in this section has been extracted from Girden (1992) and Stevens (1992).

3.3.1 Introduction

When dealing with experimental designs, two basic objectives are to: (a) eliminate systematic bias and (b) reduce error variance. To reduce the within group (error) variance a number of statistical methods may be utilised, for example, applying analysis of covariance (ANCOVA) or through blocking variables. Here, blocking refers to the arrangement of the experimental units into groups or blocks that are similar to one another. For example, consider an experiment which examined the effects a new drug to combat depression on a group of patients suffering from severe conditions of stress and anxiety. There may be two levels of treatment, i.e. drug and placebo, administered to male and female patients. Here, the sex of the patient is a blocking factor accounting for treatment variability between males and females. As such, the variability between blocks is removed from the within-variability, yielding a much more sensitive test.

In a repeated measures design, “blocking is carried to its extreme. That is to say, we are blocking on each subject. Thus, the variability among the subjects due to individual differences is completely removed from the error term” (Stevens, 1992). This in turn makes repeated measure designs much more powerful than completely randomised designs, where different subjects are randomly assigned to the different treatments. The simplest example of a repeated measures design is when the same subjects are measured repeatedly (pre-testing and post-testing) on a dependent variable with an intervening treatment. With this design, the subjects act as their own controls. Schematically, Figure 4.1 provides an example of this scenario.
Note that when performing a repeated measures analysis there are a number of different techniques the researchers can utilise, including ANOVA, t-statistics and within subject modelling, and mixed modelling. This dissertation will cover the ANOVA aspects of a univariate repeated measures design because it is the most appropriate technique to use in relation to the research design (refer to Chapter 5). For additional information on the other forms of repeated measures analysis, please refer to Stevens (1992).

<table>
<thead>
<tr>
<th>Treatments</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>...</th>
<th>k</th>
</tr>
</thead>
<tbody>
<tr>
<td>Subjects</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>:</td>
<td>:</td>
<td>n</td>
</tr>
</tbody>
</table>

Figure 3.1: An example of a repeated measures design in its simplest form

Generally, there are two options available when conducting repeated measures ANOVA: an additive model or an interactive (nonadditive) model. The differences between the two models are of no practical consequences for a single factor study, but they are relevant for more complex situations.

3.3.2 The Additive Model

One reason to why a score differs from the grand mean is that the score results from the summative effect of a particular fixed ratio, organism (or participant), and random error or unexplained factors affecting the organism at that time. In statistics, an additive model for a repeated measures ANOVA is given by:

\[ Y_{ij} - \mu = \alpha_j + \pi_i + \epsilon_{ij} \]  
(3.1)
where $Y_{ij}$ is the score of the $i$th participant (the first, etc.) in the $j$th treatment; $\mu$ is the population grand mean of response rates under all fixed ratios; $\alpha_j$ is the constant, fixed effect on rate of responding of the $j$th ratio ($\mu_j - \mu$); $\pi_i$ is the effect of the $i$th participant on the response rate ($\mu_i - \mu$); and $\varepsilon_{ij}$ is the random error of the $i$th participant under the $j$th fixed ratio ($Y_{ij} - \mu$).

Given the stipulation that $\sum \alpha_j = 0$, the organism effects ($\pi_i$) are assumed to be independent of each other and to be normally distributed, with a mean of 0 and variance equal to $\sigma^2_\pi[N(0, \sigma^2_\pi)]$. Similarly, the random, experimental errors ($\varepsilon_{ij}$) are assumed to be independent of the organism effects and of each other and to be normally distributed, with a mean of 0, and variance of $\sigma^2_\varepsilon[N(0, \sigma^2_\varepsilon)]$. This model is known as the additive model because it assumes the effect of each treatment is constant for each organism; the effects simply add to organism effects.

### 3.3.3 The Nonadditive Model

The nonadditive model, also known as the interactive model, is similar in nature to the additive model in that it proposes that a score may differ from the grand mean for the reasons mentioned above, with the addition that the effect of a particular participant will interact with that of the particular fixed ratio. In statistics, a nonadditive model for a repeated measures ANOVA is given by:

$$Y_{ij} - \mu = \alpha_j + \pi_i + \pi_\alpha_{ij} + \varepsilon_{ij} \quad (3.2)$$
with the new term, \( \pi \alpha_{ij} \), referring to the participant by fixed ratio interaction \((Y_{ij} - \mu_i - \mu_j + \mu)\): variability that remains after the unique effect of the participant and fixed ratio have been removed.

Similar to the additive model, \( \Sigma \alpha_j = 0; \pi_i \) and \( \varepsilon_{ij} \) are independent, normally distributed, with means equal to 0, and the respective distribution variances are \( \sigma_\pi^2 \) and \( \sigma_\varepsilon^2 \). The random variable \( \pi \alpha_{ij} \) of each organism is independent from each of the others, but not from different treatment levels of the same organism. These are assumed to sum to 0 for the same organism and to be normally distributed, with a mean of 0 and variance equal to \( [(J - 1)/J] \sigma^2_{\pi\alpha} \).

### 3.3.4 Assumptions

There are several assumptions of a repeated measures ANOVA which must be satisfied in order to make inferences about the coefficients derived from the model. These assumptions are listed below.

**A1. Independence:** The observations should be independent of one another. Dependence among the observations is measured by: \( R = (\text{MS}_b - \text{MS}_w)/(\text{MS}_b + (n - 1) \text{MS}_w) \), where \( \text{MS}_b \) and \( \text{MS}_w \) are the numerator and denominator of the F statistic and \( n \) is the number of subjects per group.

**A2. Homogeneity of variance:** All random variables in the sequence or vector have the same finite variance and is uncorrelated with every other variable.

**A3. Sphericity:** \( C^{'}\Sigma C = tI \). Here, \( C \) is a matrix of \((J - 1)\) independent or orthogonal contrasts among the means that have normalised, \( \Sigma \) is the population variance-covariance matrix,
C' is the transpose of C, τ is a constant and I is an identity matrix with 1.00s on the diagonal and 0s along the off-diagonal. This assumption requires that variances of differences for all treatment combinations be homogeneous.

**A4. Normality:** The data are normally distributed in the population

### 3.3.5 The Analysis

The analysis of sources of variability between scores and the grand mean proceeds with the estimations of each component. Hence, the grand mean is estimated by \( \bar{Y}_g \), which is the mean of all scores. The effect of each fixed ratio, \( \alpha_j \), is estimated by the difference between each fixed-ratio mean and the grand mean, \( \bar{Y}_j - \bar{Y}_g \). The effect of each participant, \( \pi_i \), is estimated by the difference between each participant’s mean and the grand mean, \( \bar{Y}_i - \bar{Y}_g \), which reflects differences among the subjects (also known as *between-subjects*). The interaction component, \( \pi \alpha_{ij} \), is estimated by \( Y_{ij} - \bar{Y}_i - \bar{Y}_j + \bar{Y}_g \). Random error, \( \epsilon_{ij} \), would be estimated by \( Y_{ij} - \bar{Y}_i \), and is also known as *within-subjects*, reflecting variability within each subject’s performance. When this analysis is performed on all scores and all differences are squared and summed, we arrive at a working model to determine whether the rates of responding under the four fixed ratios differ or are statistically alike:

\[
SS_T = SS_S + SS_A + SS_{SA}
\]  

(3.3)

Here, \( SS_T \) is equal to the sum of squared deviations of all scores from the grand mean, \( SS_S \) is the sum of squared deviations of subject means from the grand mean, \( SS_A \) is the sum of
squared deviations of fixed ratio means from the grand mean, and \( SS_{SA} \) represents the interaction.

<table>
<thead>
<tr>
<th>Source</th>
<th>SS</th>
<th>df</th>
<th>MS</th>
<th>F</th>
</tr>
</thead>
<tbody>
<tr>
<td>Subjects (S)</td>
<td>( J \sum [(Y_{i} - \bar{Y}_g)^2] )</td>
<td>( n_j - 1 )</td>
<td>( SS_S/n_j - 1 )</td>
<td>–</td>
</tr>
<tr>
<td>Intervals (A)</td>
<td>( n \sum [(Y_{ij} - \bar{Y}_g)^2] )</td>
<td>( J - 1 )</td>
<td>( SS_A/J - 1 )</td>
<td>( MS_A/MS_{res} )</td>
</tr>
<tr>
<td>Residual</td>
<td>( SS_T - SS_S - SS_A )</td>
<td>(( n_j - 1 )(( J - 1 ))</td>
<td>( SS_T/(n_j - 1)(J - 1) )</td>
<td>–</td>
</tr>
<tr>
<td>Total</td>
<td>( \sum [(Y_{ij} - \bar{Y}_g)^2] )</td>
<td>( \Sigma(df) )</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 3.1: Summary of ANOVA for repeated measures on a single factor

Table 3.1 provides the sums of squared deviations, dfs, and the final \( F \) ratio. Because \( SS_{SA} \) is the measured variability after the other components have been removed from \( SS_T \), it is also known as residual SS (\( SS_{res} \)). The df for \( SS_{res} \) is given by the product of the df for subjects (\( S - 1 \)) and treatment (\( J - 1 \)). The \( F \) ratio (\( MS_A/MS_{res} \)) depends on the average values of the mean squares expected if a large number of MSs were determined or, in other words, the expected mean square, \( E(\text{MS}) \). The \( MS_S \) represents an estimated variance reflecting variability in overall performance between subjects. This variability will have two sources of variance: (i) due to the uniqueness of the individual and (ii) due to random error. Therefore, the expected \( MS_S \) is given by: \( E(\text{MS}_S) = J \sigma_\pi^2 + \sigma_\varepsilon^2 \). If the fixed ratio does not affect the rate of responding, variance due to this constant effect also contributes to \( E(\text{MS}_A) \), as does random error. Thus \( E(\text{MS}_A) = n \sum \alpha_j^2/(J - 1) + \sigma_\pi^2 + \sigma^2_\varepsilon \). Finally, the expected value for the residual, \( E(\text{MS}_{res}) = \sigma_\pi^2 + \sigma^2_\varepsilon \), is a reflection of subject-treatment interactions. As a summary:

\[
E(\text{MS}_S) = J \sigma_\pi^2 + \sigma_\varepsilon^2 \quad (3.4)
\]
\[
E(\text{MS}_A) = n \sum \alpha_j^2/(J - 1) + \sigma_\pi^2 + \sigma^2_\varepsilon. \quad (3.5)
\]
\[
E(\text{MS}_{res}) = \sigma_\pi^2 + \sigma^2_\varepsilon \quad (3.6)
\]

The magnitude of an effect of an independent variable can be determined by forming an \( F \) ratio, where the denominator represents an estimation of the random error, and the numerator contains an additional component to reflect systematic variability due to the
independent variable. Using our equations from (3.6), the magnitude of the treatment effect is therefore represented by:

\[ \frac{E(\text{MS}_A)}{E(\text{MS}_{\text{res}})} = \frac{n\sum \alpha_j^2/(J - 1) + \sigma_{\alpha}^2 + \sigma_c^2}{\sigma_{\alpha}^2 + \sigma_c^2} \]  

(3.7)

The only difference between the denominator and numerator lies in the treatment component. All \( F \) ratios are formed along these lines, with one difference between the denominator and numerator:

\[ F = \frac{\text{hypothesised treatment effect} + \text{random error}}{\text{random error}} \]  

(3.8)

As such, if there is no treatment effect, the ratio would be approximately equal to 1. When there is a treatment effect, the ratio should exceed 1.

### 3.4 Neural Networks

This section covers the neural networks component of this dissertation, which is covered extensively in Chapter 5. Section 3.4.1 provides a brief introduction to this section. The next section covers the mathematical equations used to model a neural network. Then, Section 3.4.3 discusses the learning procedure for a neural network paradigm. Note that the methodology described in this section has been derived from SPSS Inc (2007b).
3.4.1 Introduction

A neural network (NN) is a mathematical or computational model that is inspired by the structure and/or functional aspects of biological neural networks. Derived from studies of brain function, the definition of a neural network varies depending upon the field in which it is being examined. In a statistical sense, a neural network applies to a loosely related family of models, characterised by a parameter space and flexible structure (SPSS Inc., 2007b). A neural network consists of an interconnected group of artificial neurons, and it processes information using a connectionist approach to computation. In most cases, a NN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase. They are usually used to model complex relationships between inputs and outputs or to find patterns in data.

3.4.2 The Neural Network Model

Neural networks are made up of numerous artificial neurons (modelled after biological neurons), each having their own associated weight. Here, a network refers to the interconnections between the neurons in the different layers of each system, and a weight refers to the parameters that manipulate the data. The weights in most neural sets can be both positive and negative, therefore providing excitatory or inhibitory influences to each input. As each input enters the nucleus, it is multiplied by its weight. The nucleus then sums all these new input values, which gives the activation. If the activation is greater than the threshold value, the neuron outputs a signal. If the activation is less than the threshold value, the neuron outputs zero. This is typically called a step function.
The layers network through the mathematics of the system algorithms. The network function \( f(x) \) is defined as a composition of the other functions \( g_i(x) \). This can be conveniently represented as a network structure, with arrows depicting the dependencies between variables. A widely used type of composition is the \textit{nonlinear weighted sum}, where:

\[
  f(x) = K(\sum_i w_i g_i(x)).
\]  

(3.9)

Here, \( K \) (commonly referred to as the activation function) is some predefined function, such as the hyperbolic tangent.

In conducting the analysis for a NN, a common procedure is to apply the multilayer perceptron (MLP). The MLP procedure produces a predictive model for one or more dependent variables based on the values of the predictor variables. What makes a MLP unique is that each neuron uses a nonlinear activation function which was developed to model the frequency of action potentials, or firing, of biological neurons in the brain (Haykin, 1998). This function is modelled in several ways, but must always be normalizable and differentiable. The two main activation functions used in current applications are both sigmoids, and are described by:

\[
  \phi(y_i) = \tanh(v_i)
\]  

(3.10)

\[
  \phi(y_i) = (1 + e^{-v_i})^{-1}
\]  

(3.11)

Here, function 3.10 is a hyperbolic tangent which ranges from -1 to 1, while function 3.11 is equivalent in shape but ranges from 0 to 1. Here \( y_i \) is the output of the \( i \)th node (neuron) and \( v_i \) is the weighted sum of the input synapses.
3.4.3 Learning

In a NN design, learning refers to using a set of observations and a set of functions, \( F \), to solve a specific task. When the task is solved in some optimal sense, it can be represented as:

\[
 f^* \in F
 \]  \hspace{1cm} (3.12)

This entails defining a cost function \( C:F \rightarrow \mathbb{R} \) such that, for the optimal solution \( f^* \) can be represented by:

\[
 C(f^*) \leq C(f) \forall f \in F \]  \hspace{1cm} (3.13)

Here, no solution has a cost less than the cost of the optimal solution. The cost function, \( C \), measures how far away a particular solution is from an optimal solution for the problem to be solved. Learning algorithms search through the solution space to find a function that has the smallest possible cost.

For the MLP, learning occurs by changing connection weights after each piece of data is processed, based on the level of error in the output compared to the expected result (Haykin, 1998). This is an example of supervised learning, and is carried out through backpropagation, a generalization of the least mean squares algorithm in the linear perceptron.

The error in output node \( j \) in the \( n \)th data point can be represented by \( e_j(n) = d_j(n) - y_j(n) \), where \( d \) is the target value and \( y \) is the value produced by the perceptron. We then make corrections to the weights of the nodes based on those corrections which minimize the error in the entire output, given by:
The advantage of utilising a neural network is that it can approximate a wide range of statistical models without requiring the researcher to hypothesise in advance certain relationships between the dependent and independent variables (Heazlewood and Keshishian, 2010; SPSS Inc., 2007b). Instead the form of the relationship is determined during the learning process. The trade-off for this flexibility is that the synaptic weights of a neural network are not easily interpretable.

3.5 Discriminant Analysis

This section covers the discriminant analysis component of this dissertation, which is mentioned in Chapter 5. Section 3.5.1 provides a brief introduction to this section as well as describing the features of discriminant analysis. Then, in Section 3.5.2, the various assumptions that must be satisfied in order to make inferences about the results of the analysis are described. Section 3.5.3 discusses significance tests in relation to discriminant analysis. Finally, Section 3.5.4 discusses two methods of interpreting discriminant functions. Note that the methodology described in this section has been derived from Stevens (1992).

3.5.1 Introduction

Discriminant analysis (DA) is generally used for two purposes: (1) classifying subjects into groups on the basis of battery measurements, and (2) describing major differences among the groups in MANOVA. For example, a sports researcher may wish to investigate which
variables discriminate between novice and expert soccer players. For that purpose the researcher could collect data on numerous variables relating to different components of soccer players’ performance. Naturally, players will fall into one of the two skill level categories. DA could then be used to determine which variable(s) are the best predictors of the athletes’ skill level.

Two useful features of DA are: (1) parsimony of description, and (2) clarity of interpretation. DA can be quite parsimonious in its ability to describe groups. For example, when comparing 6 groups on 11 variables, using DA we may find that the groups differ mainly on only two major dimensions, i.e. the discriminant functions. Discriminant functions result when DA is used to break down the total between associations in MANOVA into additive pieces. It also has clarity of interpretation in the sense that separations of the groups along one function are unrelated to separation along a different function.

DA uses linear combinations of variables to distinguish groups, in a similar way to multiple regression. It is worth noting that both DA and multiple regression are mathematical maximisation procedures. If the dependent variables are denoted by \( y_1, y_2, ..., y_p \), then in discriminant analysis the row vector of coefficients \( a_1' \) is sought which maximises:

\[
\frac{a_1'Ba_1}{a_1'Wa_1}
\]

where \( B \) and \( W \) are the between and within sum of squares and cross-products matrices. The linear combination of the dependent variables involving the elements of \( a_1' \) as coefficients is the best discriminant function because it provides for maximum separation on the groups. The above equation corresponds to the largest eigenvalue \( \phi_1 \) of the \( BW^{-1} \) matrix. The next best discriminant, corresponding to the second largest eigenvalue of \( BW^{-1} \) (let = \( \phi_2 \)) involves the elements of \( a_2' \) as coefficients in the following ratio:
and is derived to be uncorrelated with the first discriminant function. The third discriminant function would be a linear combination of the dependent variables, derived to be uncorrelated from both the first and second functions, which provides the next maximum amount of separation. The $i$th discriminant function ($z_i$) then is given by $z_i = a_i'y$, where $y$ is the column vector of dependent variables. Finally, in obtaining the discriminant functions, the coefficients, $a_i$, are scaled so that $a_i'a_i = 1$ for each discriminant function. This allows for a unique solution to each discriminant function. It is also worth noting that if $k$ is the number of groups and $p$ is the number of dependent variables, then the number of possible discriminant functions will be the minimum of $p$ and $(k – 1)$.

3.5.2 Assumptions

There are several assumptions of DA which must be satisfied in order to make inferences about the coefficients derived from the model. These assumptions are listed below.

A1. Normality: The data are normally distributed in the population

A2. Homogeneity of variance: All random variables in the sequence or vector have the same finite variance and are uncorrelated with every other variable.

A3. Correlations between means and variances: The means for variables across groups should not correlate with the variances (or standard deviations). Intuitively, if there is large variability in a group with particularly high means on some variables, then those high means are not reliable. However, the overall significance tests are based on pooled
variances, that is, the average variance across all groups. Thus, the significance tests of
the relatively larger means (with the large variances) would be based on the relatively
smaller pooled variances, resulting erroneously in statistical significance.

A4. The matrix ill-conditioning problem: The variables that are used to discriminate
between groups must not be completely redundant. If any one of the variables is
completely redundant with the other variables then the matrix is said to be ill-
conditioned, and cannot be inverted.

A5. Tolerance values. In order to guard against matrix ill-conditioning, constantly check
tolerance value for each variable. This tolerance value is computed as $1 - R^2$ of the
respective variable with all other variables included in the current model.

3.5.3 Significance Tests for Discriminant Analysis

The test procedure for determining how many discriminant functions are significant is a
residual procedure. First, all of the eigenvalues (also known as roots) are tested together,
using:

$$V = \left[ N - 1 - \frac{(p + k)}{2} \right] \cdot \sum_{i=1}^{r} \ln(1 + \phi_i)$$  \hspace{1cm} (3.16)

where $V$ is a statistic used for testing the significance of $\Lambda$ and $r$ is the number of possible
discriminant functions. Note that it has been shown that Wilk’s $\Lambda$ may be expressed as the
following function of eigenvalues ($\phi_i$) of $BW^{-1}$ (Tatsuoka, 1971):
If the $V$ statistic is significant (from equation 4.16), then the largest root is removed and a test made of the remaining roots (the first residual) to determine if this is significant. If the first residual ($V_1$) is not significant, then we can conclude that only the first discriminant function is significant. If the first residual is significant, then we can examine the second residual, i.e., the $V$ statistic with the largest two roots removed. In general, when the residual after removing the first $s$ roots is not significant, we can conclude that only the first $s$ discriminant functions are significant.

3.5.4 Interpreting the Discriminant Functions

When interpreting the discriminant functions, there are generally two utilised methods:

1. **Examining the standardised coefficients.** These are obtained by multiplying the raw coefficients for each variable by the standard deviation for that variable.

2. **Examining the discriminant functions variable correlation.** This is acquired through examining the correlations between each discriminant function and each of the original variables.

Regardless of which method is used for interpreting the discriminant functions, it is the largest (absolute value) coefficients or correlations that are used for interpretation. It should be noted that the above two methods can therefore provide different results, i.e. some
variables may have low coefficients and high correlations while other variables may have 
high coefficients and low correlations. In deciding which method to use, consider the 
following quote by Tatsuoka (1973): “both approaches are useful, provided we keep their 
different objectives in mind.” That is to say, we would use the correlations for substantive 
interpretation of the discriminant functions, but use the coefficients to determine which of the 
variables are redundant given that the others are in the set.
Chapter 4

Visual Based Instructions

In this chapter, the SATB program is introduced and we discuss how visual based instructions can be incorporated into the traditional method of training. In Section 4.1 a brief introduction to visual based learning is given. Section 4.2.1 details an experiment we conducted on a group of badminton players using visual based instructions. Here, participants were given either the traditional method of training or the SATB method of training, with their performance being recorded weekly to examine any difference(s) in skill level. In Section 4.2.1.3, a repeated measures ANOVA is utilised to examine the change in performance over the six weeks of experimentation. Then, in Section 4.2.1.4, the weekly SATB scores are provided, with the results emphasising any differences between groups. Section 4.2.2 details the problems and difficulties we encountered with this experiment and the methods we used to rectify these problems. Finally, Section 4.2.3 explains the second experiment we conducted regarding visual based instructions, taking into consideration the problems we encountered previously. All experiments conducted have been approved by the RMIT Human research committee (refer to Appendix 9.7), with participants giving consent (refer to Appendix 9.7) to be involved with the study.
4.1 Introduction

Badminton is the world’s fastest racket sport, with a top speed of 421 km/h. The importance of swift decision making has, therefore, become imperative for top level badminton players, and the need for athletes to train and improve their ability to instantaneously determine the best course of action for any situation has become essential. However, improving an individual’s capacity for decision making is more complex and detailed (Macquet and Fleurance, 2007; Huynh and Bedford, 2010) than improving physical abilities such as strength or agility. In attempting to optimise an athlete’s competency, the development of a training program that incorporates the improvement of reaction time and awareness in juxtaposition with physical performance would be ideal (Huynh and Bedford, 2010).

A number of studies have been conducted which examine the effects of visual based instructions (Abernethy, 1987; Abernethy and Russell, 1987; Blomqvist et al., 2001), however minimal research has been carried out to examine the effectiveness of a VBT method that focuses on skill acquisition. Typically, coaches and trainers place heavy emphasis on the movement execution component of the traditional training method (Blomqvist, Luhtanen and Laakso, 2001) and tend to overlook the significance of the cognitive processes of perception and decision-making. This is unfortunate, however, considering that the quality of decision-making in game situations is often as important as the execution of motor skills (Blomqvist et al., 2001; Thomas, 1994). While it is essential that athletes continuously train and improve their physical capabilities (Chin, Wong, So, Siu, Steininger and Lo, 1995; Fahlstrom, Lorentzon and Alfredson, 2002), it seems evident that the cognitive components of badminton must not be underemphasised when training athletes (Blomqvist, Luhtanen and Laakso, 2001).
It was suggested in a recent paper (Huynh and Bedford, 2010) that in attempting to optimise skill proficiency; badminton players need to incorporate a combination of both physical and cognitive aspects into their training program. The researcher developed a new VBT method of identifying and improving a badminton player’s reaction time and awareness; the Skills Acquisition Trainer for Badminton. Utilising this program, we attempted to improve the reaction, awareness and anticipatory skills of badminton players over a time frame of ten weeks.

4.2 Skills Acquisition in Badminton: A Visual Based Approach to Training

The purpose of our first study was to develop a visual based training program that aims to improve reaction time and awareness in badminton players. Particular emphasis was placed on a player’s ability to estimate and predict shuttle location. Using this program, we attempted to identify the player’s anticipatory skill and, ultimately, to improve his/her in-game performance and decision making.

In examining visual based instructions, we designed two separate experiments based around the SATB program. The first was heavily focused on indentifying the participants’ knowledge and understanding of badminton concepts, strategies and techniques. The second was designed specifically to record and examine each participant’s improvement over time using the SATB. Originally, there was no intention of conducting two separate experiments. However, a number of difficulties were encountered (refer to Section 4.2.2) with the original design which in turn led to a follow up study. The following sections will describe the methodology used for the first experiment, including the difficulties and problems that we
faced. Finally, this chapter will conclude with an explanation of the methodology utilised in the second experiment.

4.2.1 Experiment 1

The aim of the first experiment was to; (a) examine the participants’ knowledge and understanding of badminton concepts, strategies and techniques and (b) improve their cognitive performance regarding badminton via a visual based learning program. Knowledge and game understanding was examined using the SATB program over an experimental period of five weeks.

4.2.1.1 Participants

The participants for this study came from two separate groups: (i) athletes from the Australian Olympic Badminton team ($n = 3$) and (ii) university students ($n = 13$) from RMIT University. All university participants had prior experience in playing badminton, with most participants having played in high school round robins. Athletes from the Australian Olympic team in conjunction with some members from RMIT served as the experimental group ($n = 8$) and were assigned to the treatment group (age mean = 23 years, $SD = 13.46$ years). The treatment group consisted of five females and three males. University students were randomly assigned to either the treatment group (with the Olympic team) or the control group ($n = 8$, age mean = 18.63 years, $SD = 3.78$ years). The control group consisted of four females and four males. RMIT students were recruited from the University’s badminton club with the assistance of the club president. Participants all signed a consent form to be a part of
the experiment (refer to the appendix) with the understanding that they would remain anonymous for any reports or publications.

4.2.1.2 Measures

The tool that we utilised to examine decision making and reaction time for our participants was the SATB program (refer to the method section for a detailed explanation of the SATB). As a summary, the SATB can be described as a VBT program that consists of ten visual questions. Participants would watch different clips of badminton rallies being played, with sequences running for 2 to 30 seconds. Each clip was followed by a still frame for 1 second, after which participants would be asked to answer (on screen) what type of shot was about to take place (e.g. drop shot) as well as the location that shot would be played (e.g. middle right).

Prior to administering the SATB, participants were given a Knowledge Measures Test (KMT) to evaluate their comprehension and awareness of badminton rules, strategies and techniques. The KMT was a simplified version of McGee and Farrow’s (1987) book “Test questions for physical education activities,” and was designed to test participants’ knowledge of the different shot types used in badminton. Participants were timed to determine how quickly they could match up a shot type with a description of a shot from eight choices. Refer to the method section for a detailed account of the KMT.

4.2.1.3 Testing Procedure

Participants were tested before and after the treatment period for shot type knowledge and speed using the KMT. Participants in the treatment group were also administered the SATB once a week for five weeks to examine their awareness, decision making, and response
time. Participants in the control group were only given the KMT to complete twice (in week one and week five). Participants’ performance in-game was also recorded on a weekly basis to examine if they could apply the skills acquired from the SATB in a live match. These video recordings were filmed at the Melbourne Sports and Aquatic Center (MSAC) for the Olympic team and the Aqualink Leisure Centre for the university students.

The SATB was based on a weighted system, with the assistance of expert judgement and opinion (coaches and trainers who have played and taught for many years). The experts are shown the video sequences that are on the program and asked to distribute points to certain shot types. Two points were awarded for the correct shot type response, one point for other possible shot types in that situation, and no points for any other shot types. Similarly, two points were given if participants chose the correct location the shuttle would land, one point if it is adjacent to the shuttle location, and no points for any other location selection. Participants were also timed from the point the rally sequence finished to the input of their response to shot type and location, in order to examine response time. With ten questions per session, the maximum score a participant could acquire was 40, with an optimal time of 21.8 seconds. Hence, the equation for the SATB score is given by:

\[
SATB = \frac{21.8}{TIME} \times SCORE
\]  
(4.1)

From equation 1, \( TIME \) is the combined time it took participants to answer all ten questions regarding shot type and shuttle location. The value of 21.8 was based on the Jorgensen, Garde, Laursens and Jensen (2002) study “Using mouse and keyboard under time pressure: preferences, strategies and learning” (a click response time = 1.1±0.08 s), in conjunction with expert opinion that it would take two seconds to select both location and shot type. \( SCORE \) is the combined score of each correct response from the ten questions.
Therefore the maximum score an individual can acquire on the SATB is 40. Upon completion of the final SATB session (week five) participants were given the KMT once again to examine any change in badminton knowledge and awareness as a result of utilising the SATB.

### 4.2.1.4 Results

A repeated measures ANOVA for the SATB was carried out to examine the change in scores over the five weeks of experimentation. Assumptions of normality, homogeneity of variance and sphericity ($\chi^2(5) = 9.294, p = 0.102$) were met. Results showed that differences between conditions were unlikely to have arisen by sampling error ($F(3,21) = 17.23, p < .001$); an overall effect size of 0.77 (partial $\eta^2$) showed that 77% of the variation in score can be accounted for by improvement over time. A second repeated measures ANOVA was carried out to examine the significance between time and score for both the KMT and SATB. Results revealed a significant improvement in time on the KMT ($F(1,7) = 9.42, p = 0.02$) as well as the SATB ($F(3,21) = 15.12, p < .001$). Table 4.1 shows the mean and standard deviations of the three variables: score, time and SATB score across the five weeks of experimentation.

<table>
<thead>
<tr>
<th></th>
<th>Score</th>
<th></th>
<th>Time</th>
<th></th>
<th>SATB Score</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$M$</td>
<td>$SD$</td>
<td>$M$</td>
<td>$SD$</td>
<td>$M$</td>
<td>$SD$</td>
</tr>
<tr>
<td>Week 1</td>
<td>7.63</td>
<td>2.72</td>
<td>276.12</td>
<td>94.64</td>
<td>0.69</td>
<td>0.39</td>
</tr>
<tr>
<td>Week 2</td>
<td>8.13</td>
<td>5.06</td>
<td>192.21</td>
<td>31.35</td>
<td>0.98</td>
<td>0.63</td>
</tr>
<tr>
<td>Week 3</td>
<td>10.75</td>
<td>3.85</td>
<td>94.44</td>
<td>37.04</td>
<td>3.21</td>
<td>2.07</td>
</tr>
<tr>
<td>Week 4</td>
<td>11.75</td>
<td>3.92</td>
<td>63.65</td>
<td>30.77</td>
<td>4.81</td>
<td>2.89</td>
</tr>
<tr>
<td>Week 5</td>
<td>12.25</td>
<td>3.33</td>
<td>49.94</td>
<td>20.67</td>
<td>6.94</td>
<td>5.30</td>
</tr>
</tbody>
</table>

Table 4.1: The mean and standard deviations of the three variables: score, time and SATB score over five weeks of experimentation.
Similarly, a repeated measures ANOVA was carried out to examine the change in scores on the KMT across the experimental and control groups. Results revealed a significant interaction ($F(1,7) = 143.36, p < .001$) between the two groups. Table 4.2 shows the mean and standard deviations of the KMT results (both pre and post) for the experimental and control groups. Figure 4.1 shows that the experimental group improved their badminton knowledge significantly ($p < .001$) compared to the control group.

<table>
<thead>
<tr>
<th></th>
<th>Pre Scores</th>
<th>Post Scores</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>M</td>
<td>SD</td>
</tr>
<tr>
<td>Treatment</td>
<td>4.50</td>
<td>1.77</td>
</tr>
<tr>
<td>Control</td>
<td>4.75</td>
<td>1.83</td>
</tr>
</tbody>
</table>

Table 4.2: The mean and standard deviations of the KMT results for our experimental and control groups.

![Figure 4.1: Pre and post test scores on the KMT for the experimental and control groups](image)

4.2.2 Difficulties Encountered

In regards to the first experiment, a number of difficulties and concerns arose upon completion of the study. Firstly, it was believed the sample size ($n = 13$) was far too small to
state a conclusion even if significant results were obtained. This problem was easily solved by increasing the number of participants in the experiment. The follow up study therefore consisted of \( n = 41 \) participants (also obtained from the Australian Badminton team and various badminton clubs from around Melbourne).

The second problem related to the results obtained with the SATB. Participants were able to increase their SATB score over the five weeks of experimentation, which supported the hypothesis. However, upon closer examination of the results there was too much variance in the weekly mean scores. As an example, the mean SATB score for week 5 was 6.94 with a standard deviation of 5.30. Clearly, the skill level of participants in the experimental group varied significantly. Therefore, the participants were split into three categories for the follow up study: beginner \((N = 15)\), intermediate \((N = 16)\) and advance \((N = 10)\). With participants separated in this fashion, the researchers were able to clearly see the improvement across skill level over the experimental period for the participants (refer to Table 4.3).

Another problem related to participants randomly selecting answers. In the original design, participants were given 10 questions per session over five sessions. This system did not work so well, especially for participants with minimal interest in badminton. They would initiate the program effectively but lose interest from approximately question 7 onwards and just select any answer to complete the program as quickly as possible. As a counter measure, the SATB was modified to only consist of 5 questions per session. For the second study, experiments ran over 10 weeks (as opposed to five weeks) using a similar testing procedure. This meant that participants using the 5x10 design encountered the same number of questions as participants using the original 10x5 system. With these changes, participants were more inclined to complete the weekly sessions to the best of their ability and not give up and select random answers half way through the test.
4.2.3 Experiment 2

The aim of the second experiment was to use a repeated measures ANOVA to examine whether participants were able to improve their anticipatory skills over the ten weeks of experimentation. This second trial was necessary due to the difficulties faced from the first design (see above), but contained appropriate modifications to rectify these problems.

4.2.3.1 Participants

The second trial now consisted of 41 participants, divided into three skill level groups (refer to Section 4.2.2). The beginner group consisted of eleven females (age mean = 23.73 years, $SD = 3.44$ years) and four males (age mean = 23.00 years, $SD = 1.86$ years). The intermediate group consisted of nine females (age mean = 24.67 years, $SD = 8.56$ years) and seven males (age mean = 26.00 years, $SD = 5.86$ years). The advance group consisted of six females (age mean = 33.00 years, $SD = 13.27$ years) and four males (age mean = 33.50 years, $SD = 8.39$ years). The new participants were recruited from various badminton clubs around Melbourne. The necessary consent forms were also completed.

4.2.3.2 Measures

The SATB program that was introduced in the first experiment was reused for this study, save for a few minor modifications (refer to Section 4.2.2). In the original design, participants were given 10 questions per session over five sessions. The second version of the SATB program only consisted of 5 questions per session. For this experiment, the program was trialled over 10 weeks, which provided participants with the same number of questions asked in the 10x5 design of our first experiment.
4.2.3.3 Testing Procedure

The change to a 5x10 design also meant that the researchers had to change the equation for the SATB computation. With the 10x5 design, the maximum score a participant could acquire was 40, with an optimal time of 21.8 seconds. The original equation for the SATB score was given by:

\[ SATB = \frac{23.8}{TIME} \times SCORE \]  

(4.1)

However, with the change to the 5x10 system, this changed the maximum score a participant could receive to 20, with an optimal time of 11.9 seconds. Hence the SATB equation for the second experiment was given by:

\[ SATB = \frac{11.9}{TIME} \times SCORE \]  

(4.2)

Refer to the method section for a full explanation of how this equation is derived. As a summary, the SATB’s primary function was to measure participants’ responses, therefore their ability to estimate and predict shot types and direction in badminton. Participants would watch different clips of badminton rallies being played, with sequences running for 2 to 30 seconds. These were followed by a still frame for 1 second, after which participants would be asked to select what type of shot was about to take place (e.g. drop shot) as well as the location that shot would be played (e.g. middle right).

Participants who were not certain of their skill level were administered the KMT prior to experimentation to gauge shot type knowledge and speed. The KMT used in this
experiment was unaltered from the first study (see above). Participants’ performance in-game was still recorded on a weekly basis to examine whether they could apply the skills acquired from the SATB in a live match. These video recordings were filmed at the Melbourne Sports and Aquatic Center (MSAC) for the Olympic team and the Aqualink Leisure Centre for the university students and club members.

4.2.3.4 Results

The focus of the second experiment was to examine, utilising a repeated measures ANOVA, whether participants had improved their anticipatory skills over the ten weeks of experimentation. Assumptions of normality, homogeneity of variance and sphericity were met for all analyses. Results showed that differences between conditions were unlikely to have arisen by sampling error for the beginner ($F(9,126) = 59.19, p < .001$), intermediate ($F(9,135) = 79.2, p < .001$) and advanced ($F(9,81) = 88.88, p < .001$) groups. Refer to the table below. An overall effect size (partial $\eta^2$) showed that 81%, 84% and 91%, respectively, of the variation in score can be accounted for by improvement over time across the three groups. Figure 4.2 represents the change in score across the ten weeks of experimentation for the three skill level groups.

<table>
<thead>
<tr>
<th>Effect</th>
<th>$SS$</th>
<th>$df$</th>
<th>$MS$</th>
<th>$F$</th>
<th>$p$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Score</td>
<td>4909.55</td>
<td>9</td>
<td>545.51</td>
<td>196.48</td>
<td>&lt; 0.01</td>
</tr>
<tr>
<td>Score * Skill</td>
<td>279.11</td>
<td>18</td>
<td>15.51</td>
<td>5.59</td>
<td>&lt; 0.01</td>
</tr>
<tr>
<td>Error</td>
<td>949.54</td>
<td>342</td>
<td>2.78</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 4.3 Summary ANOVA table for score across skill level on the SATB.
Figure 4.2: The change in score for the SATB for the three skill level groups across the ten week experimental period

The above figure demonstrates the participants mean score on the SATB across skill level. It is worth noting that they all following a similar pattern, with participants generally improving their score every week. The exception to this was week 3 where all groups performed poorly. This suggests that the video sequences for these weeks were more difficult than previous weeks (e.g. sequences contained a lot of trick shot scenarios).

A second repeated measures ANOVA was carried out to examine the change in response time across the ten weeks of experimentation. Results showed that differences between conditions were unlikely to have arisen by sampling error for the beginner ($F(9,126) = 31.11, p < .001$), intermediate ($F(9,135) = 79.20, p < .001$) and advanced ($F(9,81) = 15.22, p = .001$) groups. Refer to the table below. An overall effect size (partial $\eta^2$) showed that
69%, 73% and 63%, respectively, of the variation in score can be accounted for by improvement over time across the three groups.

<table>
<thead>
<tr>
<th>Effect</th>
<th>SS</th>
<th>df</th>
<th>MS</th>
<th>F</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time</td>
<td>28902.50</td>
<td>9</td>
<td>3211.39</td>
<td>34.77</td>
<td>&lt; 0.01</td>
</tr>
<tr>
<td>Time * Skill</td>
<td>40349.47</td>
<td>18</td>
<td>2241.64</td>
<td>24.27</td>
<td>&lt; 0.01</td>
</tr>
<tr>
<td>Error</td>
<td>31586.18</td>
<td>342</td>
<td>92.36</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 4.4. Summary ANOVA table for time across skill level on the SATB.

Figure 4.3: Mean time on the SATB for the three skill level groups across the ten weeks of experimentation

Figure 4.3 represents the change in time across the ten weeks of experimentation for the three skill level groups. Table 4.5 shows the mean and standard deviations of the three variables: score, time and SATB score over the 10 weeks of experimentation.
<table>
<thead>
<tr>
<th></th>
<th>Score</th>
<th>Time</th>
<th>SATB Score</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$M$</td>
<td>$SD$</td>
<td>$M$</td>
</tr>
<tr>
<td>Beginner</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wk 1</td>
<td>2.67</td>
<td>1.68</td>
<td>89.54</td>
</tr>
<tr>
<td>Wk 2</td>
<td>6.13</td>
<td>1.60</td>
<td>61.59</td>
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<td>Wk 3</td>
<td>3.67</td>
<td>1.76</td>
<td>52.80</td>
</tr>
<tr>
<td>Wk 4</td>
<td>5.67</td>
<td>1.23</td>
<td>43.99</td>
</tr>
<tr>
<td>Wk 5</td>
<td>9.00</td>
<td>3.23</td>
<td>44.28</td>
</tr>
<tr>
<td>Wk 6</td>
<td>7.00</td>
<td>2.30</td>
<td>39.34</td>
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<td>10.07</td>
<td>2.49</td>
<td>31.48</td>
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<td>11.80</td>
<td>3.28</td>
<td>22.60</td>
</tr>
<tr>
<td>Wk 10</td>
<td>14.13</td>
<td>3.00</td>
<td>18.31</td>
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<tr>
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<td></td>
<td></td>
</tr>
<tr>
<td>Wk 1</td>
<td>8.44</td>
<td>1.79</td>
<td>72.34</td>
</tr>
<tr>
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<td>9.19</td>
<td>2.46</td>
<td>45.07</td>
</tr>
<tr>
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<td>6.63</td>
<td>2.16</td>
<td>38.24</td>
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<tr>
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<td>1.82</td>
<td>27.57</td>
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<td>2.44</td>
<td>30.79</td>
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<tr>
<td>Wk 6</td>
<td>11.06</td>
<td>1.65</td>
<td>24.98</td>
</tr>
<tr>
<td>Wk 7</td>
<td>12.31</td>
<td>1.70</td>
<td>23.14</td>
</tr>
<tr>
<td>Wk 8</td>
<td>13.63</td>
<td>1.45</td>
<td>21.08</td>
</tr>
<tr>
<td>Wk 9</td>
<td>15.19</td>
<td>0.91</td>
<td>19.43</td>
</tr>
<tr>
<td>Wk 10</td>
<td>17.25</td>
<td>1.00</td>
<td>16.05</td>
</tr>
<tr>
<td>Advance</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Wk 1</td>
<td>10.40</td>
<td>2.59</td>
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<td>1.58</td>
<td>32.96</td>
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<td>1.66</td>
<td>28.24</td>
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<tr>
<td>Wk 4</td>
<td>7.90</td>
<td>1.10</td>
<td>26.52</td>
</tr>
<tr>
<td>Wk 5</td>
<td>14.30</td>
<td>1.89</td>
<td>22.60</td>
</tr>
<tr>
<td>Wk 6</td>
<td>14.80</td>
<td>1.03</td>
<td>19.91</td>
</tr>
<tr>
<td>Wk 7</td>
<td>16.60</td>
<td>0.84</td>
<td>18.30</td>
</tr>
<tr>
<td>Wk 8</td>
<td>17.50</td>
<td>0.53</td>
<td>16.79</td>
</tr>
<tr>
<td>Wk 9</td>
<td>18.50</td>
<td>0.53</td>
<td>15.65</td>
</tr>
<tr>
<td>Wk 10</td>
<td>17.90</td>
<td>1.37</td>
<td>14.45</td>
</tr>
</tbody>
</table>

Table 4.5: The mean and standard deviations of the three variables: score, time and SATB score across the three groups.

This table summarises; (a) Score, (b) Response time and, (c) SATB score. Noticeably, there was a large decrease in score for all skill level groups for week 3 and week 4 of experimentation. This suggests that the video sequences for these weeks were more difficult.
than previous weeks (e.g. sequences contained a lot of trick shot scenarios). The top four sequences from these two weeks were selected and placed in the training for week 9 and 10. Interestingly, participants performed much better the second time around. They were able predict the correct responses despite not having seen that sequence for 6 to 7 weeks.

As a summary, this chapter introduces the SATB and discusses two experiments that we conducted with the program. A major problem with the traditional method of training is that there is not enough emphasis on the cognitive aspects of skill development and decision making. The results from this chapter demonstrate that a visual based approach was effective in improving the cognitive skills of badminton players. The integration of the SATB into the traditional method should allow players to improve both their physical and mental badminton capabilities. For further detail on the application of these results, please refer to Chapter 7 (Summary and Conclusion).
Chapter 5

Discriminating Expertise

In this chapter, the validity of the SATB program in its ability to discriminate experts from novices is discussed. In Section 5.1, a brief introduction regarding discriminating expertise is given. Section 5.2 describes an experiment conducted to compare the effectiveness of neural networks and discriminant analysis for evaluating the SATB’s discriminating abilities. In section 5.3, the methodology for this experiment is provided. Finally, in section 5.4 the results are discussed for both the neural networks approach and discriminant analysis approach.

5.1 Introduction

In recent years, extensive research has been carried out to analyse the physiological and biomechanical factors that characterise racket sport athletes (Manrique and González-Badillo, 2003), especially with tennis and squash players. There is, however, limited data to assess which factors are desirable in competitive badminton (Manrique and González-Badillo, 2003; Huynh and Bedford, 2010). Despite its inclusion as an official sport in the 25th Olympic Games, research in the field of performance optimisation, mental and visual
training, and skill acquisition for badminton remains scarce (Blomqvist, Luhtanen and Laakso, 2001; Huynh and Bedford, 2010; Manrique and González-Badillo, 2003).

Previous research involving VBT has shown that the ability to detect and utilise advanced visual cues allows players to predict their opponent’s actions more accurately. A classic example of this can be found in Abernethy and Russell’s (1987) study regarding the differences between expert’s and novice’s ability to discriminate visual cues. The research suggested that novice badminton players were unable to detect information regarding advance cue sources, which is the ability that provides experts with superior anticipatory skills. Specifically, the researchers stated that experts would utilise the visual cues from both their opponent’s racket and arm placement to predict stroke direction and speed, whereas novices were only capable of extracting advance information from the racket itself.

Because this dissertation utilises a VBT method to train athletes, a key component of this program will be its ability to discriminate experts from novices. Heazlewood and Keshishian (2010) used perceptron neural networks, in conjunction with discriminant analysis, to identify the variables that characterise karate athletes into high and low performance groups. Their study revealed that both perceptron neural networks and discriminant function analysis yielded a high percentage of accuracy in categorising karate athletes into high and low performance groups.

In a similar study, Condon, Golden and Wasil (1999) utilised both linear regression and neural networks to predict the performance of different nations (in terms of medals) during the 1996 Olympic Games. The authors utilised network pruning to improve the performance of the neural network analysis. Their results suggested that neural network analysis outperformed the linear regression models in predicting number of medals in a number of different simulations (e.g. their best neural network model outperformed the best regression model). These studies suggest to us strength of using neural networks to predict
performance in sport. A brief description of neural networks and discriminant analysis is provided below. For a more detailed account please refer to the method section (chapter 4) of this dissertation.

Derived from studies of brain function, the definition of a neural network varies depending upon the field in which it is being examined. In a statistical sense, a neural network applies to a loosely related family of models, characterised by a parameter space and flexible structure (SPSS Inc., 2007b). Neural networks are made up of numerous artificial neurons (modelled after biological neurons), each having their own associated weight. Buckland (2002) states that the weights in most neural sets can be both positive and negative, therefore providing excitatory or inhibitory influences to each input. As each input enters the nucleus, it is multiplied by its weight. The nucleus then sums all these new input values which gives us the activation (refer to Figure 5.1). If the activation is greater than the threshold value, the neuron outputs a signal. If the activation is less than the threshold value, the neuron outputs zero. This is typically called a step function.

If we consider the number of inputs a neuron can have as \( n \), and the corresponding weights each input can have as \( w \), then the equation for the activation value can be represented by:

\[
\alpha = \sum_{i=0}^{i=n} w_i x_i
\]  

(5.1)

The Multilayer Perceptron (MLP) procedure produces a predictive model for one or more dependent variables based on the values of the predictor variables. What makes a multilayer perceptron unique is that each neuron uses a nonlinear activation function which was developed to model the frequency of action potentials, or firing, of biological neurons in the brain (Haykin, 1998). This function is modelled in several ways, but must always be
normalizable and differentiable. The two main activation functions used in current applications are both sigmoids, and are described by:

\[ \phi(y_i) = \tanh(v_i) \] (5.2)
\[ \phi(y_i) = (1 + e^{-v_i})^{-1} \] (5.3)

Function 5.2 is a hyperbolic tangent which ranges from -1 to 1, while function 5.3 is equivalent in shape but ranges from 0 to 1. Here \( y_i \) is the output of the \( i \)th node (neuron) and \( v_i \) is the weighted sum of the input synapses.

Learning occurs in the perceptron by changing connection weights after each piece of data is processed, based on the amount of error in the output compared to the expected result (Haykin, 1998). This is an example of supervised learning, and is carried out through backpropagation, a generalization of the least mean squares algorithm in the linear perceptron.

The error in output node \( j \) in the \( n \)th data point can be represented by \( e_j(n) = d_j(n) - y_j(n) \), where \( d \) is the target value and \( y \) is the value produced by the perceptron. We then make corrections to the weights of the nodes based on those corrections which minimize the error in the entire output, given by:

\[ \mathcal{E}(n) = \frac{1}{2} \sum_j e_j^2(n) \] (5.4)

The advantage of utilising a neural network is that it can approximate a wide range of statistical models without requiring the researcher to hypothesise in advance certain relationships between the dependent and independent variables (Heazlewood and Keshishian,
Instead the form of the relationship is determined during the learning process. The trade-off for this flexibility is that the synaptic weights of a neural network are not easily interpretable. Thus, if you are trying to explain an underlying process that produces the relationships between the dependent and independent variables, it would be better to use discriminant analysis (Heazlewood and Keshishian, 2010).

As explained by Heazlewood and Keshishian (2010), discriminant analysis can be used to classify cases into the values of a categorical dependent variable, to predict group membership based on a linear combination of the interval variables. The procedure begins with a set of observations where both group membership and the values of the interval variables are known (Stockburger, 1998). The end result of the procedure is a model that allows prediction of group membership when only the interval variables are known. A second purpose of discriminant function analysis is an understanding of the data set, as a careful examination of the prediction model that results from the procedure can give insight into the relationship between group membership and the variables used to predict group membership (Stockburger, 1998).

Spieler, Czech, Joyner and Munkasy (2007) utilised multivariate ANOVA and discriminant analysis to determine factors that most accurately predicts starting status in United States collegiate football players. The researchers integrated factors such as demographic information, personality inventories, and athletic coping skills inventories to build their models. The researchers showed that age, high school size, and coping with adversity, were significant factors for predicting football starting status. These studies suggest implications for recruiters selecting athletes with similar abilities and that the use of statistical methods, such as discriminant analysis, may help in selecting the better athlete.
5.2 Discriminating Expertise on the SATB

The main aim of this study was to compare the statistical ability of both neural networks and discriminant function analysis on the SATB program. Using these statistical tools, the researchers attempted to identify the accuracy of the SATB in classifying badminton players into different skill level groups (e.g. beginner, intermediate, advanced). Finally, using these outcomes, in conjunction with the physiological and biomechanical variables of the participants, the researchers assessed the authenticity and accuracy of the SATB and commented on the overall effectiveness of the VBT approach to training badminton athletes.

5.3 Methodology

The data obtained from the previous study (refer to chapter 4) was used to compare the neural networks and discriminant analysis approaches to discriminating expertise. As such, the section below will resemble the methodology of the previous chapter.

5.3.1 Participants

Forty-one participants, classified as advanced, intermediate, or beginner skill level, participated in this study. Participants in the advanced skill level group were athletes who had played badminton for a number of years and were comfortable with coaching/teaching their skills and knowledge to others. Participants in the intermediate group were those who had played badminton for at least one year and were semi-confident with their skills and
Participants in the beginner group had very little badminton knowledge and minimal game experience. The beginner group consisted of eleven females (age mean = 23.73 years, \(SD = 3.44\) years) and four males (age mean = 23.00 years, \(SD = 1.86\) years). The intermediate group consisted of nine females (age mean = 24.67 years, \(SD = 8.56\) years) and seven males (age mean = 26.00 years, \(SD = 5.86\) years). The advance group consisted of six females (age mean = 33.00 years, \(SD = 13.27\) years) and four males (age mean = 33.50 years, \(SD = 8.39\) years). Participants were recruited from RMIT University, badminton clubs, and athletes from the Australian Badminton Olympic team. All university students had prior experience in playing badminton, with most having played in high school round robins. RMIT students were recruited from the university’s badminton club with the assistance of the club president. Participants all signed a consent form to be a part of the experiment (refer to the appendix) with the understanding that they would remain anonymous for any reports or publications.

### 5.3.2 Measures and Testing Procedure

The measure used to compare neural networks and discriminant analysis was the SATB program. The SATB is a VBT program that consists of five visual questions per session (over ten sessions). Participants would first watch different clips of badminton rallies being played, with sequences running for 2 to 30 seconds. This was followed by a still frame for 1 second after which participants would be asked to answer (on screen) what type of shot was about to take place (e.g. drop shot), as well as the location that shot would be played (e.g. middle right).

Skill level served as the dichotomous classification variable. The dependent variables in both the neural networks and discriminant analyses were represented by three different
groups of factors: anthropometric factors, motor fitness factors and SATB factors. The anthropometric factors were: height (cm), weight (kg), age (years), and experience (years); the motor fitness factors were: 20m sprint (secs), vertical jump (cm), and beep test (score); and the SATB factors were: shot type (score), court placement (score), and response time (secs).

The anthropometric and motor fitness data was provided to us by Badminton Australia. These were conducted under precise test conditions by the head coach and various experts. The sprint and beep tests demonstrate the athlete’s endurance and speed. The vertical jump test indicates how high the athlete can jump. These are all important factors during a game of badminton. For example, the higher the athlete can jump, the better the angle to have to execute a jump smash.

For this part of the experiment, the researchers were not interested in observing improvement on the SATB over time. The only concern was in relation to the SATBs’ ability to discriminate expertise. Therefore, participants were only administered the SATB once to determine their level of expertise. Prior to experimentation, participants were asked to estimate their skill level (from beginner to expert). Participants who were uncertain of their level were given the KMT to complete. Finally, after the experiment was completed, both neural networks and discriminant analysis was utilised to observe how accurate the program was in classifying participants into the correct skill level group.

5.4 Results

The results from the neural network solution indicated 100% and 57.9% classification accuracy for both the training and testing component respectively (refer to table 5.1).
The classification accuracy for the motor fitness tests was 95.5% for the training and 73.7% for the testing sample respectively (refer to table 5.2). Diagrammatic representation of the neural network architecture for SATB specific tests with one hidden layer using a hyperbolic function and the output layer a softmax function are represented in Figure 5.1.

<table>
<thead>
<tr>
<th>Predicted</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>Percent Correct</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1.Beginner</td>
<td>9</td>
<td>0</td>
<td>0</td>
<td>100.0%</td>
</tr>
<tr>
<td>2.Intermediate</td>
<td>0</td>
<td>5</td>
<td>0</td>
<td>100.0%</td>
</tr>
<tr>
<td>3.Advanced</td>
<td>0</td>
<td>0</td>
<td>8</td>
<td>100.0%</td>
</tr>
<tr>
<td>Overall Percentage</td>
<td></td>
<td></td>
<td></td>
<td>52.6% 36.8% 10.5% 57.9%</td>
</tr>
<tr>
<td>Testing</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1.Beginner</td>
<td>5</td>
<td>1</td>
<td>0</td>
<td>83.3%</td>
</tr>
<tr>
<td>2.Intermediate</td>
<td>3</td>
<td>6</td>
<td>2</td>
<td>54.5%</td>
</tr>
<tr>
<td>3.Advanced</td>
<td>2</td>
<td>0</td>
<td>0</td>
<td>0.0%</td>
</tr>
<tr>
<td>Overall Percentage</td>
<td>52.6% 36.8% 10.5% 57.9%</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 5.1: The neural network solution based on the training data set and testing (holdout) data set classified at 100% and 57.9% accuracy respectively for skill level (beginner, intermediate and advanced) for the SATB specific tests.

<table>
<thead>
<tr>
<th>Predicted</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>Percent Correct</th>
</tr>
</thead>
<tbody>
<tr>
<td>Training</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1.Beginner</td>
<td>8</td>
<td>0</td>
<td>1</td>
<td>88.9%</td>
</tr>
<tr>
<td>2.Intermediate</td>
<td>0</td>
<td>5</td>
<td>0</td>
<td>100.0%</td>
</tr>
<tr>
<td>3.Advanced</td>
<td>0</td>
<td>0</td>
<td>8</td>
<td>100.0%</td>
</tr>
<tr>
<td>Overall Percent</td>
<td>36.4% 22.7% 40.9% 95.5%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Testing</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1.Beginner</td>
<td>9</td>
<td>1</td>
<td>0</td>
<td>90.0%</td>
</tr>
<tr>
<td>2.Intermediate</td>
<td>3</td>
<td>2</td>
<td>1</td>
<td>50.0%</td>
</tr>
<tr>
<td>3.Advanced</td>
<td>0</td>
<td>0</td>
<td>3</td>
<td>100.0%</td>
</tr>
<tr>
<td>Overall Percent</td>
<td>63.2% 15.8% 21.1% 73.7%</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 5.2: The neural network solution based on the training data set and testing (holdout) data set classified at 95.5% and 73.7% accuracy respectively for skill level (beginner, intermediate and advanced) for the motor fitness tests.
Figure 5.1: Diagrammatic representation of neural network architecture for SATB specific tests

Table 5.3 and Figure 5.2 indicate that the most important discriminating variables in the neural network analysis are shot type and location selection. Similar analysis using the general motor fitness data, which classified 95.5% correctly from all ability groups, indicated that the 20m sprint test (100% normalised) and vertical jump test (74.6% normalised) were the most important discriminators for the motor fitness tests.

<table>
<thead>
<tr>
<th>Independent variable</th>
<th>Importance</th>
<th>Normalised importance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shot type</td>
<td>.409</td>
<td>100.0%</td>
</tr>
<tr>
<td>Location placement</td>
<td>.407</td>
<td>99.5%</td>
</tr>
<tr>
<td>Time response</td>
<td>.183</td>
<td>44.7%</td>
</tr>
</tbody>
</table>

Table 5.3: Independent variable importance and normalised values for SATB specific constructs
Discriminant analysis was equally effective in classifying ability level when using the SATB specific tests, however slightly less accurate when using the motor fitness tests. The motor fitness tests produced 73.2% (Wilks’ Lambda = .394, \( p < .001 \)) and SATB specific tests produced 80.5% (Wilks’ Lambda = .23, \( p < .001 \)) correct classifications, respectively. The means and standard deviations for the 20m sprint, beep test, and vertical jump tests are displayed in Table 5.4, with higher skill level participants displaying higher scores on the vertical jump and beep tests, and lower scores on the sprint tests (possibly due to age).

<table>
<thead>
<tr>
<th></th>
<th>Sprint test</th>
<th>Beep test</th>
<th>Vertical jump test</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( M )</td>
<td>( SD )</td>
<td>( M )</td>
</tr>
<tr>
<td>Beginner</td>
<td>4.34</td>
<td>.37</td>
<td>7.77</td>
</tr>
<tr>
<td>Intermediate</td>
<td>3.86</td>
<td>.29</td>
<td>8.61</td>
</tr>
<tr>
<td>Advance</td>
<td>3.41</td>
<td>.19</td>
<td>9.82</td>
</tr>
</tbody>
</table>

Table 5.4: Means and standard deviations for beginner, intermediate and advanced badminton athletes based on motor fitness variables

Table 5.5 indicates the accuracy of classification based on motor fitness constructs. In this model 73.2% of all three ability groups were classified correctly. In this context the classification was marginally lower (22.3%) than the neural network solution.
The means and standard deviations for the SATB specific tests: shot type, court placement and response time are displayed in table 5.6. Once again, the scores are higher for those of a higher skill level when compared to those of a lower skill level. The timed score for the SATB response time reflects that a lower score is equated with higher ability on these tests.

<table>
<thead>
<tr>
<th>Shot type</th>
<th>Location</th>
<th>Time response</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>M</td>
<td>SD</td>
</tr>
<tr>
<td>Beginner</td>
<td>1.8</td>
<td>.94</td>
</tr>
<tr>
<td>Intermediate</td>
<td>5.06</td>
<td>1.34</td>
</tr>
<tr>
<td>Advance</td>
<td>6.2</td>
<td>1.48</td>
</tr>
</tbody>
</table>

Table 5.6: Means and standard deviations for beginner, intermediate and advanced badminton athletes based on SATB variables

Table 5.7 indicates the accuracy of classification based on SATB specific constructs.

The classification accuracy was 80.5% (Wilks’ Lambda = .23, p < .001) correct classifications.
Finally, a Pearson’s correlation coefficient was computed to assess the relationship between participants’ skill level and the dependent variables, across all three groups (anthropometric, motor fitness and SATB specific). Table 5.8 summarises these results.

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Skill level</td>
<td>--</td>
<td>.44**</td>
<td>- .78**</td>
<td>.42**</td>
<td>.44**</td>
<td>.80**</td>
<td>.65**</td>
<td>-</td>
<td>.15</td>
</tr>
<tr>
<td>2. Age</td>
<td>--</td>
<td>.22</td>
<td>.05</td>
<td>.03</td>
<td>.33*</td>
<td>.39*</td>
<td>.28</td>
<td>.17</td>
<td></td>
</tr>
<tr>
<td>3. BMI</td>
<td>--</td>
<td>.03</td>
<td>.04</td>
<td>.14</td>
<td>-.09</td>
<td>.10</td>
<td>-.16</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. Sprint test</td>
<td>--</td>
<td>-.63**</td>
<td>.45**</td>
<td>-.09</td>
<td>-.65**</td>
<td>-.47**</td>
<td>.50**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5. Beep test</td>
<td>--</td>
<td>.51**</td>
<td>.40**</td>
<td>.24</td>
<td>-.19</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6. Vertical test</td>
<td>--</td>
<td>.51**</td>
<td>.35*</td>
<td>-.25</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7. Shot type</td>
<td>--</td>
<td>.56**</td>
<td>.36*</td>
<td></td>
<td></td>
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Table 5.8: Correlation results examining skill level across anthropometric, motor fitness and SATB specific factors.

Note: Correlations marked with (*) were significant at p<.05
Correlations marked with (**) were significant at p<.01

These results show that the multilayer perceptron neural network marginally outperformed the discriminant function analysis as a predictor of badminton skill level, specifically when incorporating the SATB system. Nonetheless, both neural networks and discriminant analysis were accurate statistical tools in predicting and classifying group membership among badminton players. It is clear from these results that the physical aspects of training are just as important as the perceptual training (as indicated by the reasonably accurate classification of the anthropometric and motor fitness tests). This provides a number of implications for the training of badminton players, specifically, the way in which we currently train can be improved upon, but should not be completely removed (i.e. keep the physical aspects of training, but integrate a perceptual aspect as well). In conjunction with the results from Chapter 4, the SATB program shows promising results in the field of skill.
acquisition training, in terms of training and identification. The next chapter of this
dissertation will then be to examine a theoretical concept of perceptual motor skill acquisition
and how it can be integrated into badminton.
Chapter 6

Knowing When to Throw in the Tau

In this chapter, general tau theory is discussed in relation to the sport of badminton. The first half of this chapter will discuss some of the main principles and concepts of tau theory, keeping in mind this dissertation. The second half of this chapter will examine how coaches and trainers can utilise tau theory to train their athletes. To begin, in Section 6.1, a brief introduction to tau theory is provided. Section 6.2 describes the idea of motion gaps in relation to badminton. In Section 6.3, I discuss tau-coupling and badminton in relation to this dissertation. Then in Section 6.4, I discuss the time-to-contact notion in relation to badminton. The second half of this chapter begins with Section 6.5, where I discuss tau theory and skill development. Section 6.5.1 will then consider using tau to anticipate time during a game of badminton. Section 6.5.2 discusses how we can incorporate general tau theory into the SATB program, to aid and assist beginner badminton players. Finally, Section 6.5.3 discusses the required velocity model in relation to this dissertation.
6.1 Introduction

A crucial technique for surviving in any environment revolves around the ability to anticipate approaching objects and when they will reach a desired goal or target (Hancock and Manser, 2009). This skill is of particular importance in any fast paced sport, where movement has to be controlled by perceiving what is likely to occur next (Kayed and Van der Meer, 2009). Catching a cricket ball or striking a badminton shuttle requires precise prospective control of the interceptive action and one must be prepared in advance to allow the body time to organize. It can therefore be suggested that prospective control is dependent on perceptual information guiding the action so that an extrapolation of movements can be made into the future (Kayed and Van der Meer, 2009; Lee, 2005; Von Hofsten, 2007). This theory of prospective control is commonly known as general tau theory and has been associated with various forms of development and anticipation. This chapter will examine tau in its detail and explain how it can be used by badminton players for skill acquisition training.

In adhering to an acceptable theory relating to movement guidance, an adequate theory regarding tau must be able to “explain how movements are perceptually and intrinsically guided. It must explain the form of the guiding perceptual information that enables prospective guidance of movement. And it must be biologically plausible” (Lee, 2005, p.5). In understanding general tau theory, it is essential that we cover motion-gaps, tau-coupling and time-to-contact concepts.
6.2 Motion Gaps and Badminton

In badminton, the aim of the game is to hit the shuttlecock over the net in such a manner that your opponent(s) cannot return the shuttle. In general, movement guidance is obtained through several perceptual systems (e.g. vision systems and the articulatory system of sensors in joints, muscles and skin). Regardless of the type of perceptual systems involved, it is the change in the motion-gap between an effector and its goal that allows for the prospective control of this gap (Lee, 2005). The concept of a motion gap can generally be described as changing the gap between a current state and a goal state in a given event (Lee, 2005). Using the badminton example above, we can make a statement regarding the motion gap for a player during a badminton rally. In this sense, the current state would be the position of the player’s racket, the effector would be the racket itself, and the goal state would be the shuttlecock. Therefore, it can be argued that “moving an effector to its goal does not reside in the pattern of limb movements that move the effector. Rather it lies in the form of closure of the motion-gap between the effector and the goal” (Lee, 2005).

The scenario above provides an example of closing a distance motion-gap during a game of badminton (when reaching for the shuttlecock with the racket). There are of course numerous other forms of motion-gaps in badminton. Changing your vision to examine a shuttlecock lobbed into the air is an example of an angular motion-gap between the current vision direction and the direction of the shuttlecock. A jump in badminton is an example of a force motion-gap between the current force and the force required for a satisfactory jump. It is worth noting that the dimension of the motion-gap varies in each of these examples, suggesting that the concept of motion-gaps is not tied to a particular dimension (Lee, 2005).

In any given game of badminton, it will be very unlikely that an action will only have one example of a closure motion-gap. In reality, we need to control several motion-gaps at
the same time to perform a successful action. Executing a jump smash in a game of badminton is an example of closing several motion-gaps at the same time. The player needs to coordinate the closure of vision-shuttlecock, racket-shuttlecock, and jump-court motion-gaps to perform the jump smash adequately. Performing a jump smash can be a difficult task, especially for such a fast paced sport. And yet, temporal accuracy has been observed with estimates of time windows for successful performances in the order of a few milliseconds (Regan, 1992; Tresilian, 1993; Land and Mcleod, 2000; de Azevedo Neto and Teixeira, 2009). To explain how performance with such a strict temporal constraint can be executed based exclusively on raw visual information, it would be ideal to examine the concept of tau and motion-gaps.

### 6.3 Tau-coupling and Badminton

Lee (1998) suggests that tau, as a single type of temporal variable of a changing motion-gap, would provide sufficient information for controlling the closure of said motion-gap. The notion of tau is based on Gibson’s (1966) work on ecological invariants in visual flow fields. Tau of a motion-gap is the time-to-closure of the motion-gap at its current closure-rate:

$$\tau(x, t) = \frac{x(t)}{x(t)}$$

(6.1)

where $\tau(x, t)$ represents the tau of the motion-gap at time $t$. Because tau is a measure on any motion-gap of any dimension, it explains how a single type of temporal variable can account for controlling the closure of perceptual information from different dimensions of motion-gaps.

The notion of tau-coupling refers to when two taus are coupled over a period of time if they remain in constant proportion during that time (Lee, 2005):

$$\tau(x, t) = K\tau(y, t)$$

(6.2)
where $x(t)$ and $y(t)$ represent the taus of two gaps, a badminton example for tau-coupling is provided (refer to Figure 6.1). Consider a badminton player intercepting the shuttlecock at point $X$. He notices his opponent at point $Y$ so decides to hit the shuttlecock to point $Z$ (because he assumes it will be the most difficult spot for his opponent to reach given his current position on the court). To execute this action successfully, the badminton player needs to control the closure of the shuttle trajectory motion-gap, $A$, as well as the angular motion-gap, $B$, between the shuttlecock pathway and his opponent at point $Z$ simultaneously. Utilising the equation above (6.2), this scenario can be expressed symbolically as:

$$\tau_B = K\tau_A \quad (6.3)$$

Also consider a second scenario where a badminton player running to the left side of the court to return his opponent’s stroke from point $A$ (refer to Figure 6.2). To execute this properly, the player has to control the closure of both gaps from the player to the shuttlecock, $X$, and the shuttlecock trajectory route, $TR$, simultaneously. This can be expressed symbolically as:

$$\tau_X = K\tau_{XTR} \quad (6.4)$$
Coordinating and executing actions within a dynamic environment often involves temporal information about events based on raw visual sequences (Proffitt and Caudek, 2003). For example, when attempting to return the shuttlecock, we need to have the racket in the right position before the shuttle makes contact. This is the general principle behind the time-to-contact ($T_c$) theory, which can be summarised as; the idea that living organisms are able to perceive using visual information to judge distance and speed with respect to time. (Bootsma and van Wieringen, 1990). In determining $T_c$, we can utilise tau (mentioned above) as our optical invariant because it accounts for perceptual information coming from different dimensions (in this case speed and distance).

Tau relates the optical size of an object to its rate of expansion and can be expressed as:

$$ \tau = \theta / \delta \theta / \delta t $$

(6.5)
where $\theta$ represents the angle of extension of the object in radians and $\frac{\delta \theta}{\delta t}$ represents the rate of expansion. Under $T_c$ conditions, tau specifies that an object must move with constant velocity. As an example, consider a game of badminton played by experts. Instinctively, players are able to return shots of up to 421 km/h based on collecting visual information from their opponent’s actions. This plays an important role in the development of skill acquisition and training and will be discussed later.

In summary, we can infer two main conclusions regarding the nature in which humans use tau to guide their movements. Firstly, an action is initiated when a certain threshold value of tau is reached. Secondly, tau may be used in controlling a continuous motion based on the changing value of tau. By combining visual information with an internal forward model of the external state, the relationship between position and $T_c$ becomes easily predictable by most humans (de Azevedo Neto and Teixeira, 2009). In the same sense, it would be possible to improve a badminton player’s decision making capabilities utilising a visual based model focused on skill acquisition.

### 6.5 Tau and Skill Development

Thus far we have covered the concepts of motion-gaps and tau-coupling in relation to playing badminton. We will now examine how knowledge of these concepts can help to train and improve a player’s skills, techniques and overall in-game performance. The ability to execute high end techniques in badminton requires controlling the closure of a set of motion-gaps in a specific manner (refer to the example regarding the execution of the jump smash). Lee (2005) suggests that skilled movements may be acquired by coupling the taus of the motion-gaps onto the taus of other motion-gaps and further onto tau-G guides (refer to Lee, 2005 for a detailed explanation of tau-G). As an example, badminton players learn to adjust
their movement around the court by absorbing the visual information provided by their opponents. When following the shuttlecock with their eyes, players not only learn to sense the motion-gap between their gaze and the shuttle, but also how to control the optimal amount of time spent (in the order of a few milliseconds) in looking at the shuttle and the decision that would follow. Of course, no real life event is ever repeated, in the same sense that no badminton rally is ever identical. Thus, players learn to improve their skills through constant adjustments of the calibration process of regulating power to the muscles on the basis of prospective sensory information about the taus of motion-gaps (Lee, 2005).

6.5.1 Using Tau to Anticipate Time

By making use of tau and the knowledge of $T_c$, players can estimate when the shuttlecock will land at a location on the court. However, this does not mean that the shuttlecock will definitely come into contact with the racket, for this requires an action on the part of the player that must be geared towards tau (Bootsma and van Wieringen, 1990). The synchronisation between movement and visual information can generally be achieved by executing the same movement repeatedly, with as little variation as possible. A classic example of this is Bootsma and van Wieringen’s (1990) study relating to timing forehand drives in table tennis. The researchers suggest that with enough repetition, players have automatically geared themselves towards making the optimal forehand drive. In this sense, the only challenge players’ face is deciding when to initiate the drive. The same principle can be applied to our badminton example. Players could wait until tau reaches a critical value which would indicate the optimal time to execute the movement. Using this technique coaches can train their athletes to identify the ideal time to execute an action for any situation during a badminton game. For example, coaches may hit a large number of shuttlecocks to
the same location on the court with as little variability as possible. Players would then keep returning these shuttles until they discover the optimal time to initiate the movement execution process (assuming they have already decided the type of shot they will make). This approach allows players to develop visual cues which act as signals during real game situations.

6.5.2 Incorporating a Visual Based Training Method

The above approach (Section 6.5.1) to training badminton players is ideally suited for athletes who are already at a considerably high level (i.e. experts). This is because the training method assumes the athletes already know the optimal shot to make in any given situation. As such, it provides considerable limitations to training individuals who have just started learning (i.e. beginners). The most generally accepted method for advancing skills and techniques in badminton would be to undergo physical type training and to improve by simply playing the game. As badminton is the world’s fastest racket sport, another method of training would involve the development and expansion of a player’s cognitive skills (e.g. their decision making in a game situation) via visual based methods. Considering the nature of tau and its heavy emphasis on perceiving visual information, it seemed appropriate to examine a visual based training program and how it can help train badminton players.

Huynh and Bedford (2010) introduced a new visual based training method of identifying and improving a badminton player’s reaction time and awareness: the Skills Acquisition Trainer for Badminton (SATB). The program focused on examining how players would react based upon their opponent’s actions, and attempted to improve their skills over 10 weeks of visual training. Basically, participants using the SATB would watch different clips of badminton rallies being played, with sequences running for 2 – 30 seconds. These were
followed by a still frame for 1 second after which participants would be asked to enter what type of shot was about to take place (e.g. drop shot) as well as the location that shot will be played (e.g. middle right). In their study, participants were administered the SATB once a week for ten weeks of experimentation (with each week having different sequences to examine). The researchers hypothesised that the utilisation of a VBT program will ultimately allow participants to predict their opponent’s actions in real game situations. The researchers concluded that VBT methods did indeed improve the participants’ ability to predict their opponent’s actions in a game situation.

Therefore, in relation to tau training (especially for beginners), it would be beneficial for athletes to undergo some form of visual training to develop the necessary visual cues that allow for optimal game play. With an adequate framework in place, players would be able to physically train their bodies to anticipate a critical value of tau and execute an optimal in-game performance.

6.5.3 The required velocity model

Finally, we shall examine the required velocity model and how it can be beneficial for the training of athletes. Peper et al. (1994) suggest a required velocity model which examines $T_c$ and how it can be used to intercept moving objects. The model itself specifies how an individual utilises visual information regarding his environment continuously to control the hand’s acceleration and match the required velocity needed to intercept an object. Generally, the current hand velocity at a given instant $t$ can be increased or decreased for the hand to move at the required velocity (Davids, Button and Bennett, 2008) to intercept an object. In a study conducted by Peper et al. (1994) the researchers examined the required velocity to
catch a ball approaching a person at a specific speed. The equation they suggested for the required velocity model can be derived as:

\[ \ddot{X}_h = \alpha \dot{X}_{h\text{req}} - \beta \dot{X}_h \]  

(6.6)

with \( \dot{X}_{h\text{req}} = \frac{x_h - x_b}{T_{c_1}} \)  

(6.7)

where \( \ddot{X}_h, \dot{X}_{h\text{req}}, \) and \( \dot{X}_h \) are the hand’s current acceleration, current required velocity, and required velocity respectively, and \( \alpha \) and \( \beta \) are constants, and where \( X_h, X_b \), and \( T_{c_1} \) are the hand’s current position, the projection of the ball’s current position on the hand-movement axis, and the first-order \( T_c \) between the ball and the hand-movement axis.

Using this model, we can derive a similar equation for the required velocity a badminton player needs to intercept a shuttlecock hit in-game:

\[ \text{Required velocity} = \frac{x_{\text{hand}} - x_{\text{shuttle}}}{T_{c_1}} \]  

(6.8)

Because it is such a high velocity game, players will have to decide when to give up a shot or when to attempt the return. Knowing which shots are possible from their current position (specifically hand position) and the required velocity they would need to reach that point could potentially save them a lot of energy from unnecessary movement. Naturally, players wouldn’t have the time to be calculating required velocity in-game, however this model may be effective during the training period of the athlete. Coaches and trainers may train players to mentally recognise shuttle velocity in relation to their current position such that, in a real game situation, they would recognise which shots they should disregard to conserve energy for the next point.
In summary, this chapter discusses a theoretical model of perceptual motor skill acquisition and how it can be integrated into the sport of badminton. The ability to predict the velocity and direction of an approaching object is a powerful technique that all animals find useful. In sporting events, this is especially important. In badminton, knowing where the shuttlecock will land as well as the time it will require a player to reach that position on the court is definitely an advantage. This dissertation focuses on how we can utilise a VB program to improve the perceptual abilities of decision making and awareness. Tau theory provides another example of how humans can perceive their surroundings and the environment. Currently, the SATB program only functions as a two dimensional model that facilitates off court training. Future studies that utilise three dimensional VBT programs (e.g. virtual reality goggles) should consider certain aspects of general tau theory, such as the required velocity model, to train athletes.
Chapter 7

Discussion, Conclusions and Recommendations for Future Research

This dissertation has utilised mathematical models and computer programming techniques to provide a VBT method for training badminton players. In broad terms, the early chapters of this dissertation focused on reviewing the traditional methods of skill acquisition and training, while the later chapters introduce a new paradigm for guiding the badminton players of the future. Each of the chapters which form the foundation of this dissertation has been previously peer-reviewed in either a journal or conference proceedings. The remainder of this chapter summarises each of the previous chapters and the potential for future research.

7.1 Discussion

In Chapter 4, a new VBT method was proposed to improve the overall in game performance of badminton players. It was believed that the traditional method of training was not optimal, not containing the necessary cognitive components that would optimise a players capabilities. The new program showed results which were consistent with other VBT studies
that have utilised similar methods in attempting to improve athletes’ skills and performance 
(Blomqvist, Luhtanen and Laakso, 2001; Christina, Barresi and Shaffner, 1990). Blomqvist 
and colleagues (2001) argue that although general tactics will develop in athletes 
automatically from just playing the game, good decision making skills will only develop if 
taught extensively. The authors suggest that visual-based learning tasks encourage 
participants to develop their tactical awareness, bringing cognitive aspects of their game to a 
conscious level. Similarly, the present study found that participants who used the SATB 
showed a consistent improvement in their ability to predict and react to the visual-based 
sequences over the eight week period.

In sessions involving athletes they have already seen play (from past sequences), their 
score on the SATB was higher than it was if they were seeing those athletes play for the first 
time. Tong and Hong (2000) suggest that there are many different playing styles in 
badminton, varying from strength types to speed types. The authors suggest that knowing an 
opponent’s play style can help predict what type of shot they will play and where they will hit 
the shuttle. The SATB supported this notion, with participants scoring significantly higher in 
sessions where they have an understanding of an athlete’s playing style from viewing them 
play in previous sessions.

Further points regarding style of play was noted by the researchers after viewing the 
video recordings of both the treatment and control groups’ matches and training. Firstly, 
participants in the treatment group were able to improve their overall badminton skills as well 
as respond more efficiently (with greater speed and reaction time) to their opponents’ actions. 
Secondly, participants in the control group were able to improve their overall badminton 
skills and showed slight improvement in their ability to predict their opponents’ next action. 
Both groups played/trained in badminton on a weekly basis so it was expected that both 
groups would improve their in-game skills but it was surprising to find that the control group
had also improved in predicting their opponents’ actions. A possible explanation for this might be that the control group only consisted of eight participants and after eight weeks of playing/training together, they had already played with each member in that group numerous times. This essentially leads the players to become used to each others’ playing styles, hence the increase in accurately predicting their opponents’ actions.

A number of points about the methodology should be noted. In their study Blomqvist et al. (2001) suggested that age and experience affected the outcomes of the experiment. The present study supported this notion with the results being skewed by participants who were in a lower skill level group yet possessed high anticipatory capabilities. These conditions were rare but did occur. The most common scenario was where participants classified as beginners, because they had played minimal badminton and were not completely confident with their understanding of the rules (thus receiving a low score on the KMT), obtained exceptional anticipatory results on the SATB program because they were proficient in other racket sports (e.g. tennis). Care must be taken when interpreting these outcomes, as experts from other sports may affect the groups by being placed in the beginner or intermediate categories. The KMT would need to be modified for future studies to allow for such discrepancies.

Additional modifications would be required if attempting to apply the SATB program to other sports. Although this study can be extended, it is not applicable to invasion type games (e.g. soccer, hockey) due to differences in the number of players and the tactical aspects of evasion games (Blomqvist et al., 2001). The sports that would be applicable to this type of study would ideally be racket sports such as tennis and squash. The SATB program would need to be rewritten to allow utilisation for invasion games.

In Chapter 5, the researcher compared the statistical ability of both neural networks and discriminant analysis on the SATB program. Using these statistical tools, the researcher identified the accuracy of the SATB in classifying badminton players into different skill level
The findings from this study were consistent with that of Heazlewood and Keshishian (2010), suggesting that neural networks, specifically the multilayer perceptron (MLP) networks, are more effective in predicting group membership, and displayed higher predictive validity than discriminant analysis. Furthermore, the study was successful in supporting the accuracy of the SATB program with the analyses for the neural networks and discriminant analysis resulting in a 100% and 80.5% accuracy rating respectively.

The MLP did, however, maintain a high percentage rating for correctly discriminating between motor fitness tests, which is consistent with Heazlewood and Keshishian’s (2010) study. The authors found that karate specific tests were better predictors of ability level than motor fitness tests. The researcher supports this concept, with the present study suggesting that SATB specific tests (shot type, court placement, and response time) were better predictors of badminton ability than motor fitness tests. Tong and Hong (2000) suggest that due to the numerous patterns and play types in badminton (e.g. strength type, speed type, etc) familiarity with the strategy and playing style of opponents (similar to the factors that the SATB attempts to improve) is essential for improving skill level.

As a further point of interest, the researcher discovered that participants were more likely to predict the correct shot type than location placement on the SATB program. This was consistent across all three skill level groups. This can potentially be explained due to the complex nature of shot types and the varied options with location selection. Because the sequences that participants viewed were from top level badminton matches, with athletes capable of performing a variety of trick/fake shots that could land in almost any position, participants found location selection to be more challenging than shot selection. However, the same can be said about shot type with many athletes giving the impression they may perform a certain shot, yet executing a completely different shot (e.g. faking a smash shot to perform a
drop shot). Additional studies are required to determine the underlying reasons that participants are able to identify shot types more accurately than shuttle destination.

Overall, the multilayer perceptron neural network marginally outperformed the discriminant function analysis as a predictor of badminton skill level, specifically when incorporating the SATB system. Nonetheless, both neural networks and discriminant analysis were accurate statistical tools in predicting and classifying group membership among badminton players. The SATB program was tested and validated, and can be implicated for future research in the field of VBT training.

In Chapter 6, general tau theory is discussed in relation to badminton. The first section of this chapter attempted to summarise three main concepts of tau theory (motion-gaps, tau-coupling and time-to-contact) in relation to the sport of badminton. The second section examined various ways of training badminton players while utilising a general tau theory as a background.

Overall, the theory relates to the movement guidance of animals and how they acquire understanding of their surrounding environments through perceiving visual information. There are currently numerous methods of training badminton players, ranging from physical to cognitive methods. There are, however, limited studies regarding the relationship between training badminton players and tau theory. Future studies should examine the concept of tau in relation to training badminton players. Specifically, it would be plausible to set up an experiment regarding the required velocity model and how different skill level participants require varying velocities to reach a specific point on the court (given the necessary equipment and adequate sample sizes).

Additionally, the required velocity model should be of particular interest for future studies. Being the world’s fastest racket sport, this places an enormous amount of pressure on players to be swift and agile. Each and every rally is quite energy consuming, placing a lot of
strain on the players’ bodies. Being able to estimate the required velocity to reach a certain point on the court will allow players the option of knowing when to concede certain points. In doing so, they would be conserving their energy for the rallies where they are more confident of winning a point. As such, the required velocity model is worth examining for future studies attempting to optimise badminton game performance.

### 7.2 Conclusions

In summary, this dissertation examined and utilised the SATB as a VBT program to train and improve the anticipatory skills of badminton players. In addition, video recordings and feedback (from the coaches/trainers) were utilised to examine on court performance following the SATB training. These results revealed a significant improvement in anticipatory capabilities for all skill level groups, in particular, beginners demonstrated the largest signs of improvement – both cognitively and physically. With the majority of coaches and trainers placing little emphasis on the cognitive aspects of training, these findings provide implications for traditional training regimes to be reviewed and modified, to allow for the inclusion of visual based development. Overall, the utilisation of a VBT method facilitates the acquisition of perceptual expertise, allowing athletes to train and improve off-court, and in a self paced manner.


7.3 Recommendations for Future Research

As a future task, we would like to develop the program in such a way that it operates as a web based function. During August 2010 the team had a placement student working with us for a month who helped develop the first components on the SATB website (included in the Appendix). The final task would be to finish off her work with us, to allow the SATB function from any remote location with access to the internet.

In addition, the next step might be to integrate the SATB program into a three dimensional system which allows for other theoretical theories of skill acquisition, such as tau coupling. We would have participants stand on an actual badminton court, with the net replaced with a giant screen/projector. Having participants physically move to the location they think the shuttlecock will land is more dynamic than how the SATB currently operates. This provides implications for training at the beginner or intermediate level. People at the lower levels would be able to physically move and respond to the actions of an athlete at the professional level. This allows them to train against someone at a much higher level, which they would not normally have the chance to do.

Finally, although not mentioned in this dissertation, the athlete’s self perception concerning the efficacy of the interventions should be considered for future research. Additional studies could examine the athlete’s actual perceptions regarding the program, the training or any other aspect of this study and see if this has an effect on decision making and awareness.
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Chapter 8

Appendix

8.1 VBA Macros

This section covers the VBA code used to build and operate the SATB program. Keep in mind, the majority of the program operates off a userform, so the codes that follow are for the buttons of the userform.

8.1.1 Calculating Scores

Sub AllCalc()

If Range("I2").Value = "1" Then Range("J2").Value = "0"
If Range("I2").Value = "2" Then Range("J2").Value = "0"
If Range("I2").Value = "3" Then Range("J2").Value = "0"
If Range("I2").Value = "4" Then Range("J2").Value = "0"
If Range("I2").Value = "5" Then Range("J2").Value = "0"
If Range("I2").Value = "6" Then Range("J2").Value = "0"
If Range("I2").Value = "7" Then Range("J2").Value = "0"
If Range("I2").Value = "8" Then Range("J2").Value = "0"
If Range("M2").Value = "1" Then Range("N2").Value = "0"
If Range("M2").Value = "2" Then Range("N2").Value = "0"
If Range("M2").Value = "3" Then Range("N2").Value = "0"
If Range("M2").Value = "4" Then Range("N2").Value = "0"
If Range("M2").Value = "5" Then Range("N2").Value = "0"
If Range("M2").Value = "6" Then Range("N2").Value = "0"
If Range("M2").Value = "7" Then Range("N2").Value = "0"
If Range("M2").Value = "8" Then Range("N2").Value = "0"
If Range("M2").Value = "9" Then Range("N2").Value = "0"
If Range("M2").Value = "10" Then Range("N2").Value = "0"
If Range("M2").Value = "11" Then Range("N2").Value = "0"

If Range("U2").Value = "1" Then Range("V2").Value = "0"
If Range("U2").Value = "2" Then Range("V2").Value = "0"
If Range("U2").Value = "3" Then Range("V2").Value = "0"
If Range("U2").Value = "4" Then Range("V2").Value = "0"
If Range("U2").Value = "5" Then Range("V2").Value = "0"
If Range("U2").Value = "6" Then Range("V2").Value = "0"
If Range("U2").Value = "7" Then Range("V2").Value = "0"
If Range("U2").Value = "8" Then Range("V2").Value = "0"

If Range("Y2").Value = "1" Then Range("Z2").Value = "0"
If Range("Y2").Value = "2" Then Range("Z2").Value = "0"
If Range("Y2").Value = "3" Then Range("Z2").Value = "0"
If Range("Y2").Value = "4" Then Range("Z2").Value = "0"
If Range("Y2").Value = "5" Then Range("Z2").Value = "0"
If Range("Y2").Value = "6" Then Range("Z2").Value = "0"
If Range("Y2").Value = "7" Then Range("Z2").Value = "0"
If Range("Y2").Value = "8" Then Range("Z2").Value = "0"
If Range("Y2").Value = "9" Then Range("Z2").Value = "0"
If Range("Y2").Value = "10" Then Range("Z2").Value = "0"
If Range("Y2").Value = "11" Then Range("Z2").Value = "0"
If Range("AG2").Value = "1" Then Range("AH2").Value = "0"
If Range("AG2").Value = "2" Then Range("AH2").Value = "0"
If Range("AG2").Value = "3" Then Range("AH2").Value = "0"
If Range("AG2").Value = "4" Then Range("AH2").Value = "0"
If Range("AG2").Value = "5" Then Range("AH2").Value = "0"
If Range("AG2").Value = "6" Then Range("AH2").Value = "0"
If Range("AG2").Value = "7" Then Range("AH2").Value = "0"
If Range("AG2").Value = "8" Then Range("AH2").Value = "0"
If Range("AK2").Value = "1" Then Range("AL2").Value = "0"
If Range("AK2").Value = "2" Then Range("AL2").Value = "0"
If Range("AK2").Value = "3" Then Range("AL2").Value = "0"
If Range("AK2").Value = "4" Then Range("AL2").Value = "0"
If Range("AK2").Value = "5" Then Range("AL2").Value = "0"
If Range("AK2").Value = "6" Then Range("AL2").Value = "0"
If Range("AK2").Value = "7" Then Range("AL2").Value = "0"
If Range("AK2").Value = "8" Then Range("AL2").Value = "0"
If Range("AK2").Value = "9" Then Range("AL2").Value = "0"
If Range("AK2").Value = "10" Then Range("AL2").Value = "0"
If Range("AK2").Value = "11" Then Range("AL2").Value = "0"
If Range("AS2").Value = "1" Then Range("AT2").Value = "0"
If Range("AS2").Value = "2" Then Range("AT2").Value = "0"
If Range("AS2").Value = "3" Then Range("AT2").Value = "0"
If Range("AS2").Value = "4" Then Range("AT2").Value = "0"
If Range("AS2").Value = "5" Then Range("AT2").Value = "0"
If Range("AS2").Value = "6" Then Range("AT2").Value = "0"
If Range("AS2").Value = "7" Then Range("AT2").Value = "0"
If Range("AS2").Value = "8" Then Range("AT2").Value = "0"
If Range("AW2").Value = "1" Then Range("AX2").Value = "0"
If Range("AW2").Value = "2" Then Range("AX2").Value = "0"
If Range("AW2").Value = "3" Then Range("AX2").Value = "0"
If Range("AW2").Value = "4" Then Range("AX2").Value = "0"
If Range("AW2").Value = "5" Then Range("AX2").Value = "0"
If Range("AW2").Value = "6" Then Range("AX2").Value = "0"
If Range("AW2").Value = "7" Then Range("AX2").Value = "0"
If Range("AW2").Value = "8" Then Range("AX2").Value = "0"
If Range("AW2").Value = "9" Then Range("AX2").Value = "0"
If Range("AW2").Value = "10" Then Range("AX2").Value = "0"
If Range("AW2").Value = "11" Then Range("AX2").Value = "0"
If Range("BE2").Value = "1" Then Range("BF2").Value = "0"
If Range("BE2").Value = "2" Then Range("BF2").Value = "0"
If Range("BE2").Value = "3" Then Range("BF2").Value = "0"
If Range("BE2").Value = "4" Then Range("BF2").Value = "0"
If Range("BE2").Value = "5" Then Range("BF2").Value = "0"
If Range("BE2").Value = "6" Then Range("BF2").Value = "0"
If Range("BE2").Value = "7" Then Range("BF2").Value = "0"
If Range("BE2").Value = "8" Then Range("BF2").Value = "0"
If Range("BI2").Value = "1" Then Range("BJ2").Value = "0"
If Range("BI2").Value = "2" Then Range("BJ2").Value = "0"
If Range("BI2").Value = "3" Then Range("BJ2").Value = "0"
If Range("BI2").Value = "4" Then Range("BJ2").Value = "0"
If Range("BI2").Value = "5" Then Range("BJ2").Value = "0"
If Range("BI2").Value = "6" Then Range("BJ2").Value = "0"
If Range("BI2").Value = "7" Then Range("BJ2").Value = "0"
If Range("BI2").Value = "8" Then Range("BJ2").Value = "0"
If Range("BI2").Value = "9" Then Range("BJ2").Value = "0"
If Range("BI2").Value = "10" Then Range("BJ2").Value = "0"
If Range("BI2").Value = "11" Then Range("BJ2").Value = "0"
End Sub

Sub Total()
    Range("Q2") = Range("J2") + Range("N2")
    Range("AC2") = Range("V2") + Range("Z2")
    Range("AO2") = Range("AH2") + Range("AL2")
    Range("BA2") = Range("AT2") + Range("AX2")
    Range("BM2") = Range("BF2") + Range("BJ2")
End Sub

Sub TotalScore()
    Range("BN2") = Range("Q2") + Range("AC2") + Range("AO2") + Range("BA2") + Range("BM2")
End Sub

Sub RawTime()
    Range("BO2") = Range("P2") + Range("AB2") + Range("AN2") + Range("AZ2") + Range("BL2")
End Sub

Sub HintUsed()
    Range("BP2") = Range("O2") + Range("AA2") + Range("AM2") + Range("AY2") +
    Range("BK2")
End Sub

Sub TimeTotal()
    Range("BQ2") = Range("DX2") + Range("DW2")
End Sub

8.1.2 Selecting options on the SATB

Private Sub CommandButton1_Click()
    Unload Answer1b
    Sheets("Sheet3").Activate
    Range("P2") = (Now() - Range("F2")) * 100000
    Answer1c.Show
End Sub

Private Sub CommandButton10_Click()
    Sheets("Sheet3").Activate
    Range("M2") = "2"
    [K2].NumberFormat = "hh:mm:ss"
    NowTime = Now() - StartTime
    [K2] = NowTime
    Range("L2") = (Range("K2") - Range("F2")) * 100000
End Sub

Private Sub CommandButton11_Click()
    Sheets("Sheet3").Activate
    Range("M2") = "3"
    [K2].NumberFormat = "hh:mm:ss"
    NowTime = Now() - StartTime
    [K2] = NowTime
    Range("L2") = (Range("K2") - Range("F2")) * 100000
End Sub

Private Sub CommandButton12_Click()
    Sheets("Sheet3").Activate
    Range("M2") = "4"
    [K2].NumberFormat = "hh:mm:ss"
    NowTime = Now() - StartTime
    [K2] = NowTime
    Range("L2") = (Range("K2") - Range("F2")) * 100000
End Sub

Private Sub CommandButton13_Click()
    Sheets("Sheet3").Activate
    Range("M2") = "5"
    [K2].NumberFormat = "hh:mm:ss"
    NowTime = Now() - StartTime
    [K2] = NowTime
    Range("L2") = (Range("K2") - Range("F2")) * 100000
End Sub
Private Sub CommandButton14_Click()
    Sheets("Sheet3").Activate
    Range("M2") = "6"
    [K2].NumberFormat = "hh:mm:ss"
    NowTime = Now() - StartTime
    [K2] = NowTime
    Range("L2") = (Range("K2") - Range("F2")) * 100000
End Sub

Private Sub CommandButton15_Click()
    Sheets("Sheet3").Activate
    Range("M2") = "7"
    [K2].NumberFormat = "hh:mm:ss"
    NowTime = Now() - StartTime
    [K2] = NowTime
    Range("L2") = (Range("K2") - Range("F2")) * 100000
End Sub

Private Sub CommandButton16_Click()
    Sheets("Sheet3").Activate
    Range("M2") = "8"
    [K2].NumberFormat = "hh:mm:ss"
    NowTime = Now() - StartTime
    [K2] = NowTime
    Range("L2") = (Range("K2") - Range("F2")) * 100000
End Sub

Private Sub CommandButton17_Click()
Sheets("Sheet3").Activate
Range("M2") = "9"
[K2].NumberFormat = "hh:mm:ss"

NowTime = Now() - StartTime

[K2] = NowTime

Range("L2") = (Range("K2") - Range("F2")) * 100000

End Sub

Private Sub CommandButton2_Click()

Sheets("Sheet3").Activate

Range("I2") = "4"

[G2].NumberFormat = "hh:mm:ss"

NowTime = Now() - StartTime

[G2] = NowTime

Range("H2") = (Range("G2") - Range("F2")) * 100000

End Sub

Private Sub CommandButton20_Click()

Sheets("Sheet3").Activate

Range("I2") = "1"

[G2].NumberFormat = "hh:mm:ss"

NowTime = Now() - StartTime

[G2] = NowTime

Range("H2") = (Range("G2") - Range("F2")) * 100000

End Sub

Private Sub CommandButton21_Click()
Sheets("Sheet3").Activate

Range("M2") = "11"

[K2].NumberFormat = "hh:mm:ss"

NowTime = Now() - StartTime

[K2] = NowTime

Range("L2") = (Range("K2") - Range("F2")) * 100000

End Sub

Private Sub CommandButton22_Click()
    Sheets("Sheet3").Activate
    Range("M2") = "11"
    [K2].NumberFormat = "hh:mm:ss"
    NowTime = Now() - StartTime
    [K2] = NowTime
    Range("L2") = (Range("K2") - Range("F2")) * 100000
End Sub

Private Sub CommandButton23_Click()
    Sheets("Sheet3").Activate
    Range("M2") = "11"
    [K2].NumberFormat = "hh:mm:ss"
    NowTime = Now() - StartTime
    [K2] = NowTime
    Range("L2") = (Range("K2") - Range("F2")) * 100000
End Sub

Private Sub CommandButton24_Click()
    Sheets("Sheet3").Activate
Range("M2") = "10"

[K2].NumberFormat = "hh:mm:ss"

NowTime = Now() - StartTime

[K2] = NowTime

Range("L2") = (Range("K2") - Range("F2")) * 100000

End Sub

Private Sub CommandButton25_Click()

SMASH.Show

End Sub

Private Sub CommandButton26_Click()

CLEAR.Show

End Sub

Private Sub CommandButton27_Click()

DROP.Show

End Sub

Private Sub CommandButton28_Click()

BLOCK.Show

End Sub

Private Sub CommandButton29_Click()

DRIVE.Show

End Sub

Private Sub CommandButton3_Click()

Sheets("Sheet3").Activate

Range("I2") = "3"

[G2].NumberFormat = "hh:mm:ss"
NowTime = Now() - StartTime

[G2] = NowTime

Range("H2") = (Range("G2") - Range("F2")) * 100000

End Sub

Private Sub CommandButton30_Click()
    PUSH.Show
End Sub

Private Sub CommandButton31_Click()
    NET.Show
End Sub

Private Sub CommandButton4_Click()
    Sheets("Sheet3").Activate
    Range("I2") = "2"
    [G2].NumberFormat = "hh:mm:ss"
    NowTime = Now() - StartTime
    [G2] = NowTime
    Range("H2") = (Range("G2") - Range("F2")) * 100000
End Sub

Private Sub CommandButton6_Click()
    Sheets("Sheet3").Activate
    Range("I2") = "5"
    [G2].NumberFormat = "hh:mm:ss"
    NowTime = Now() - StartTime
    [G2] = NowTime
    Range("H2") = (Range("G2") - Range("F2")) * 100000
End Sub

Private Sub CommandButton7_Click()
    Sheets("Sheet3").Activate
    Range("I2") = "6"
    [G2].NumberFormat = "hh:mm:ss"
    NowTime = Now() - StartTime
    [G2] = NowTime
    Range("H2") = (Range("G2") - Range("F2")) * 100000
End Sub

Private Sub CommandButton8_Click()
    Sheets("Sheet3").Activate
    Range("I2") = "7"
    [G2].NumberFormat = "hh:mm:ss"
    NowTime = Now() - StartTime
    [G2] = NowTime
    Range("H2") = (Range("G2") - Range("F2")) * 100000
End Sub

Private Sub CommandButton9_Click()
    Sheets("Sheet3").Activate
    Range("M2") = "1"
    [K2].NumberFormat = "hh:mm:ss"
    NowTime = Now() - StartTime
    [K2] = NowTime
    Range("L2") = (Range("K2") - Range("F2")) * 100000
End Sub
8.2 HTML Programming

This section covers the HTML programming component of this dissertation. As mentioned in Chapter 8, one of the future tasks of this research is to develop the program into a web based function. The following instructions for web based integration was designed by the placement student Pauline Danino in 2010.

1.2 Development application

To visualize and modify the code, the only thing you really need is any text editor. Nevertheless, it can be easier to use a web development application such as Dreamweaver or Microsoft Expression Web or any other one because it recognizes the language used and highlights the code properly, which makes it easier to read, and it can also be linked to the local server so that any change made in the code is automatically applied to the website.

The only detail that can be annoying is that the code contains .ctp files, which is a cakePHP standard and the editor would not recognize them. There is always a “trick” to add this extension to the list of extensions the editor knows. Those tricks are very easy to find on Google. I used Dreamweaver, so here is the way to it for this editor:

In the folder that you installed Dreamweaver, in my case this is C:\Program Files\Adobe\Adobe Dreamweaver CS3\configuration, open up “Extensions.txt” and on the first line at the very end add THTML and CTP separated by commas, so the line should read:

```
...MASTER,THTML,CTP:All Documents
```

Similarly add these two extensions to the “PHP Files” line:

```
PHP,PHP3,PHP4,PHP5,TPL,THTML,CTP:PHP Files
```

Next open the “DocumentTypes” folder and edit the “MMDocumentTypes.xml” file. Just open it up using notepad or wordpad. Search for the line which has an id “PHP:MySQL” and add the THTML/CTP file extensions to both the “winfileextension” and “macfileextension” so the line should read:

```
# winfileextension="php.php3.php4.php5,thtml,ctp"
# macfileextension="php.php3.php4.php5,thtml,ctp"
```

The final file is another version of the “Extensions.txt” which is located in your “Documents and Settings” Folder. In my case this is “C:\Documents and Settings\User\Application Data\Adobe\Dreamweaver 9\Configuration” just add the very same things you inserted earlier.

Finally restart Dreamweaver to apply the changes.
Figure 1: MVC Architecture of CakePHP (source: cakephp.org)
INVITATION TO PARTICIPATE IN A RESEARCH PROJECT
PROJECT INFORMATION STATEMENT

PROJECT TITLE: Improving reaction time and awareness in badminton to optimise in-game performance

INVESTIGATORS: Minh Huynh (Principal Investigator, Masters Student, Research Assistant, School of Mathematical and Geospatial Sciences, RMIT University. Minh.huynh@rmit.edu.au)
Dr Anthony Bedford (Principal Investigator, Senior Lecturer, School of Mathematical and Geospatial Sciences, RMIT University. anthony.bedford@rmit.edu.au 9925 6119)

Dear Participant,

You are invited to participate in a research project conducted by RMIT University. This information sheet describes the project in straightforward language, or 'plain English'. Please read this sheet carefully and be confident that you understand its contents before deciding whether to participate. If you have any questions about the project, please contact one of the investigators.

Who is involved in this research project? Why is it being conducted?

This research is conducted by Minh Huynh (Principal Investigator) and Dr Anthony Bedford (Investigator), of the School of Mathematical and Geospatial Sciences. It is being conducted as part of a Masters in Statistics and Operations Research. The project has been approved by the RMIT Human Research Ethics Committee.

Why have you been approached?

You have been approached for this project as you have sufficient knowledge, understanding and skill of the sport badminton. Your feedback on the process is valuable to us and is vital
in developing a training program that is effective for both current and future badminton athletes.

What is the project about? What are the questions being addressed?

The aim of this research is to examine whether certain player attributes (height, weight, sprint speed, etc) affect their decision making during a match. Decision making is defined as an outcome of cognitive processes; leading to the selection of a course of action among several alternatives. Aims may include increasing scoring opportunities, deciding the best shot to make, anticipating the location the opponent will return the shot, or increasing overall reaction time during a match.

In determining player attributes and capabilities, we will be incorporating a ratings model for individual players within a team. Using these ratings, player performance and judgment assessment will be established. A working simulation of the ratings system in conjunction with a multiple regression analysis will be designed as a useful tool for coaches to assess their player’s decision making capabilities.

In summary, the research aims to answer the following questions:

- Do certain player attributes (height, weight, agility, etc) influence their awareness and reaction time to a shuttle during a match?
- Is it possible to enhance a player’s awareness and reaction time by utilizing a digital program designed for increasing their performance?

If I agree to participate, what will I be required to do?

Your participation will involve testing a new computer based program that aims to improve reaction time and awareness. There will be weekly sessions for this experiment, which will initially be conducted in the presence of the researcher to ensure the program is functioning accurately. Once the coding for the program has been applied to a web site, participants may complete the weekly sessions in the leisure of their own homes or any location that has internet access. Participation in this research is completely voluntary and you may withdraw from it at anytime.

What are the risks or disadvantages associated with participation?

There are no perceived risks or disadvantages in participation in this study.

What are the benefits associated with participation?

It is expected that the research will optimise in-game performance by increasing participants’ (i) reaction time, (ii) awareness and (iii) decision making skills.

What will happen to the information I provide?

The electronic program will ask you to enter your name at the start of each session. This is so that we can record and observe the improvement in your awareness and decision making.
skills over a period of time. This information will be used to assess and improve the training program and quantitatively analysed for journal publications.

Any information that you provide can be disclosed only if (1) it is to protect you or others from harm, (2) a court order is produced, or (3) you provide the researchers with written permission. The research data will be kept securely at RMIT for a period of 5 years before being destroyed.

**What are my rights as a participant?**

As a participant you have the right to withdraw your participation at any time, without prejudice. You have the right to have any unprocessed data withdrawn and destroyed, provided it can be reliably identified. You also have the right to have any questions answered at any time.

**Whom should I contact if I have any questions?**

Contact Minh Huynh or Dr Anthony Bedford if you have any questions regarding this research.

Yours sincerely

Minh Huynh
Dr Anthony Bedford
8.4 Consent forms

RMIT University
School of Mathematical and Geospatial Sciences
Building 8, Level 9
360 Swanston Street, Melbourne, 3000
Ph: +61 3 9925 2283
Fax: +61 3 9925 1748
Email: maths@rmit.edu.au

PARENT/GUARDIAN CONSENT FORM

I (print name) ........................................................................................................ give consent
for my child (print name) ........................................................................................ to
participate in the proposed research (please refer to the plain language statement for details)
described below.

PROJECT TITLE: Improving reaction time and awareness in badminton to optimise in-game
performance

INVESTIGATORS: Minh Huynh (Principal Investigator, Masters Student, Research Assistant, School
of Mathematical and Geospatial Sciences, RMIT University.
Minh.huynh@rmit.edu.au)

Dr Anthony Bedford (Principal Investigator, Senior Lecturer, School of
Mathematical and Geospatial Sciences, RMIT University.
anthony.bedford@rmit.edu.au 9925 6119)

In giving my consent I acknowledge that:
1. The procedures required for the project and the time involved have been explained to me and any questions I have about the project have been answered to my satisfaction.

2. I have read the Plain Language Statement and have been given the opportunity to discuss the information and my child's involvement in the project with the researchers.

3. I have discussed participation in the project with my child and my child assents to their participation in the project.

4. I understand that my child's participation in this project is voluntary; a decision not to participate will in no way affect their standing with the team and they are free to withdraw their participation at any time.

5. I understand that my child’s involvement is strictly confidential and that no information about my child will be used in any way that reveals my child’s identity.

6. I understand that video recordings will be made as part of the study. Players may request to see the recordings with the permission of the coach and only the recordings of their performance (no one else's). These recordings will take place during:

a. Badminton training sessions at the Melbourne Sports and Aquatic Center, from January 2010 – December 2010

Signed...........................................................................................................................

Date...............................................................................................................................
8.5 The questions on the KMT

Figure A1: Section A, question 1 of the KMT

Figure A2: Section A, question 2 of the KMT
Figure A3: Section A, question 3 of the KMT

Figure A4: Section A, question 4 of the KMT
Figure A5: Section A, question 5 of the KMT

Figure A6: Section A, question 6 of the KMT
Figure A7: Section A, question 7 of the KMT

The following figures (36 – 42) show the questions asked in Section B of the KMT:

Figure B1: Section B, question 1 of the KMT
Figure B2: Section B, question 2 of the KMT

Figure B3: Section B, question 3 of the KMT
Figure B4: Section B, question 4 of the KMT

Figure B5: Section B, question 5 of the KMT
Figure B6: Section B, question 6 of the KMT

Figure B7: Section B, question 7 of the KMT
9.6 SATB help options

Figure S1: The screen that appears when the help for smash shot is selected

Figure S2: The screen that appears when the help for clear shot is selected
Figure S3: The screen that appears when the help for drop shot is selected

Figure S4: The screen that appears when the help for block shot is selected
Figure S5: The screen that appears when the help for drive shot is selected

Figure S6: The screen that appears when the help for push shot is selected
Figure S7: The screen that appears when the help for net shot is selected
8.7 Ethics Approval for Human Research

14th December 2009

Minh Huynh
School of Mathematical &
Geospatial Sciences
RMIT University
Building 8, Level 9,
City Campus

Dear Minh,

BSETAPP 63 – 09 HUYNH Improving reaction time and awareness in badminton to optimize in-game performance

Thank you for submitting your amended application for review.

I am pleased to inform you that the Science, Engineering & Health College Human Ethics Advisory Network (CHEAN) has approved your application for a period of 12 Months to December 2010 and your research may now proceed. The CHEAN considers this to be a Low Risk (formerly Level 2) proposal.

The CHEAN would like to remind you that:

All data should be stored on University Network systems. These systems provide high levels of manageable security and data integrity, can provide secure remote access, are backed up on a regular basis and can provide Disaster Recover processes should a large scale incident occur. The use of portable devices such as CDs and memory sticks is valid for archiving; data transport where necessary and for some works in progress.
The authoritative copy of all current data should reside on appropriate network systems; and the Principal Investigator is responsible for the retention and storage of the original data pertaining to the project for a minimum period of five years.

Annual reports are due during December for all research projects that have been approved by the College Human Ethics Advisory Network (CHEAN).

The necessary form can be found at: http://www.rmit.edu.au/governance/committees/hrec

Yours faithfully,

Diana Donohue
Chair, Science Engineering & Health
College Human Ethics Advisory Network ‘A’

Cc: CHEAN Member: George Lenon, School of Health Sciences
Supervisor: Anthony Bedford, School of Mathematical & Geospatial Sciences
8.8 Modern rules and regulations of badminton

This section will give a brief outline of the rules and regulations of badminton as specified by the BWF, the governing body of the sport. Keep in mind that the rules and regulations as described in this section are in respect to the standardised guidelines as set by the Laws of Badminton and Regulations (Badminton World Federation, 2010) and may differ in subsequent or previous years (due to the constant evolution of the game).

8.8.1 Court Dimensions

In badminton, the court is rectangular and is marked out with lines 40 mm wide. The line markings of the court are preferably to be in distinguishable colours such as white or yellow (refer to Figure 8.3 for an example of a badminton court and its markings). The posts holding up the net shall be 1.55 meters in height from the surface of the court and shall remain vertical when the net is strained. The post shall be placed on the doubles sidelines (refer to figure 8.3) regardless of whether a game of doubles or singles is being played. The net is prepared with fine cord of dark colour and even thickness with a mesh of no less than 15 mm and not more than 20 mm. The net itself is 760 mm in depth and at least 6.1 meters wide, with the top being edged with a 75 mm white tape doubled over a cord or cable. The cord or cable is stretched firmly, and flush with the top of the posts. When completely stretched out, the top of the net from the surface of the court should be 1.524 meters from the center of the court and 1.55 meters over the doubles sideline.
Figure 8.3: The optimal dimensions of both a singles and doubles badminton court

8.8.2 The shuttlecock

In badminton, the object that players hit to one another is known as the shuttlecock and can be crafted with or without feathers. Typically, in high-end tournaments (e.g. Olympic Games) the use of feathered shuttlecocks is required (refer to Figure 8.4).

The feathered shuttlecock has 16 feathers fixed at the base, with feathers uniformly in length between 62 mm to 70 mm when measured from the tip to the top of the base. The tips of the feathers are placed on a circle with diameter 58 mm to 68 mm. The overall weight of the feathered shuttlecock should be between 4.74 and 5.50 grams.

The non-feathered shuttlecock uses synthetic materials to replace the natural feathers. It generally has the same dimensions as the feathered shuttlecock, however, because of the differences in the specific gravity and other properties of the synthetic materials when compared to feathers, a variation of up to 10 per cent (in size and weight) is acceptable.
The frame of the racket used in badminton can be divided into three components: the head, the shaft and the handle (refer to figure 8.5 for an example of the racket). Overall, the racket must not exceed 680 mm in length and 230 mm in width.

The head of the racket is connected the throat (if present) which in turn is connected to the shaft. The head also bounds together the stringed area. This area is flat and consists of a pattern of crossed strings either alternatively interlaced or bonded where they cross. The pattern is generally uniform, with the same density in all areas.
The shaft connects the handle to the head of the racket and is generally made out of light weight materials. The handle is the part of the racket intended to be gripped by players. Overall, the shaft and the handle must be free of attached objects and protrusions, and must not contain any device that makes it possible for a player to change materially the shape of the racket.

Figure 8.5: The components of a racket utilised in badminton

8.8.4 Playing the game

Matches are played to the best of three games, with games being decided by the side which first reaches 21 points. The side winning a rally shall add a point to its score. A side shall win a rally, if the opposing side commits a fault or the shuttle ceases to be in play because it touches the surface of the opponent’s court. If the score becomes 20-20, then the first side to gain a two point lead shall be determined the winner. If the score reaches 29-29, then the first side to gain the next point shall win that game. The side that wins a game shall serve first in the next game. At the end of every game the players will change ends (court sides). If there is a third game, players will alternate ends when a side first reaches 11 points.
8.8.5 Service

To execute a legal serve, the server must adhere to the following conditions:

(a) The server and the receiver shall stand within diagonally opposite service courts without touching the boundary lines of these service courts.

(b) Some part of both feet of the server and the receiver shall remain in contact with the surface of the court in a stationary position from the start of the service until the service is delivered.

(c) The server’s racket shall initially hit the base of the shuttle.

(d) The whole shuttle shall be below the server’s waist at the instant of being hit by the server’s racket. The waist shall be considered to be an imaginary line around the body, level with the lowest part of the server’s bottom rib.

(e) The flight of the shuttle shall be upwards from the server’s racket to pass over the net so that, if not intercepted, it shall land in the receiver’s service court (i.e. on or within the boundary lines.

(f) In doubles, during the delivery of the service, the partners may take up any positions within their respective courts, which do not unsight the opposing server or receiver.

8.8.6 Faults and service errors

In badminton, faults fall under three categories: (a) service faults, (b) shuttle faults, and (c) player faults:
Services are considered faults or service errors when the following occurs:

- When players don’t abide to the rules specified in the service section (mentioned above).
- When players serve or receive out of turn.
- When the service lands outside the boundaries of the service court (when the shuttle is served out or into the net).

Shuttle faults are called when the following occur:

- The shuttle lands outside the boundaries of the court (i.e. not on or within the boundary lines).
- The shuttle passes through or under the net.
- The shuttle fails to pass over the net.
- The shuttle touches the ceiling or side walls.
- The shuttle touches any other person or object outside the court.
- The shuttle is caught and held by the racket and executed as a stroke (commonly known as a carry).
- The shuttle is hit twice in succession by the same side.

A player fault is called when the following occurs:

- A player touches the net or its supports.
- A player invades an opponent’s court over or under the net with racket or person; such that an opponent is obstructed or distracted.
- A player deliberately distracts an opponent by any action such as shouting or making gestures.

In the event of a fault or service error, the rally is ended and the opposing team wins the point.
8.8.7 Lets

In badminton, ‘lets’ are decided by the umpire and may fall under the following categories:

- During service, the server serves when the receiver is not ready.
- During service, both the receiver and server are faulted.
- After the service return, the shuttle is caught on the net and remains suspended on its top.
- During play, the shuttle disintegrates and the base completely separates from the rest of the shuttle.
- In the opinion of the umpire, play is disrupted or a player of the opposing side is distracted by a coach.
- A line judge is unsighted and the umpire is unable to make a decision.

In the event that a let occurs, play since the last service shall not be counted and the player who served last shall serve again.

8.8.8 Singles

Prior to commencing a game, a coin toss is conducted and the winner of the toss may decide whether to serve or receive first, as well as which side of the court they would like to start in. Service shall commence from the right service court, with the receiver receiving the service from the diagonally opposite court. Service will always be on the right side service court when the score is zero or sums to an even number (e.g. 2-2). Service will always be on the left side service court when the score sums to an odd number (e.g. 2-1). Following the service, the shuttle may be hit by either the server or the receiver alternatively, from any
position on that player’s side of the net, until the shuttle ceases to be in play. If the server wins the rally then they shall serve again from the alternate service court. If the receiver wins the rally then the receiver becomes the new server and shall serve on the corresponding service side depending on the sum of the score.

8.8.9 Doubles

Prior to commencing a game, a coin toss is conducted and the side winning the toss may decide whether to serve or receive first, as well as which side of the court they would like to start in. Service shall commence from the right service court, with the receiver receiving the service from the diagonally opposite court. Service will always be on the right side service court when the score is zero or sums to an even number (e.g. 2-2). Service will always be on the left side service court when the score sums to an odd number (e.g. 2-1). The player of the receiving side who served last shall stay in the same service court from where he or she last served. The reverse pattern applies to the receiver’s partner. The players shall not change their respective service courts until they win a point when their side is serving. Following the return of service, the shuttle may be hit by either player of the serving side and either player of the receiving side alternatively, from any position on that player’s side of the net, until the shuttle ceases to be in play. If the serving side wins the rally then they win a point and shall serve again from the alternate service court. If the receiving side wins the rally then they win a point and the receiving side shall then become the new serving side.

In doubles badminton, the sequence of service shall pass consecutively (following the loss of a rally from the serving side) as follows:

1. The initial server who started the game from the right service court.
2. The partner of the initial receiver.

3. The partner of the initial server.

4. The initial receiver.

5. The initial server and so on.

Either player of the winning side may serve first in the following game. Subsequently, either player of the losing side may receive first in the following game.
8.9 Video footage utilised for the SATB

Australian Open 2009

Men’s Singles: Dionysius Hayom Rumbaku (ID) versus Alamsyah Yunus (ID)

Women’s Singles: Maria Febe Kusumastuti (ID) versus Yip PuiYin (HK)

Badminton Asia Championships 2009

Men’s Singles: Bao Chunlai (CHN) versus Chen Long (CHN)

Women’s Singles: Zhu Lin (CHN) versus Xie Xing Fang (CHN)

Malaysian Open 2009

Men’s Singles: Lee Chong Wei (MY) versus Chen Long (CHN)

Women’s Singles: Wang Shixian (CHN) versus Wang Xin (CHN)