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INDIVIDUAL FEELING STATES AND PERFORMANCE DURING TENNIS MATCHES: AN INTEGRATION OF THE IZOF AND IAPZ MODELS

By

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ABSTRACT

INDIVIDUAL FEELING STATES AND PERFORMANCE DURING TENNIS MATCHES: AN INTEGRATION OF THE IZOF AND IAPZ MODELS

By

M. Ryan Flett

For those researchers and practitioners interested in optimal performance in sport, feeling states are one of the most important predictors of performance. Feeling states are a broad category that encompasses affective (e.g., emotions, moods), somatic (e.g., physical sensations), and other forms of feeling. All of these terms are difficult to define, and there is no consensus for any of them. Among these feeling states, emotions play the most prominent role in predicting performance; and are also the most researched, best-defined, and most theoretically mature construct in the feeling / affect literature.

Feeling states are, however, only half of the feeling-performance relationship. The most prolific theory in the field is the idiosyncratic Individual Zones of Optimal Functioning theory (IZOF: Hanin, 1978, 1997, 2000a). More recently, Tenenbaum and colleagues have developed the Individual Affect Performance Zone (IAPZ; Kamata, Tenenbaum, & Hanin, 2002; Tenenbaum, Edmonds, & Eccles, 2008). In this study, both idiographic models were combined in the following ways. (1) Rather than describing feelings as continuous two-dimensional constructs (wherein players rate the pleasantness and arousal-level of their feeling state), discrete items (e.g., confidence, worry, calmness) were selected to create each profile. (2) Ordinal Logistic Regressions were conducted to develop probabilistic estimates for four feeling categories (based on positive-/negative-valence and functional/dysfunctional groupings).

Ten male college tennis players volunteered to participate in this study. Participants developed individualized profiles, and then monitored the intensity of each item in the profile during competitive intra-squad matches. In total, 918 observations were recorded. Ordinal logistic regressions were conducted to identify probabilistic performance curves.

Visual comparisons of individual zone profiles, qualitative comparison of the discrete items selected by each participant, and statistical analyses provided support for the validity of the combined IZOF-IAPZ method used in this dissertation as well as for the idiosyncratic nature of feeling-performance relationships. Statistical analysis identified 76.3% interindividual differences based on comparisons of the location and width of each feeling-performance zone. Intraindividual differences did not emerge across context: only 12.5% of the zone comparisons for serving and returning serve displayed significant differences. Ordinal Logistic Regression (OLR)-based models were generally accurate. The complete four-category (function-valence) model predicted performance correctly 63.5% of the time (more than twice that of chance); and the four "trigger" items chosen by each player as the most important for his performance were 66.4% accurate—the top three trigger items were accurate 70.0% of the time.

The dissertation offers important data in the field of IZOF research because a large sample was collected during performances, and it was shown that OLR may be used to develop probabilistic feeling-performance profiles using discrete feeling items. As such, the interaction of valence and function can be studied along with simple profiles with only three self-selected performance predictors.

I have learned a great deal about research and the science of sport psychology from my graduate training. I am grateful and appreciative for the excellent schools and professors that I have learned from. With a truly humble appreciation for everything that is bigger than me—where I am from—I dedicate this to all of the coaches, athletes, parents, friends, and family (in particular, my uncle, Dan Marisi), who have provided me with a special understanding of, and appreciation for, applied sport psychology. There are great teachers available wherever you are in life—you just have to keep your eyes and ears open.

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First and foremost, I want to thank my participants in this study for their exceptional focus and patience. They did not have any complaints, or express concerns with how their participation in this study might affect their personal performance. They are good guys. My time with them and with the coaches of the team has been a highlight of the past three years. I wish them all the best. Every one of them has an incredible future ahead of him!

I am indebted to my committee for their assistant with this project. Dr. Feltz is a fantastic leader in our field and in our building. I cannot thank her enough for the resources that she has provided me with. Dr. Ewing has been so generous with her time over the years. I appreciate her open door and her practical insight. She has always given me good, plain advice. Dr. Wong taught the best class I have taken at MSU and one of the two of three best I have ever taken (I don't have an official ranking system worked out, but I am confident in that ranking). His class is what I expected every graduate class would be: a carnival of ideas without mere regurgitation of text.

In 2004, I decided to return to school in Fall 2005. I talked to some people I trusted. Asked them who the best person in sport psychology was. I was told that the best man—the most quality person—in our field was Dan Gould. I laughed and pointed out that he was the biggest name in applied. I did not see how he could be at the top of the field and also be a person who I could see eye-to-eye with. But I trusted the advice I had asked for and applied to MSU. The story does not end at my application—my *first* application to MSU—but for the sake of interjecting some brevity, I will end the story there. Dan is one of the best people I have ever known. I can't imagine how much crap he has taken for my disregard for stupid things that only exist to help insecure people who are scared to leave the flock. Dan has supported me to be myself, regardless of where that takes me, and that is where it will take me. For everything that Dan has done for me personally, I am also indebted to Larry Lauer. He has been a friend and a good person to talk shop with.

The most important acknowledgement goes to my family. Some are here, some are there, some are all over. I have had no greater inspiration in my life than from my grandpa. It is too bad there is not a heaven. I would like to make ravioli with him; or have lunch with him and grandma again—chicken sloup and ham sandwiches. Don't know why grandma pronounced it sloup. My mom and dad did good. I am a pretty impossible person. They could have traded me in for one of the simple kids I think. My mom said she was put here just to look out for me, and that is a full time job. I wish, too, that my dad could read and understand the stuff that I have been doing over the past four years—he was diagnosed with Alzheimer's and Dementia in the first year of my doctorate.

I am grateful for the assistance and friendship that Tracey, Darcie, Jo Ann, Verna, and Jan have provided me. I would also like to thank my friends here at MSU for their support and fun—especially thank RJ, Francois, Jenn, and Amanda. When I moved to Gainseville, I lost touch with many friends from Saskatchewan. I regret this. Having learned my lesson, I am thankful for my friends in Regina and Saskatoon who made so much time for me during the holidays, and even went out of their way to visit me here. Thanks to Kelly, Kyla, Connor, Blair, Jac, Ty, Scott, Steve, Mark, Scott, and Brian.

Music really makes a difference in my life. I am thankful for all the artists who share their world-view, their creativity, and their liberation. I find peace in music and in the Dharma, and I am looking forward to finding more time for those things once again. I am thankful for my experiences—good and bad.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER ONE

INTRODUCTION

Have you ever been involved in, or seen, a sporting event that did *not* involve emotion? Tears, screams, laughter, and dejected silence are as much a part of sport as scoring and rules. Sport and emotion are inseparable. As the forthcoming review of literature in emotion will explain, it is impossible to remove emotions from sport experiences. Motivation, personal challenge, physical and psychological threat, reward opportunities, and the need for strong coping skills—all of these things are implicit to both sport and emotion (Lazarus, 1991, 2000b). So long as athletes have an interest in the outcome of their training or competition, they will experience emotions.

Some coaches, athletes, and even sport scientists incorrectly view emotions as bad things that undermine performance (Botterill & Brown, 2002). In addition to this bias against emotions (and feelings in general), some in sport believe that emotions should be avoided or ignored because of their complexity. However, these perspectives are more likely to harm performance than to facilitate it. Feelings are adaptive mediators of person-goal relationships, and they are unavoidable. So athletes and practitioners must accept them and learn to control them. Emotions and other feelings can enhance performance by: (a) improving metacognitive understanding of the effects that emotions have on functioning; (b) improving emotional self-awareness; and (c) by developing psychological skills and routines that meet the unique emotional needs of athletes.

Feelings and Performance in Sport

The objective of this study is to examine the relationship between feeling states and performance in sport. More specifically, the effects of feelings on performance during competitive tennis matches will be assessed for the purpose of integrating the Individual Zones of Optimal Functioning (IZOF) and Individual Affect-Related Performance Zones (IAPZ) models. The design of the study was informed by appraisal theories of emotion, and reviews of Individual Zones of Optimal Functioning (IZOF; Hanin, 1997, 2000a), and Individual Affect Performance Zones (IAPZ; Kamata, et al., 2002; Tenenbaum, et al., 2008) literature. In addition to scientific foundations, the design and procedures for this study were influenced by the investigator's applied experiences working with athletes. The study of feelings in sport is important because athletics provide an ideal context for the study of emotional appraisal and expression. As such, this research provides an opportunity for sport psychology to contribute to the knowledge of general psychology.

Affect-Related Terminologies

One problem in sport psychology research and in practice is the failure to recognize distinctions between similar affect-related terminologies. While these definitions are somewhat contentious, researchers must nevertheless establish common meanings for the words they use (Ekkikakis & Petruzzello, 2000). As much as possible, it is important for these technical definitions to connect with non-academic practitioners such as coaches and athletes. While this dissertation is interested in more general feeling states (e.g., feeling strong, confident, worried, satisfied, etc.), emotions are of particular interest because they comprise the majority of items in individuals' profiles, and there is more advanced research and theory in the area of emotion than for any of the other affect-related terminology. In addition to feeling and emotion, the terms affect, mood, anxiety, arousal, and activation are described in the following section. In the second chapter, theories are explored that describe how and why emotions function. These theories provide a foundation for feeling-performance models such as Hanin's (2000) IZOF.

Feeling states. Feeling states are perhaps the broadest category and are synonymous with both affective conditions and physiological sensations such as pain. According to Lazarus (1991, 2000b), sensations are reflexes, rather than emotions. Reflexes are considered "pre-emotions" because they can promote certain emotional states and occur without thought (Lazarus, Averill, & Opton, 1970). For instance, if George were to burn his hand on a pot, the immediate reaction to pull his hand away from the pot is considered a reflex. Because of his pain, the reflex is likely to precipitate an emotion such as anger or fear. The onslaught of profanity uttered by George is a behavioral aspect of emotion (e.g., coping), not of the reflex. Based on the connection with somatic sensations, feelings like light, strong, quick, and fierce may be considered feeling states.

Lazarus (1991, p. 57) clarified the distinction between feeling and emotion:

> The distinction between reflex and emotion is much like one that has been made between *feeling* and *emotion*. These terms are often used interchangeably, but I think it would be more precise to speak of feelings as sensory perception, as in feeling pain, pleasure, and distaste, rather than as emotion. Although we speak constantly about feelings when we mean emotions…it is more precise to restrict the word *feeling* to the awareness of bodily sensations and to reserve the word *emotion* for occasions on which there has been an appraisal of harm or benefit.

Clifford Saron, psychologist at the Albert Einstein Medical School in New York City elaborated in Goleman (1997, pp. 82-83):

> Our common sense vocabulary is a central problem in talking about emotions...doubt is not considered a basic emotion, like anger, happiness, or sadness. However, it is certainly a feeling state that we can identify. When you say 'doubt,' I know what you mean...Certainty, confidence, and pride would be considered emotions.

The current study assumes a pragmatic point of view and includes the broadest definition of possible affect-related states. This is because feeling confident, feeling strong, or feeling sluggish, (etc.) may be very important for athletes. These items certainly describe the athlete's feeling state, but they are not true emotions in the view of most researchers. As such, these descriptive items should be included within idiographic performance profiles. Also, several items on the positive-negative affect scale (PNA, Hanin, 1993b; Syrja & Hanin, 1997) are not considered to be basic emotions (e.g., fast, inspired, aggressive, sluggish, helpless, and confident). Lazarus (2000b) has, for instance, identified 15 core emotions. The PNA is quite liberal, and by releasing some constraints, Hanin has developed a more comprehensive list of performance-related factors. To account for this broad, liberal criterion, the term "feeling states" will be used throughout this dissertation to describe emotions, moods, somatic sensations, and other feeling-related states.

Affect. Affect is the experience of pleasant and unpleasant responses (valence) and does not include any type of cognitive component (Frijda, 1993). Affect is a general term that applies to both moods and emotions (Campos, Keltner, & Tapias, 2004; Ekkikakis & Petruzzello, 2000). As Ortony, Clore, and Foss (1987) explained, "the word 'affect' entails that all emotions are affective conditions, but that not all affective conditions are emotions" (p. 343). Unlike emotion, affect cannot be reduced to describe more specific phenomenon (Ekkikakis & Petruzzello, 2000). For instance, emotions may be categorized into different discrete forms, such as anger, joy, anxiety, etc. Affect does not comprise specific categories in the ways that emotion and mood do because affect is a global term—as Frijda described, it is a component of emotion and mood. However, affect can be described in terms of the intensity of feeling and in terms of hedonic tone (also referred to as valence or pleasantness).

Emotion. Emotion is probably the most relatable, yet the most difficult term to define or explain. It is a functional process in that it promotes adaptational responses to environmental demands, and in turn, facilitates survival and well being (Campos, et al., 2004; Ekkikakis & Petruzzello, 2000). Emotions are subjective in nature, involve physiological responses, and result in behavioral effects (Botterill & Brown, 2002). Deci and colleagues (Deci, 1980; Deci & Ryan, 1985) defined emotion as "a reaction to a stimulus event (either actual or imagined)…[That] involves a change in the viscera and musculature of the person; is experienced subjectively in characteristic ways [known as affect]; is expressed through such means as facial changes and action tendencies; and may mediate and energize subsequent behaviors" (p. 85) (Deci, 1980).

While these descriptions help to explain what emotion is, we can also explain emotion by what it is not. What separates emotions from non-emotional phenomenon? Lazarus (1991) noted that emotions can also be defined by three components of reactions proposed by Drever (1952). First, emotions elicit an impulse to act, such as fight or flight responses—or typically in sport, reverting to habit. Second, there are patterns of somatic changes that facilitate the aforementioned tendency in order to reach adaptational goals. In sport, these changes include increased heart rate, butterflies in the stomach, etc. The third component of an emotional reaction is the subjective experiential component—also known as affect—which includes appraisal and evaluative judgment. An example of this component would be a nervous athlete thinking, "this [anxiety] is good for me—I feel energized and ready to perform."

Emotions are unique from non-emotional phenomena such as reflexes, motivation, cognition, or feeling states in the following four ways: (1) emotions involve the presence of personally meaningful relational content; (2) emotions involve an appraisal of potential harm or benefit; (3) emotions involve the potential for action-readiness; and most of all (4), emotions involve physiological (nervous system and hormonal) changes (Lazarus, 2000a). Specific examples of "emotions" can be derived from Lazarus' (2000b) 15 emotional categories, which include: anger, anxiety, fright, guilt, shame, sadness, envy, jealousy, happiness, pride, relief, hope, love, gratitude, and compassion. Emotion will be described in greater detail in the following sections. Though the focus of this dissertation includes all feeling states, emotions have a particularly strong impact on performance because emotions are more intense and dynamic than moods, and more specific than affect or feeling states (Ekkikakis & Petruzzello, 2000; Mellalieu, 2003). Specific theories of emotion will be provided in the following chapter.

Mood. Compared to emotions, moods are characterized as being less intense, longer in duration (Albert & Rosen, 1990), and as having no specific target or source (Frijda, 1993). Moods may be considered to be sustained emotions. Common examples of mood include being relaxed or depressed. The term "mood states" is somewhat oxymoronic because mood is more trait-oriented and dispositional, whereas emotions are state-oriented experiences. Like affect, mood is a too-often misrepresented term, which Levin describes as “a clumsy phenomenological term” (Levin, October 3, 2003, p. 48). While emotion and mood are generally believed to be cognitive in nature, and mediated by appraisal processes, the critical difference between these states is the source of appraisal. Moods are not a reaction to a specific event, but rather to a more holistic existential evaluation of well-being (Ekkikakis & Petruzzello, 2000; Lazarus, 1991). As such, moods are more stable than emotions, and they relate to more dispositional person-related factors. Although mood is often believed to be a product of perceived physical energy, the opposite is true: “psychic energy” is a *result* of mood (Morris, 1992). Another difference between mood and emotion is that action tendencies are nearly irrelevant in the case of moods (Lazarus, 2000b).

Anxiety, arousal and activation. Anxiety is a negative (i.e., unpleasant) emotion resulting from perceived threat (Campos, et al., 2004; Raglin & Hanin, 2000). Anxiety is characterized by vigilance and is closely associated with, but unique to, arousal. According to Lazarus (1991), emotions (including anxiety) must elicit physiological changes (e.g., autonomic nervous system stimulation, CNS stimulation, and hormonal changes), but not necessarily arousal. Arousal is a condition of preparedness that includes various levels of emotional display, physical energy, mental activity, and associated physiological activity (Campos et al., 2004). Arousal can be described as an activation level, ranging from low (e.g., sleepy) to high (e.g., manic). As well as being synonymous with arousal, activation may refer to the intensity of an affective state. To be more precise, activation describes the readiness or preparedness of a performer (Hardy, Jones, & Gould, 1996). It is common to use the terms intensity, arousal, and activation interchangeably (Lang, 2000; Zaichkowsky & Naylor, 2004).

The Emotion-Performance Relationship

One of the oldest and most researched topics in sport psychology is the anxiety-performance relationship. Within this line of inquiry, the earliest, yet least researched description of the arousal-performance relationship, was the Drive Theory (Spence & Spence, 1966), which predicted a simple linear relationship between arousal and performance. This relationship was explained by social facilitation theory (Zajonc, 1965), which explains that higher activation is helpful for simple or well-learned tasks. This model predicts that high arousal will facilitate activities like weight-lifting; and that an experienced tennis player will serve better under pressure than a player who has just learned how to serve. However, due to the over-simplicity of the model (i.e., its inability to account for enough relevant factors), Drive theory has limited and equivocal support.

Researchers turned next to the Inverted-U hypothesis, or the Yerkes-Dodson law, which describes the arousal-performance relationship as being curve-linear (See, Landers, 1980; Yerkes & Dodson, 1908). In short, optimal performance occurs at a moderate level of arousal (hence the inverted-U shape of the curve). Easterbrook's (1959) Cue Utilization theory lent a scientific explanation for the Inverted-U hypothesis. This theory explains that high arousal is associated with narrow attentional focus, and that very low arousal fosters a wider 'spotlight' of attention. Very wide attention (low arousal) may cause athletes to process too much information, whereas very narrow attention may cause an athlete to miss information.

Further exploration led sport scientists to realize that simple anxiety / arousal models could not account for performance effects. As Landers (1980) explained, "anxiety is a multidimensional phenomenon and we should use multi-method procedures to examine it" (p. 217). This means that, in order to effectively profile/predict performance, multiple feelings must be accounted for. To this end, Martens, Vealey, and Burton (1990) produced the Multidimensional Anxiety Theory (MDAT). The MDAT is the first affect-performance model to acknowledge that physical activation and mental activation should be differentiated; and that influence of confidence should also be considered. Although there is general support for each dimension of the MDAT, examinations of the collective postulates of the model have yielded inconsistent results. MDAT failed to account for the simultaneous interactive effects of each dimension. More importantly, and like all models up to this point, MDAT failed to acknowledge individual differences, favoring instead to provide the same predictions for every athlete.

The Cusp-Catastrophe model (Hardy, 1990, 1996; Hardy & Frazey, 1987, June) contends that performance is a function of interaction of physiological arousal and cognitive anxiety. Based on complex mathematics, the Catastrophe theory succeeded in modeling the anxiety-arousal-confidence-performance relationship within four-dimensional space, but failed to yield consistent statistical support.

All of the theories presented above have two fundamental flaws. First, as nomothetic models they cannot account for individual differences. Second, they fail to recognize that an even broader sample of emotions was necessary in order to explain how and why affect influences performance. Hanin's (Hanin, 1997, 2000a, 2003, 2007) Individual Zones of Optimal Functioning (IZOF) model accounts for idiosyncrasies in affect-performance relationships. Also, rather than being confined to multidimensional anxiety, Individual Zone profiles include any emotion that is personally relevant to an athlete.

However, before describing the IZOF model that is central to this dissertation, we should preface the discussion by defining emotions themselves.

The Individual Zones of Optimal Functioning Model

The theoretical foundation of this dissertation is the IZOF model (Hanin, 2000a, 2000d). Hanin's original model emerged from his applied experiences consulting elite Soviet athletes. These experiences contradicted the established (nomothetic) anxiety-performance models of the time. Based on his training and experiences, Hanin developed the Zones of Optimal Functioning model (Hanin, 1978). With each series of studies conducted by Hanin and others, the model was continually refined, until it evolved into what could be termed the modern Individual Zones of Optimal Functioning model (Hanin, 1997, 2000a, 2003). The IZOF model establishes idiographic (individually unique) profiles that describe the relationship between an individual athlete's feelings and best/worst performances. Each profile incorporates a constellation of emotions (and other psychobiosocial states), as well as the specific intensity zones associated with either optimal functioning or with dysfunction. Within each profile, emotions are organized into four categories based on the functional/dysfunctional effects and positive/negative valence of each feeling state.

There are numerous ways to generate idiographic profiles (See, Hanin, 2003). In-depth interviews, metaphoric description, and narrative procedures each have particular advantages and weaknesses (Hanin & Stambulova, 2002; Robazza, 2006; Ruiz & Hanin, 2004). However, the most commonly used method is called the Individual Emotion Profiling (IEP) system. These stepwise procedures begin by having athletes recall their personal best- and worst-ever performances. Then, based on these competitions, athletes identify the positive and negative emotions associated with each performance and estimate the intensity of the feeling state. Emotions associated with best performances are deemed to be 'functional' and worst performances identify 'dysfunctional' emotions. All together, this information generates two graphic representations of individualized emotion-performance relationships: a zone of optimal functioning (where intensity level for functional categories are higher and dysfunctional affect is lower); and a zone of dysfunction (with opposite characteristics).

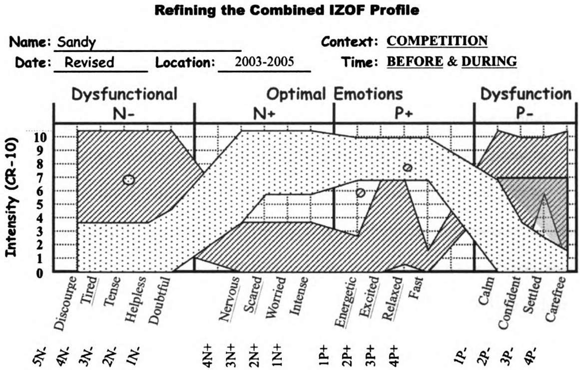
Hanin has made three landmark contributions to the field of sport psychology. Within the topic of emotion-performance relationships and in the realm of applied sport psychology, Hanin has helped to shift the paradigm from exclusively nomothetic perspectives, to consider individual differences. Secondly, more than any other framework in Kinesiology, IZOF has promoted the study of emotions (Lazarus, 2000b). And finally, for those who study emotion or regulate emotion in sport, Hanin has been a major influence in how we see emotions. IZOF has promoted the view that emotions are not inherently bad, but functional and adaptive—in this sense, Hanin's proof that negative emotions can be helpful to functioning is theoretically and practically important to our field. For instance, anxiety is a negative emotion that can be either helpful or harmful to functioning—depending on the intensity level of the feeling, and on whether or not an athlete interprets anxiety as being helpful or harmful to performance.

Despite these principal contributions, Hanin's IZOF model cannot evade criticism. IZOF-based analyses typically produce two profiles describing only poor and optimal performance levels. The failure of this system to account for moderate performance levels would prevent a graphic problem that undermines the predictive ability of the model. Because typical profiles include gaps and/or overlaps between the optimal and dysfunctional zones (See Figure 1), the IZOF model is sometimes ambiguous and cannot predict performance. Figure 1 is a typical final IZOF profile. There are two zones representing optimal (the dotted pattern) and poor (the striped pattern) performance. Discrete items are located on the x-axis and organized into valence-function categories. Intensity defines the parameters of each optimal and poor zone, and is described on the y-axis. Note that there are gaps in the optimal feeling categories (P+ and N+) and overlaps in the dysfunctional categories (N- and P-).

For example, Jack White's optimal zone for confidence is from 6-8 (on a 10-point scale) and his dysfunctional zone ranges from 2-4. Would his performance at a "five" be poor, optimal, or average? If the gap was larger, uncertainty would be even greater. Likewise, what if John Lennon's zones were 2-6 and 5-8? Intensity ratings of less than two, five to six, and more than eight are undefined or ambiguous. Hanin and colleagues do not explain or even acknowledge these very fundamental problems. The existence of gaps and of overlaps in idiographic profiles creates theoretical and practical problems for researchers and practitioners in terms of the predictive ability of the IZOF model. These issues are addressed by the Individual Affect-Related Performance Zone (IAPZ) model described in the following section. One last critique of the IZOF model is that it may be too complex. Specifically, a complete profile for an individual athlete normally includes 16-20 discrete feeling items. The challenge for researchers and practitioners is always to develop models that are complete, yet parsimonious. The IZOF model is more comprehensive than it is parsimonious.

Figure 1

Example of an Individual Profile Graph for a College Distance Runner



Note. The figure includes two zone profiles associated with optimal (zone with dots) and poor performance (zone with diagonal stripes). Discrete feelings are organized into four categories (negative-dysfunctional, negative-functional, positive-functional, and positive-dysfunctional) and located on the x-axis; while the intensity of each feeling is described on the y-axis. The intensity ratings act as parameters for optimal- and poor-zones.

The Individual Affect Performance Zones Model

As an extension of the IZOF model, IAPZ uses logistic regression to establish probabilistic estimates for performance. Continuing from the previous example, IAPZ could specify that at a "six," Lennon has a 25% chance of functioning poorly, a 45% probability of moderate performance, and a 30% chance of optimal functioning. This would therefore be defined as a moderate performance zone. In this way, it is clear to see that IAPZ avoids the all-or-none descriptions of optimal and poor results predicted by

IZOF's in-out of zone hypothesis. IAPZ has also made contributions to the field by conducting more direct assessments of emotion during competition (Cohen, Tenebaum, & English, 2006; Edmonds, Mann, Tenenbaum, & Janelle, 2006; Johnson, Edmonds, Moraes, Medeiros Filho, & Tenenbaum, 2007; Medeiros Filho, Moraes, & Tenenbaum, 2008). Tenenbaum and colleagues' Individual Affect Performance Zone (IAPZ) model resolves the gap and overlap faults by establishing probabilistic estimates for optimal, moderate, and poor performance levels across the entire range of emotional intensity (Kamata, et al., 2002; Tenebaum, Kamata, & Hanin, 2002; Tenenbaum, et al., 2008).

However, relative to the body of IZOF literature, IAPZ studies have tended to be less ecologically valid (Edmonds, et al., 2006; Tenebaum, et al., 2002) and less generalizable to mainstream sports. For instance, because they use such fine motor skills, both archers (Johnson, Edmonds, Moraes, et al., 2007; Medeiros Filho, et al., 2008) and golfers (Cohen, et al., 2006) aspire to reduce arousal as much as possible—an ironic characteristic of two sports included in emotion research. This minor critique is most applicable to negative feelings such as anxiety, anger, aggressions, and worry, etc. Certainly, athletes in aiming sports generally desire high levels of positive feelings such as confidence or calmness.

An additional concern is that every study conducted thus far has assessed general dimensional affect, rather than discrete emotions. In other words, rather than assessing the intensity of relaxation, anger, or focus, IAPZ measures the valence (pleasant / unpleasantness), arousal (similar to intensity), and sometimes also, the functionality of their global affective state. This view of affect has empirical support (Russell, 1980, 1997; Russell, Weiss, & Mendelsohn, 1989; D. Watson, 2002), but there are also significant disadvantages with the approach (Lazarus, 1991, 2001). These concerns are described in detail in the second chapter.

Issues with the IZOF and IAPZ Models Examined in this Study

This dissertation addresses the utility of using a combined IZOF and IAPZ model to predict tennis player performance. In doing so, the following IZOF- and IAPZ-related issues are addressed. (a) Probabilistic estimates were conducted on each of Hanin's four (function-valence) categories of discrete emotions to determine if IAPZ-based logistic regressions can be used with discrete, rather than continuous, feelings. (b) Feeling states and performance will be assessed during competition in a more vigorous and emotionally intense sport (tennis) than has been used in the previous research. As such, the transferability of applying the IAPZ framework to more vigorous, emotionally intense sports than golf and archery (wherein the object of those sports is to suppress negative feelings—be they functional or dysfunctional) are tested. (c) Building upon the strength of previous IAPZ research to collect large numbers of observations (relative to smaller sample sizes in IZOF studies), the proposed study attempted to acquire between 800-1200 observations across nine collegiate tennis players. (d) Complete individual profiles consisting of 10-14 emotional items were compared to more parsimonious models featuring each athlete's self-selected favorite four items. (e) Finally, though not addressed previously in this introduction, the proposed study will integrate some qualitative procedures—in the form of brief, occasional collaborative discussions with each player—to refine the IZOF profiles, to develop IZOF-based routines and psychological skills goals, and to obtain feedback about the procedures.

Purposes and Hypotheses

Purposes

This dissertation had three objectives. The primary purpose of this study was to integrate elements of two idiographic feeling-performance models and assess whether this integrated model can predict athletic performance. Specifically, can ordinal logistic regression (a foundation of the IAPZ method) be used to identify zones of functioning for discrete feeling states (a foundation of the IZOF theory). The benefit of the integrated system would not necessarily be a better performing (i.e., more accurate) model, but would have the theoretical and practical advantages of using discrete feeling items rather than continuous descriptions of global affect. The second objective was to explore the context dimension of the psychobiosocial model by comparing the zone profiles of during service games to return of serve games. The third objective was to determine if a small number of critical items determined by an athlete can predict performance as well as a traditional, complete IZOF profile. Based on these three purposes, there were three corresponding hypotheses.

Hypotheses

Hypothesis 1. It was hypothesized that idiosyncratic feeling-performance profiles can be developed for each participant using elements from both the IZOF and IAPZ methods. Specifically, discrete feelings will be arranged into valence-function categories, and these categories will predict the probabilities of poor, average, and good performances based on ordinal logistic regression modeling. Separate tests will be performed for each feeling category and performance level. Each test will compare the shape of each zone—represented by the means and variances—between individuals. This hypothesis is foundational for the entire study because it will determine if IZOF and IAPZ methodologies can be integrated to produce meaningful idiosyncratic profiles.

Hypothesis 2. It was hypothesized that idiographic profiles will vary between serve and return of serve contexts for each player. Feeling intensity and variance of profiles will be compared within players across the two contexts for each feeling category and performance level. This is an important test of the understudied dynamic context-dimension of the psychobiosocial model put forth by Hanin (2000).

Hypothesis 3. It was hypothesized that critical the four discrete items chosen by players as being their most important performance-feelings would not predict performance as well as the full profiles (with 12 items) would. However, the four simple "trigger items" would be nearly as effective in profiling and predicting performance. To determine which were more effective, the accuracy of performance predictions for zones in the four valence-function categories and the four trigger items were compared. Players selected the "trigger" items from among the 12 items chosen in their profile.

Definition of Terminologies

The following section provides summary definitions of important terminology that is frequently used in subsequent chapters of this dissertation. These terms are organized into two sections for affect-related phenomena and feeling-performance models.

Affect-Related Terms

Feeling States. The broadest category of affect-related terminologies, feeling states are an umbrella term that includes affective conditions and physiological sensations such as pain. Lazarus (1991, p. 57) clarified the distinction between feeling and emotion because the terms are too often "used interchangeably, but I think it would be more precise to speak of feelings as sensory perception, as in feeling pain, pleasure, and distaste, rather than as emotion…to restrict the word *feeling* to the awareness of bodily sensations." Feelings such as reflexes are considered "pre-emotions" because they can promote certain emotional states and occur without thought (Lazarus, et al., 1970). For the purposes of this dissertation, feelings include performance-related descriptors like quick, confident, and tired among others.

Affect. Affect is the experience of pleasant and unpleasant responses (also referred to as valence, pleasantness, or hedonic tone). Affect does not involve a cognitive component (Frijda, 1993), and is a global term that applies to both moods and emotions (Campos, et al., 2004; Ekkikakis & Petruzzello, 2000). As Ortony, Clore, and Foss (1987) explained, "the word 'affect' entails that all emotions are affective conditions, but that not all affective conditions are emotions" (p. 343).

Emotion. Emotion is very difficult to define. This term will be differentiated from related concepts such as affect, mood, arousal, and feeling states in the beginning of the second chapter. Emotions are adaptive situational responses to appraised threat that are strongly mediated by motives, attributions, and coping skills (Lazarus, 1991, 2000b; Scherer, 2001; Schorr, 2001). These adaptations can be functional or dysfunctional. A mood is a less intense but more sustained feeling state than an emotion.

Valence. Also referred to as hedonic tone, valence describes the pleasantness of an affective state (ranging from unpleasant to very pleasant). Examples of negative valence include anxiety, anger, sluggishness, and fear. Examples of positive valence include confidence, happiness, and boldness (Lang, 2000; Smith & Lazarus, 1990, 1993).

Arousal. Arousal describes the degree of activation in the body, ranging from low (sleepy) to high (manic) (Zaichkowsky & Naylor, 2004). Neurophysiological indicators for arousal include changes in heart rate, skin conductance, and hormone levels. These physiological responses to stressors are mediated by cognitive processes (Raglin, 2004). Arousal is closely related to the intensity dimension of affect (Martens, et al., 1990).

Anxiety. Anxiety is an emotion characterized by threat or challenge that is perceived to be greater than the person's capacity (Campos, et al., 2004; Raglin, 2004). Anxiety is considered a negative emotion in terms of hedonic tone (Zaichkowsky & Naylor, 2004).

Feeling-Performance Models

IZOF. Hanin's (1997; 2000; 2003) Individual Zones of Optimal Functioning model. This model describes the relationship between emotions and related psychobiosocial factors and optimal functioning.

IAPZ. The Individual Affect-Related Performance Zones model (IAPZ; Kamata, et al., 2002; Tenebaum, et al., 2002) is an extension of the IZOF model. IAPZ develops probabilistic estimates for poor, moderate, and optimal performance levels.

Zones. Zones, in both the IZOF and IAPZ models, refer to the parameters (or bandwidth) of feeling intensity that define the lower- and upper-bound at which a certain performance level is most likely. For example, on an 11-point intensity rating for a certain feeling, poor performance may be more likely than any other outcome from intensities between 0-5.5; average performance is most likely from 5.6-7.9, and good performance is the most likely outcome if feelings are in a zone between 8.0-11.0. These are typically referred to as poor-zones, average-zones, and good-zones. Originally, Hanin defined a zone of optimal functioning as one-half of a standard deviation above and below the anxiety level associated with a best-ever performance.

Discrete Feelings. Feelings (emotions in particular) can be described by various continuous dimensions or labeled as discrete items. Discrete feelings include categories like happy, sad, and angry. A person can feel more than one discrete item at a given moment. For example, before a tennis match, a player may simultaneously feel confident, mentally calm, physically anxious, and excited.

Continuous Feelings. Feelings can also be described in terms of several continuous dimensions. These dimensions describe characteristics of emotions or feeling states, such as valence, arousal, and motivation-consistency, etc. Dimensional descriptions of feelings provide a more descriptive account of an individual's general state. For example, at a given moment, a player who feels somewhat anxious may describe slightly negative valence, and moderate arousal. While simpler than rating the intensity of several discrete feelings, continuous descriptions cannot account for multiple co-existing feelings (such as feeling simultaneously confident, calm, anxious, and excited).

Valence-Function Categories. Discrete feelings can be organized into categories based on a two-by-two pleasant/unpleasant-functional/dysfunctional matrix. This matrix results in four categories: positive-functional, negative-functional, negative-dysfunctional, and positive-dysfunctional groups. The IZOF model uses these groupings to organize individual constellations of discrete feelings. All players in all sports can organize their idiosyncratic profiles into these four categories.

Idiosyncratic Models. IZOF and IAPZ are idiosyncratic models of feeling-performance relationships because they are founded on the premise that all athletes have unique, individualized relationships between feeling and performance. Confidence may be important to John, but irrelevant to Paul. Anxiety may be important for both Ringo and George, but Ringo plays great at moderate levels of anxiety, where George must have very low levels of anxiety. These are examples of idiosyncratic differences.

Idiographic Differences. Idiographic differences are essentially a synonym for idiosyncratic differences. In the IZOF and IAPZ literature, idio-*graphic* differences generally refer to the shape of the individual profiles, or parameters of each zone. If, for instance, if Woody's average-zone is from 4.0-5.5, and Ledbelly's average-performance zone is from 5.5-9.0, their profiles are idiographically unique. In this case, they are different in terms of their size (width) and location within the intensity continuum (Ledbelly's average-zone s twice as big and much higher).

Nomothetic Models. Early models of feeling-performance relationships were nomothetic in nature because they described all individuals as sharing the same feeling-performance relationships. For instance, the Multidimensional-Anxiety Model (Martens, et al., 1990) predicts that all athletes will perform at their best when somatic-anxiety is moderately intense. These nomothetic models contradict idiosyncratic models because they treat all athletes the same and cannot account for interindividual differences.

CHAPTER TWO

REVIEW OF LITERATURE

This dissertation is designed to integrate elements of the IZOF and IAPZ models for the purposes of identifying feeling-performance relationships; exploring these relationships across different tennis contexts; and determining if a simple set of feeling-items can predict performance as well as a more complete profile. Given these purposes, the review of literature is separated into three sections. The first section provides a theoretical foundation by describing the role that feelings and emotions have in human functioning. The second section describes the first of two feeling-performance models that are foundational to this dissertation: Hanin's (2000) IZOF. The third section describes a newer model that is based on the idiosyncratic IZOF model: the IAPZ.

Why and How Feelings Affect Functioning

As explained in the previous chapter, the performance profiling that is fundamental to this dissertation will not be exclusive to emotions. To determine what factors most determine players' performance levels, factors like confidence, fierceness, and quickness must be considered along with true emotions such as relaxed, happy, nervous, and angry. For this reason, general feeling states are of interest. However, due to a lack of research and theory on feeling states, it is necessary that the focus of this review of literature now be on emotions. In order to understand precisely how feelings influence performance, the only option is to review theories of emotion and then to generalize this science to broader feeling states. To that end, not only may some non-emotion feeling states affect performance in a manner similar to emotions, but it is important to recognize that the majority of items identified by athletes as being critical to performance are, indeed, proper emotions. Consequently, the following section offers valuable theoretical insight that is relevant to most, if not all, of the performance profiles developed by athletes.

Emotion and Adaptation

Evolution. Emotions are very advanced and complex extensions of stimulus-response reflexes that help all animals to survive in their environments (Darwin, 1998; James, 1884; Lazarus, 1991, 2000a). As life evolved, automatic responses to the environment (i.e., reflexes) became less influential. Instead, humans appraise the threat potential of the environment (as well as the opportunity potential). This appraisal process enables people to process more information, consider past experiences, account for motivational factors, and contemplate coping/response options. The evolution of cognitive operations has the additional advantage of allowing us to predict environmental conditions and to prepare response strategies (Csikszentmihalyi, 1993). For instance, not only do emotions help people to adapt to the biological demands of a situation, but also to the social demands. Emotional processes resolve many of life's challenges, such as cooperation, social hierarchies, reproduction, and social interactions (Campos, et al., 2004; Ekkikakis & Petruzzello, 2000; Goleman, 1995; Mayer & Salovey, 1997; Salovey & Mayer, 1990)

However, such that emotions are a product of appraisal, it is reasonable to say that perception is more important than is reality (i.e., the physical environment or actual threat). While there is still debate as to exactly what constitutes an emotion, the "appraisal models" proposed by cognitive psychologists provide the strongest theories available in my view (For reviews see, Campos, et al., 2004; Frijda, 1993; Frijda & Zeelenberg, 2001; Lazarus, 1991, 2001; Lazarus & Folkman, 1984; Mayer & Salovey, 1997; Ortony, Clore, & Collins, 1988; Scherer, 2001; Schorr, 2001).

Relational meaning, valence, and appraisal. Emotions are driven by motivational and perceptual dispositions that function to establish a desired relationship between the person and an environment (i.e., Relational Meaning) (Frijda & Zeelenberg, 2001). For example, the more someone cares about a competition, the more emotional they will be. To regulate relational meaning, emotions elicit action tendencies. By way of these action tendencies, emotions facilitate behavioral responses to threat (e.g., fight, flight, or startle responses). Action tendencies are an important component of emotional adaptation in terms of coping (Lazarus, 1991, 2000b).

Valence (or hedonic tone) is another important attribute of emotions. In the distant past, pleasure and positive emotional valence served evolutionary purposes (Lang, 2000; Lazarus, 1991; Schorr, 2001). Positive emotions reinforce actions and objects that promote the survival of our species. Likewise, negative emotions can be either aversive (helping us to avoid negative things) or attacking (helping us to challenge negative environment relationships). Positive valence is associated with superior health (Botterill & Brown, 2002; Lazarus, 1991).

Emotions evolved to promote positive adaptations and they help people to reach their goals—whether those goals are to avoid being prey, to win a fight for food, to make a body check in hockey, or to dribble a ball up court. But how, exactly, are emotions evoked? Lazarus' (1991) Cognitive Motivational Relational Theory describes the appraisal process by which emotions are elicited. People appraise the relational meaning of a situation or challenge in two stages. Primary appraisal is based on individual stake (or motives). In some form, a person assesses three questions: do I care about the outcome; is the outcome likely to be very good or bad; and how does the outcome affect my ego? Secondary appraisal focuses on attributional (Weiner, 1985) considerations and coping options (Lazarus & Folkman, 1984). A person considers the following three questions: is my relational status attributed to personal or external causes; is my status controllable; and is my status likely to remain stable? For example, if Dylan believes that he can do something to either control his feelings or to change the situation that is affecting his emotions, then his emotions are likely to be more helpful.

Adaptation. This biological perspective has an important practical implication in that *unpleasant* emotions (i.e., "negative" states including fear, anger, anxiety, etc.) can be *helpful* because they mobilize people to modify threatening or even harmful relationships with the environment. From this perspective, we can see why emotions are considered to be adaptational and fundamental to meeting the demands of a challenge. However, for emotions to have this functional/adaptational significance they must be more than just "feelings"—they must be capable of promoting action. Emotions promote relational changes with the environment by moderating attention and behavioral systems. In terms of species survival, attention is primarily controlled by emotional-motivational systems (Graham, 1979; Lang, 2000). Control over attention is important because it enables a person to focus on threats, thus facilitating solution-development. Appetitive and defensive emotions also have action tendencies associated with them (Davis, 1992; Masterson & Crawford, 1982). Action tendencies are uniquely associated with each emotion, which ensures that an emotional response will be adaptationally specialized for the perceived threat.

Before a tennis match, for example, a player may feel jittery, butterflies in his/her stomach, or sweaty palms, etc. According to scientific theory, this response is more likely when the player is very close to reaching a goal (e.g., playing someone of relatively equal ability, or a close match), and when the player cares more about the outcome. In this case, human experience supports theory: athletes are typically more nervous in tight, highly competitive matches where the outcome is important to the player. These physiological responses are typical action tendencies for emotions like nervousness. They are part of the adaptive quality of that emotion in that they help the players to generate energy and redistribute blood flow away from vital organs in favor of working tissue (muscles). These adaptations are part of the fight/flight response, which helps athletes to perform better in physical challenges. As such, a lack of nervousness can result in a lack of energy and an inefficient distribution of blood circulation.

Maladaptive responses. Emotions are a product of highly-evolved cognitive processes, but the underlying mechanisms that control these processes are outdated in some ways (Csikszentmihalyi, 1993; Lazarus, 1991, 2000b). Consequently, emotions are imperfect in that they can cause maladaptive responses. Consider a scenario where a deer is crossing a highway, but freezes in the headlights of an oncoming vehicle. This startle response is normally adaptive and beneficial because it enables an animal to go unnoticed (camouflage) or appear dead to a stalking predator. It also provides animals with time to make effective decisions. However, in this instance, evolution has failed to account for highway traffic and automobiles (Scherer, 2001). As a result, the deer's startle response is maladaptive because it assures the animal's demise.

In sport, a common example of maladaptive feelings comes from how some athletes perceive anxiety (or any other form of pre-competition activation). Athletes often become worried and suffer performance decrements because of anxiety. This is because symptoms of anxiety such as butterflies in the stomach and increased heart rate (which are a helpful adaptation that enables athletes to mobilize more energy in order to compete) are interpreted as being uncomfortable and bad. As such, athletes will lose focus due to extreme worry. Appraisal can be distorted and reinforced by pleasure-seeking (addictive) activities that may possess negative consequences—such as drug abuse, unplanned pregnancy, eating disorders, and gambling debt, etc. (Csikszentmihalyi, 1993). In sport, positive feelings (e.g., calm or overjoyed) can be maladaptive in that they may reduce intensity or foster complacency. Negative feelings can be maladaptive if they are overwhelming (e.g., being too nervous or too aggressive).

Characteristics of Emotion

Motivational and emotional intensity. Early theories in emotion—such as Instinct Models and Drive Theories—were behavioral in orientation and generally neglected cognitive factors. Ironically, physiology-based research has recently begun to support cognitive approaches. Remember that emotions are associated with two biologically driven motives: appetitive-approach (fight), and defensive-avoidance (flight) (James, 1884; Lang, 2000; Miller, 1959). Motivation is one of the most important and fundamental mediators of emotion. From most points of view, motivation and emotional *intensity* are closely associated and highly related to distance from a perceived threat, benefit, or goal (Lang, 2000). An athlete, for example, will generally be more anxious as competition draws closer, or will be less motivated when they are losing by an overwhelming score. Therefore, even from a biological/neurophysiological perspective, emotion, motivation, and the relationship that a person has with his/her environment are critical interrelated factors. Motivational and relational factors are highly cognitive in nature. As such, biological perspectives support cognitive theories of emotion in some ways (i.e., motivation). Cognitive Appraisal theories will be described in subsequent sections. The motivational significance of emotion is particularly relevant for, but not exclusive to, appraisal models—motivation is a universal feature of affect.

Describing valence. Whether you prefer a cognitive or a physiological perspective, valence is a universal component of emotion. People are hardwired, it seems, to organize emotions hierarchically into pleasant (a.k.a., positive) and unpleasant (a.k.a., negative) categories (Ortony, et al., 1988; Ortony, et al., 1987). Valence is associated with motivation in that people are attracted to positive valence, and aversive to negative valence. In other words, we are motivated to do things that feel good, and that we avoid things that do not feel good. In this sense, emotions help to explain gambling, drug, and sexual addictions, the obesity epidemic, and every-day concerns, such as why a person may not attend to tedious chores. People are not only attracted to an object or experience that inspires an emotional state (e.g., a rollercoaster, or scoring a goal), but to the emotion associated with that experience. It is emotions, more so than experiences, people, or objects, which influence human motives and behaviors.

Whereas emotional intensity is described within a continuum from low to high, valence can be either continuous or categorical: one can describe a feeling in one of two categories (pleasure and displeasure), or on a dimensional continuum from very pleasant to very unpleasant (Lang, 2000; Lazarus, 1991). While the dimensional descriptions are parsimonious, their simplified nature can obscure some of the important distinctions that define emotions and make them unique. Most importantly from Lazarus' (1991; 2000a; 2001; also Ortony et al., 1988) perspective, dimensional frameworks obscure the relational meaning of emotions as separate categorical states. Examples of discrete emotional "categories" include anger, fear, happiness, and pride. Discrete categories retain intensity as a continuous factor, but view it as subordinate to the qualitative content of each emotion. From a categorical perspective, it may be said that intensity does not define an emotion—as it does from a dimensional approach—but describes an emotion quantitatively (Ekkikakis & Petruzzello, 2000).

It is not a question of which is right or wrong, but of which is most appropriate for the research question of interest (Lazarus, 2000a). A dimensional approach is better suited for more general macro-descriptions and for exploratory studies of affective states; whereas categorical descriptions are better for micro-descriptions of specific emotions (Deiner, Smith & Frijda, 1995; Ekkikakis & Petruzzello, 2000; Russell, 1997).

Action-tendencies. Just as there are causes of emotions, there are also effects of emotional expression. It is these effects that are, perhaps, the most important characteristic of emotion in relation to sport performance. Emotional effects include action tendencies, physiological changes, subjective affect, and subsequent (cognitive and motivational) appraisals (Lazarus, 2000a). Action tendencies are a product of emotion and can be part of the coping process. That said, coping is generally psychological, deliberate, complex, and it involves planning. Action tendencies are "biologically driven and therefore fairly rigid and [virtually] automatic (though capable of suppression and transformation)" (Lazarus, 2000a, p.58). While action tendencies are fairly rigid, they are probably the least definite and predictable component of the emotional process (Frijda & Zeelenberg, 2001). Action tendencies are not consistent because they can be mediated by coping processes (Lazarus, 2001). On the other hand, appraisal patterns—the "causes" of emotions—are viewed as being more stable than action tendencies. The problem is that action tendencies do not involve overt locomotor behaviors or the development of specific motor programs, per se (Lang, 2000). Instead, "tendencies" include processes such as attention focusing, increased arousal, felt readiness, and muscle priming. For this reason, Frijda and Zeelenberg (2001) prefer to use the term "action readiness," rather than action tendency.

Appraisal Models

Having explained the purpose, and in part, the functional characteristics of emotions, let us now consider the causes, or antecedents, of emotions. Early theories in emotion proposed that emotions were elicited by the environment, and did not account for evaluative potential of the person. For instance, Stimulus-Response Theories (J. B. Watson, 1919), Physiological CNS Processes (Cannon, 1927), PNS Autonomic Activity (James, 1894), Fight-Flight Theory (James, 1884; 1894), and Motivational Theories focused on primitive hunger (Tomkins, 1962) and intimidation (Parkinson, 1997) drives. These Biology-based models do not consider cognitive factors and are unable to explain the idiosyncratic nature of emotion. Roseman and Smith (Roseman, 1996, 2001; Roseman & Smith, 2001) compiled a list of questions that justify why cognitive models are necessary to explain emotion. Why are there intra- and inter-individual differences in emotional responses to the same stimulus? Why can a variety of different situations elicit the same emotional response? What elicits an emotion when the environment does not appear to be stimulating? Why and how is it that emotional responses can be both functional and dysfunctional? How is it that emotions can be controlled, or modified?

As such, appraisal models developed from the field of cognitive psychology were developed to address the flaws in purely biological and behavioral theories. Among these appraisal models, the Cognitive Motivational Relational Theory (CMRT; Lazarus, 1991, 2000b) is arguably the strongest, but certainly the most accepted to sport researchers interested in emotion-performance relationships.

The basic assumptions (Lazarus, 1991, 2000b; Roseman & Smith, 2001; Schorr, 2001) of Appraisal Theories are as follows: (a) emotions are mediated by cognitive appraisals and each emotion (e.g., anger, joy, etc.) is a product of specific appraisal patterns, or processes; (b) Appraisals initiate the emotional process, which includes physical, neurological, and behavioral changes (Roseman, 1996, 2001; Weiner, 1985); (c) Differences in appraisal patterns account for intraindividual (temporal) and interindividual differences; (d) A situation that elicits the same appraisal pattern will evoke a consistent emotional response; (e) The appraisal process will generally ensure that a response is appropriate—however, a misappraisal (caused by conflicting, inappropriate, or incomplete processing) will result in an ineffective and maladaptive emotional state (Lazarus, 2000a). It is important to recognize that appraisal can occur through deliberate (volitional) control, or implicitly through automatic parallel processing (Lazarus, 1991; 2001; Roseman, 2001).

The Cognitive Motivational Relational Theory (CMRT). Lazarus' (1991) Cognitive Motivational Relational Theory (CMRT) is probably the most accepted appraisal model of emotion in the domain of sport psychology (Botterill & Brown, 2002; Hanin, 2000a). The model is *cognitive* in nature as it is a form of appraisal theory. Appraisal is the foundation of emotion and adaptation. "Feelings," without appraisals, are not emotions—they are mere reflexes. Though we cannot ignore the role of the environment, emotions are strongly regulated by appraisal processes (Scherer, 2001). As we saw from the review of biological perspectives in emotion, *motivation* is a critical factor in determining emotional form, valence, and intensity (Lang, 2000). Accordingly, Lazarus has incorporated motivational considerations into the CMRT. *Relational* dynamics refer to the relationship between a person and his or her environment (or perceived challenges, etc.), in terms of threat/well-being evaluations. Each discrete emotion is derived from a unique relational meaning (Lazarus, 2000b; 2001). Relational meaning is the core element of the CMRT. Lazarus (2000b) affirmed this notion by explaining: "appraisals and the meanings generated from them are always relational because they must simultaneously take into account personal factors and environmental demands, constraints, and opportunities" (p. 233). The term *relational theme* is used to summarize the six components of appraisal (described in the following section). As such, a "core relational theme" is the foundation of an "appraisal pattern."

Lazarus (2000a) has identified three working assumptions for the CMRT. Firstly, an emotion is defined by its core relational theme, its appraisal pattern, and its action tendency. Secondly, each distinct emotion is associated with unique physiological changes. Thirdly, specificity of physiological responses are related to the action tendencies associated with that emotion.

Structure of the Cognitive Motivational Relational Theory (CMRT). The following section describes how the CMRT explains and predicts the influence that emotions have on adaptation and performance. There are three important structural components of the CMRT: primary appraisal, secondary appraisal, and coping.

Primary appraisal. There are two levels of appraisal in CMRT: primary and secondary. Primary appraisal is based on individual stake in the object of focus (Lazarus, 1991; 2001a). There are three types of goal-related (stake) appraisals in this first stage. The first is evaluation of "goal relevance." If a goal is not important to a person, appraisal will either elicit very weak emotional activation, or fail to stimulate emotion altogether. This is why we see more tears in the Stanley Cup finals or Wimbledon than we see in exhibitions. The second is "goal congruence," which refers to the potential benefit or harm associated with the interpretation. As described earlier, goal congruence will, therefore, determine the (positive or negative) nature of the emotion (i.e., valence or hedonic tone). For example, an appraisal that anticipates victory will lead to pleasant emotions. These emotions may result in facilitative pleasant feelings (motivation), or inhibitory pleasant feelings (complacency). The third type of primary appraisal is the "type of ego-involvement." This is sometimes referred to as goal content (Lazarus, 1991). Type of ego-involvement determines the more precise nature of the emotional state (Lazarus, 2000a). Anger for instance, relates to ego-identity; shame is related to ego-ideal; and guilt is a function of moral value.

Secondary appraisal. Just as personal relevance is an important basis for determining emotional affect, so too is consideration of possible options (i.e., coping) related to the challenge. This evaluation includes three factors that are comparable to Weiner's (Weiner, 1985) attributional model: Is my relational status attributed to personal or external causes; is my status controllable; and is my status likely to remain stable? Secondary appraisal, then, is defined as assessments of coping options and prospects. The first of three secondary appraisals is evaluation of "blame and credit." This is essentially an attributional consideration. While Lazarus focuses on control (controllable / uncontrollable) and causality (internal / external), interpretation of environmental stability may also be relevant (Weiner, 1985). Attributing to blame or credit will, for example, distinguish between feelings of anger and shame, respectively.

The next secondary appraisal involves "coping potential" as a prediction of how the situation may change, for better or worse, because of the person's ability to manage the demands. There is a Tibetan saying that, 'if you can fix a problem, there is no need to worry about it.' A person will not feel extreme negative states as often if there is a great deal of self-efficacy and good coping skills (Lazarus, 2000b).

Finally, in addition to the ability to cope, "expectations of the future" will influence secondary emotional appraisal. Expectations of the future include consideration of what we think will change and whether or not we expect the change to be beneficial or harmful. This is similar to, but slightly different from, coping potential. Although both involve an anticipated change in the current relational state, expectations of the future involve a variety of sources for change, whereas coping potential involves more internal and controllable factors. Ultimately, primary and secondary appraisals are driven by motivational objectives, and core relational themes between (perceived) current and ideal states (Lazarus, 1991; 2000b).

Coping. Effective adaptational coping requires the integration of motor, attentional, motivational, and energy resources. There are two types of coping: emotion-focused and problem-focused (M. V. Jones, 2003; Lazarus, 1991; Lazarus & Folkman, 1984). Coping in sport can be emotion-focused, such as relaxed breathing before a free-throw (probably an adaptive strategy), or yelling at a disgruntled fan (likely a maladaptive strategy) (M.

V. Jones, 2003; Lazarus, 2000a). Coping can also be problem-focused, and it is in this instance that the adaptational potential of emotions in sport, and the importance of this topic in sport psychology, are revealed (M. V. Jones, 2003; Lazarus, 2000a). There is an old saying, 'don't get mad, get even.' When done in a manner that is productive and sportsman-like, this is sage advice. Rather than managing an emotion directly, we can control valence and intensity by changing relational appraisal—this is the essence of problem-focused coping. An athlete may say, "I am losing, but rather than quitting or focusing on my frustration and sadness, let's start winning!" But how? If the athlete makes an appropriate decision (secondary appraisal) to work harder, smarter, focus on a new strategy, relax, or focus on better cues, there is a great opportunity to positively change both the level of performance (relational component) and resultant emotional state. In this way, emotions and coping can help athletes reach goals and perform better (Botterill & Brown, 2002; Lazarus, 2000a).

Summary of the Relationship between Feelings and Performance

One may ask, what is the point of considering all of these technical and semantic items (e.g., levels of appraisal, dimensions, categories, subconscious processes, motivational drives, affect, mood, etc.)? In addition to providing a more complete understanding of emotion, these descriptions illustrate the complexity and idiosyncratic nature of feelings. To understand the relationship between affect and performance, we must integrate the complexities of emotion and affect with the variability of performance.

In addition to being idiosyncratic and complex, emotions are adaptive, and to be adaptive, they have to integrate a variety of actionable modalities (i.e., cognitive appraisal, motor systems, attentional systems, motivation, energy production/activation, and coping strategies). Motivation and activation (energy production) are critical components of emotional processes, and important factors in performance. Because of the role of motivation and activation, emotions help us to reach goals and to create positive relational interpretations of benefit/threat.

Emotions are not an unnecessary form of "baggage" that interferes with performance. Emotions are vital and adaptive processes that integrate perception, motivation, action tendencies, and coping behaviors. The only way to avoid emotions is: to not care (have no stake); to not evaluate the meaning of things around us (have no thoughts); and to believe every challenge is completely and effortlessly manageable. Obviously this is not possible, so as long as there is competition in sport (be it task- or ego-oriented), there will be emotion. Emotions, and the cognitive and behavioral components that they affect, greatly influence functioning and performance. It is important to know *why* and *how* emotions facilitate sport performance. However, before we can determine why and how emotions (and other dimensions of psychobiosocial form) effect human functioning, we must determine *what* emotions facilitate and inhibit functioning. To do this, we must understand the relationship between affect and performance across time, context, age, sport type, task type, and group dynamic.

Hanin's Individual Zones of Optimal Functioning

Space limitations prevent an exhaustive review of all anxiety/arousal/emotion models that explain the relationship between these states and performance. As such, the current section focuses on the IZOF model, precluded by a brief description of its development.

Evolution of The "Zones" Model

Idiosyncrasies. As its name infers, the Individual Zones of Optimal Functioning (IZOF) theory is an idiosyncratic model that describes the range and combination of emotional (and other psychobiosocial) items that facilitate optimal functioning (and dysfunction) (Hanin, 1995, 1997, 2000c, 2003, 2004; Robazza, 2006). The modern IZOF model initially began as the Zone of Optimal Functioning (ZOF) model (Hanin, 1978). The ZOF model was divergent from mainstream perspectives such as the Inverted-U Theory (See Landers, 1980; Yerkes & Dodson, 1908), Multidimensional Anxiety model (Martens, et al., 1990), Cusp Catastrophe theory (Hardy, 1990; Hardy & Frazey, 1987, June), and other nomothetic anxiety-performance theories because it postulated that optimal anxiety was individualized and highly variable—not standardized at a "mid-point" level (Hanin, 1978, 1986).

Zones. Where popular models described the optimal anxiety level as a single point, Hanin postulated that there is actually a zone (a bandwidth of one standard deviation). It is because of this feature that Hanin called his theory a "zones" model of functioning. As the theory evolved, Hanin (1995) recognized that there is individual variability in both the width of the zone and the intensity level of the zone's midpoint. In other words, some people may have a large optimal zone, others a very small bandwidth; some zones may be located at a moderate intensity level, while others may be very high or low.

Multidimensional interactions. Multidimensional profiling uses several types of feelings to predict performance (e.g., confidence, anxiety, relaxation, anger, etc.) rather than a single feeling, such as arousal. Multidimensional profiling is more complex, so it provides a more complete understanding of feeling-performance relationships.

Unidimensional profiling is akin to assess how good a tennis player a woman is based on her backhand—without assessing her forehand, volleys, or serve.

Contrary to popular criticism, Hanin's early model did account for the multidimensional nature of anxiety, as the State-Trait Anxiety Inventory (STAI; Spielberger, 1988b) is a multidimensional measure of anxiety (Hanin, 2000c, 2007; Raglin & Hanin, 2000). As Hanin (Hanin, 2000c, p. 74) explained, "that the STAI uses a single combined score of state anxiety…led to the mistaken view that the scale was unidimensional. However, one could argue that the combined score is an index of the interaction effects of [emotion]." Also, after comparing the STAI and CSAI-2 across three methods of IZOF profiles (i.e., recall, direct, and graphic methods), Pons, Balaguer, and Garcia-Merita (2001, p. 9) concluded that the consistency between the two measures "does not support the widely held view that sport specific psychological measures are more useful than general measures." However, because the STAI combines each dimension and does not have independent subscales, Hanin's early work did not examine the separate effects and explicit interactions of cognitive and somatic anxiety.

Emotions in sport. In retrospect, the discussion over multidimensional interactions between somatic anxiety, cognitive anxiety, and confidence (Hardy & Frazey, 1987, June; G. Jones, Swain, & Hardy, 1993; Landers, 1980; Martens, et al., 1990; Woodman & Hardy, 2001) was only scratching the surface of the real issue in affect-performance research. The two most important developments in the study of anxiety-performance relationships are the (aforementioned) acknowledgement of idiosyncratic differences and the realization that there is more to the equation than anxiety or arousal. Hanin (1993b, 2000a) recognized that researchers and practitioners must open the scope of their interest to include a complete list of emotions (i.e., anxiety, anger, etc.). Not only must we consider a variety of emotions (Botterill & Brown, 2002; Lazarus, 2000a, 2000b), but we should explore the interactions of different emotions and feeling states (Hanin, 2000a; Hardy, et al., 1996). These interactions are commonly referred to as emotional constellations (Hanin, 2007) or recipes (Gould, Flett, & Bean, 2009; Hardy, et al., 1996).

The turning point for Hanin's original ZOF theory came shortly after Gould and Tuffey's (1996) review, when Hanin published his seminal 1997 article. This 1997 article transitions into the Individual Zones of Optimal Functioning model. The IZOF model is more theory-based than its predecessor. It substantially expands the multidimensionality trend to include an infinite number of discrete, idiosyncratic emotions.

Critique of Hanin's ZOF. In 1996 Gould and Tuffey reviewed the literature on the ZOF model and found general support for the ZOF model, but recommended more precise methods and a stronger theoretical foundation.

Support. Although the explained variance in many ZOF studies was quite low, and there are some exceptions to the "in/out of zone" principle, Gould and Tuffey concluded that there was "fairly good" (p. 59) support for Hanin's (1995) ZOF model. The authors commended the practicality and intuitive appeal of the model. While the initial research on ZOF was supported, Gould and Tuffey emphasized the need for more and better research, and did so with a series of methodological recommendations described below.

Recommended methods. Gould and colleagues (Gould & Krane, 1992; Gould & Tuffey, 1996) emphasized the need for intraindividual assessment of anxiety over time—rather than interindividual comparison to group standards. While one cannot assume that median intraindividual scores represent moderate anxiety, this method is, overall, more appropriate than nomothetic comparisons. Another methodological criticism concerns the use of recall methods that are potentially biased by outcomes, mood at the time of recall, and forgetting. Though imperfect, the recall method is ecologically valid and pragmatic (Hanin & Syrja, 1996; Jokela & Hanin, 1999; Tenebaum & Elran, 2003; Tenenbaum, Loyde, Pretty, & Hanin, 2002). Performance measures are also subject to the same challenges. The key is to use the most appropriate method based on the research question, and to be as vigilant and methodologically systematic as possible. For some of these issues, there is no perfect solution. However, Gould and Tuffey proposed two simple recommendations: larger sample sizes and sustained repeated measures assessment.

Recommended theory. Gould and Tuffey (1996) described Hanin's ZOF model as "an empirical finding in need of a theory" (p. 59). Ultimately, future research should address two questions: *why* do zones of functioning exist; and *how*, from a mechanistic perspective, do ZOFs influence performance? Multidimensional studies of affect items and their interactions may help to answer these questions by revealing more about the affect-performance relationship. Do ZOFs change over time? If so, then understanding how and why they change may contribute to our understanding of why and how feelings influence performance. Another way to better understand the theoretical underpinnings of ZOFs may be to look at the generalizability of individual zones across contexts, sport tasks, and non-sport domains.

The Modern Individual Zones of Optimal Functioning Model

The ZOF model was revised to the current Individual Zones of Optimal Functioning Model over the course of three decisive publications (Hanin, 1997, 2000a, 2003). Over these revisions, Hanin and his colleagues made several improvements and addressed each of Gould and Tuffey's (1996) critiques. The IZOF model emphasizes individual differences, extends the model to include emotions and other psychobiosocial states, reinforced the reflective method, and includes several different methods of determining individual profiles (Hanin, 1997, 2000d, 2003). Hanin also identified two theoretical bases: the mobilization-utilization theory and the application of a dynamical systems model to organize psychobiosocial components of the model (Hanin, 2000a). Each of the refinements of the IZOF models are described in the proceeding section.

Defining characteristics of IZOF. The following section defines each component of the acronym IZOF. In short, it is an idiographic feeling-performance model comprised of (intensity) zones that represent various levels of functioning.

Individual. IZOF is in contrast with nomothetic models that ignore individual differences in favor of general group trends. The individual aspect of the theory means that each athlete's optional state of functioning is associated with a unique combination of emotions and intensities of emotions. The emotions that help John might not help, or may even hurt, Paul's performances. Likewise, even if Ringo and George had similar critical emotions, Ringo might need to be moderately anxious, moderately confident, and very focused, while George has to be very anxious, extremely confident, and moderately focused. The idiosyncratic nature of the theory has overwhelming empirical support and practical implications and is one of the most important contributions Hanin has made to Sport Psychology (For reviews, see Hanin, 2000a, 2007; Robazza, 2006; Tenenbaum, et al., 2008). Although the model favors an idiographic representation of emotion and performance, "the model also attempts to generalize data across individuals, teams, and

[the] larger group" (Hanin, 2000c, p. 66). Such generalizations help to make the model more practical.

Zones. "The zones principle implies a specific relationship between the perceived intensity of optimal and dysfunctional emotional states and the quality of performance" (Hanin, 2000c, p. 66). The basic zone concept was described in the previous section and did not vary during the evolution towards the IZOF model. The relevance of the zones concept is elaborated upon in subsequent sections.

Optimal. Optimal feeling states are those that are most important for a particular athlete in a particular context. Hanin uses the term optimal to differentiate his theory from the flow construct (Csikszentmihalyi, 1994) and from ideal performance states (Loehr, 1994; Orlick, 1986, 2008). These constructs focus on very exceptional experiences and only on the effects of positive feelings. IZOF accounts for the helpful and harmful effects of both positive and negative hedonic tone, as well as on high-quality, but not necessarily extreme peak performances.

Function. One of the problems with early research in this area was the use of outcomes as a dependant variable. Hanin has always focused on process measures of performance because they are more controllable and more closely related to emotions as predictors. As such, while outcome measures can be included, IZOF studies should use performance criterion as the dependant variable. Performance measures vary depending on sport, and there are many ways to assess performance. The simplest is to have athletes rate their performance on various likert-type scales. Neurophysiological and biomechanical measures of motor control are other examples of performance measures.

Theoretical underpinnings: Psychobiosocial dynamical model. In response to Gould and Tuffey's criticism, Hanin (2000) transformed the ZOF model into a more complex and theoretically justified model. Whereas the ZOF model was a simple anxiety theory, the IZOF model looks at multidimensional feelings and interactive psychobiosocial (PBS) states. Hanin's current theoretical approach is inspired by dynamical systems models, and in particular, the work of Ganzen (1984). The PBS model incorporates three *structural dimensions* (intensity, form, and content) and two *dynamic dimensions* (time and context) (Hanin, 2000; Robazza, 2006). Structural elements are more person-oriented and dynamics are environment-oriented, making this an interactionist-model. The five dimensions of the PBS model are described in the following paragraphs.

Content. The qualitative, or informational, characteristics of the IZOF model are described in the content dimension. The content dimension describes the functional (facilitative/debilitative), hedonic (positive/negative), performance (optimal/suboptimal), and task (task relevant/irrelevant) attributes of the model. The common example of how this dimension is applied in the IZOF model is the distinction between positive-helpful, positive-harmful, negative-helpful, and negative-harmful categories of emotions.

Form. Form is the foundation of the PBS-IZOF theory. The form dimension organizes PBS feeling states into seven 'psycho' (cognitive, motivational, and emotional/affect), 'bio' (bodily-somatic and movement/motor), and 'social' (performance, inter-personal, and communication) elements. Within each category of the form dimension are discrete, descriptive items such as happy, anxious, focused, hard working, teamwork, tense, etc. IZOF research has consistently examined multidimensional emotions, rather than simple anxiety or arousal. IZOF is the only performance model in sport that evaluates emotion, rather than basic anxiety or arousal. Researchers have recently studied other "forms" of the PBS model, such as motivation and bodily-somatic (Bortoli & Robazza, 2002; Bortoli, Robazza, & Nougier, 1997; Hanin & Stambulova, 2002; Robazza & Bortoli, 2003; Robazza, Bortoli, & Hanin, 2004; Ruiz & Hanin, 2004). However, the other four forms have not been researched at this point.

Intensity. Intensity quantitatively describes the level, range, or zone of the form. The intensity dimension describes a person's effort, energy mobilizing (demobilizing), and energy organizing (disorganizing) characteristics. Intensity is often determined using Borg's (1998) CR-10 Scale, which is described in detail in the third chapter. Most importantly perhaps, the intensity dimension is essential to the in-out of zone concept—which is also described later in this review.

Time. The time qualities of the PBS state have most often described experiences before, during, or after competition. However, the time dimension may also include the duration of the experience, time of description (i.e., predicted, actual, or recalled experiences), the frequency of an experience, or the date of a performance within the calendar year or periodized stage. While longitudinal studies have been more frequent in recent IAPZ research, the time dimension remains relatively unstudied.

Context. Context refers to situational, interpersonal, inter-/intra-group, and cultural considerations. The most common contextual distinction is between practice and competition. Context is a drastically understudied yet promising area of research. For instance, do athletes have different profiles for 'regular' games compared to 'big' games and playoffs? Is a basketball player's optimal recipe the same while defending as while shooting free throws? Hanin (2002) theorized about some of the temporal and contextual differences that might emerge in individual profiles, but little-to-no research has been conducted in these areas. Comparing the structural and the dynamic components of the PBS model, the dynamic elements—time and context—are by far the least researched. Among other objectives, this dissertation examines the dynamic context dimension.

Theoretical Predictions of the IZOF Model

In-out of zone prediction. The in-out of zone hypothesis states that an athlete is more likely to perform at a high level if she or he is within the idiographic zone of optimal functioning. While the precise description of a zone is individually unique, the in-out prediction is nomothetic, because it can be applied to all athletes. In line with Gould and Tuffey (1996), a meta-analysis of ZOF research performed by Jokela and Hanin (1999) revealed moderate effect-sizes supporting the "in-out of zone" hypothesis. Subsequent IZOF research has generally had higher effect-sizes because of theoretical changes to the model and better methodology. In particular, the modern IZOF model includes two zones: a zone of optimal functioning (ZOF), and of dysfunction (ZDy). As such, the in-out principle typically compares best and worst performance states.

According to this hypothesis, being 'in-zone' does not guarantee optimal performance: it simply increases the probability of optimal performance. However, Hanin's model does not provide specific probabilistic estimates of performance success. Another concern with the in-out principle is that it fails to account for a complete working emotional range and a complete range of performances. The in-out principle only accounts for intensity levels associated with best and worst performances: intensities that lie outside of the optimal and dysfunctional zones are not accounted for and moderate performances are not recognized.

Energy mobilization-utilization hypothesis. In addition to the PBS model and the in-out of zone hypothesis, Hanin developed the energy mobilization-utilization hypothesis to explain and predict how feelings determine performance and functioning. Compared to some emotion-performance theories (Beilock & Carr, 2001; Easterbrook, 1959; Eysenck & Calvo, 1992; Hardy, 1990; Hardy & Frazey, 1987; G. Jones, et al., 1993; Wegner, 1994) the mobilization-utilization hypothesis is not a particularly sophisticated model (for reviews see, Hanin, 2007; Hardy, et al., 1996; Janelle, 2002; Williams, Davids, & Williams, 1999; Woodman & Hardy, 2001). While the hypothesis has roots in earlier publications, Hanin described this hypothesis in the seminal 1997 article and did not fully articulate the hypothesis until 2000. The mobilization-utilization hypothesis has not been researched beyond the scope of the IZOF model, has never been tested directly, and its description is limited to three pages of Hanin's 395-page book "Emotions in Sport" (Human Kinetics, 2000). However, the hypothesis is effective, intuitive, and based on a thorough review of relevant research.

The basic premise is that emotions regulate the mobilization and the organization of energy—which is implicitly supported throughout mainstream psychology. One of the foundations of Hanin's hypothesis is Martens' (1987) description of "psychic energy"—which is synonymous with vigor, force, intensity of effort, and persistence (See Hanin, 2000c, p. 84-86). In this sense, emotion is both energy and the direction of energy. According to Hanin's hypothesis, emotions have two functions: energizing and organizing (Hanin, 2000c). Energizing mutually involves the mobilization and demobilization of resources. Organizing involves efficient utilization (or misuse)—a concept that shares an intriguing connection with Csikszentmihalyi's (1994, 1996) description of 'psychic entropy' in relation to optimal experience and mental functioning. So how does the connection between emotion and energy determine performance? In sport, optimal performance requires (a) enough energy for substantial physical exertion and mental stamina, and (b) efficient use of psychomotor resources. In short, emotions, and more generally, feelings, help us to meet the energy and resource demands of sport.

How do specific emotions influence energy mobilization and utilization? The key to Hanin's hypothesis is the specific description of the effects that emotional valence and function have on energy mobilization and utilization. Specifically, IZOF categories are associated with the following functional energy effects. Positive-functional emotions serve to mobilize and effectively organize energy. Negative-functional emotions assist more in mobilizing than in utilizing energy. Positive-dysfunctional emotions reduce effort and energy generation, as well reducing efficient utilization via inefficient processing and low alertness. Negative-dysfunctional emotions distract cognitive and motor resources away from relevant and towards irrelevant cues. Clearly, the magnitude of the effects of each category depends upon the intensity of each content item (emotion) in the category. For instance, the motivational effects of negative hedonic tone may be either facilitative or debilitative. This implication is supported by the cue-utilization and processing efficiency theories (Easterbrook, 1959; Eysenck & Calvo, 1992).

According to the hypothesis, functional emotions are associated with the anticipation of challenge, threat, or opportunity (a process focus). Dysfunctional emotions anticipate positive or negative outcomes. Consequently, dysfunction emotions have a negative effect because the athlete becomes a less active agent in determining personal performance. Whether or not an athlete anticipates winning or losing, the effect is the same: less effort and a more outcome- or ego-oriented focus. According to Hanin the functionality of emotion and energy can describe two personality types, which are in line with Eysenck and Calvo's (1992) processing efficiency theory. "Smart users of energy" do not require high activation levels (Hanin, 2000c, p. 86). Contrary to these low-energy performers, high anxious athletes mobilize more energy resources and tend to be less efficient due to the strain placed on processing and attentional resources.

An important implication of this theory—an implication that is highly relevant to this dissertation—is that the organization of feelings into functional and dysfunctional, and positive and negative categories is essential in order to understand exactly how an athlete's feelings affect his or her performance. As noted earlier in this section, the Energy Mobilization-Utilization Hypothesis is conceptually and intuitively strong, but lacks formal empirical support. Though, it is beyond the purpose of this dissertation to test the hypothesis, the organization of discrete feelings into valence-function categories is foundational as it allows comparisons between otherwise unique individual profiles. In other words, let us say that Scott's profile has four items (intense, overjoyed, anxious, and angry); and Shawn's has confident, calm, unsure, and scared. Clearly, these unique items cannot be compared. However, if each represented a different valence-function category (e.g., positive-helpful, positive-harmful, negative-helpful, and negative-harmful), comparisons could be made as both players have feelings that may be organized within those valence-function categories. This is especially reliable if multiple discrete items represent each category.

Methods and Measures of Performance Profiling

The following section examines two major topics in the area of assessing individual profiles. The first part will describe four established methods for determining individual emotional recipes for performance excellence. The second part describes the positive-negative affect scale, which is central to the assessment of individual profiles. The third part reviews literature that has examined the reliability of emotional recall methods.

Methods of developing idiographic profiles. Several methods have been developed to determine the exact recipes of feelings that most help and hurt a player perform. While the method section will describe the techniques most relevant to this study, the subsequent sections are intended to provide an overview of the options available to researchers and practitioners alike. Hanin (2003) illustrated four methods: in-depth interviews, individualized emotion profiling (Hanin's stepwise procedures), self-generated metaphors, and narrative descriptions. In addition to these relatively qualitative approaches, many researchers have simply used psychometric questionnaires such as the STAI, SAS, POMS, and CSAI-2 in either a recall or a real-time pregame protocol. Though most researchers have focused primarily on precompetitive anxiety, these methods may be used to assess pre-, mid-, or post-competition states. The proposed study will primarily utilize the stepwise procedure (IEP) method—which will be augmented with elements of interview and narrative procedures.

In-Depth interviews. The first method of collecting individual data is the use of in-depth interviews that include open-questions and questionnaires. One of the best-known semi-structured questionnaires is Terry Orlick's (1986) "competitive reflections" survey, but psychometric tools may also be used to supplement interview data. Athletes can recall their performance state at any time of the competition, so this method is not restricted to, for instance, pre-competition assessments only. As the most open-ended technique, interviewing is very flexible and sensitive to individual differences. Interviewees have the opportunity to describe personally meaningful events and relevant feelings. However, this method relies on the athlete's ability to remember and to verbalize his/her thoughts.

For this reason, Hanin (2003; 2007) has consistently recommended that interviews be conducted with experienced and more verbally skilled athletes, and that interviews focus on more unique and memorable performances (e.g., best and worst ever). In addition to being able to recall and verbalize their experiences, it is also important to ensure that interviewees have had sufficient experiences to draw upon—which is a limitation for any IZOF-related assessment. If an athlete has not experienced a sufficient number of exceptional performances, how can she describe her ZOF? Other disadvantages of interviewing include that it can be more time consuming, and that interviews may vary significantly from one athlete to another.

Individualized emotion profiling (IEP). The IEP, which is commonly referred to as the stepwise procedures, evolved with the development of the modern IZOF model (Hanin, 1997, 2000c). The IEP is the gold standard and most frequently used method of IZOF assessment. The first step in the IEP is to identify and describe previous best and worst performances (See Figure 2 in the Appendix). While Hanin does not specify how many best or worst performances should be included, most studies have included only one example of each. Though timesaving, the use of only a single best, and a single worst performance is concerning. Clearly, a single competition cannot describe two-dimensional zones (i.e., range or bandwidth). The reflective stage offers a more concrete description based on specific performances rather than conceptual or metacognitive representations.

The second step uses the Positive and Negative Affect scale/list (PNA; Hanin, 1993; Syrja & Hanin, 1997) to identify emotions and related feeling states that are personally relevant for each athlete (Figure 3 in the Appendix). The PNA-77 is a list of positive and negative emotion-oriented words that are associated with best and worst functioning (Hagtvet & Hanin, 2007; Hanin, 1993b; Hanin & Syrja, 1995; Lukkarila & Hanin, 2001). Details about the PNA are included in the next section. From the positive list, athletes are generally instructed to choose 4 or 5 items that are relevant for best performances, and 4 or 5 items associated with worst performances. The same procedure is followed for negative emotions. The result is an individual profile of 16-20 idiosyncratically important descriptors. This step allows participants to describe personally meaningful factors, rather than being restricted by predetermined profile items. Syrya and Hanin (1997) found that as much as 85% of individually relevant emotion-type items were not included in common emotion-performance scales.

The third step uses a modified Borg's CR-10 scale (Borg, 1998) of perceived exertion to estimate the intensity dimension of each emotion or related feeling state (Hanin, 2000c; Tummavuori & Hanin, 2000). Borg's scale is well-known to all disciplines of kinesiology. It is best known to exercise scientists as the rate of perceived exertion scale. The likert scale ranges from 0 ("nothing at all") to 11 ("maximal possible") and can be used to describe physical effort or the intensity of any feeling state. Participants are required to recall the intensity of each item from the PNA for each competition in their best/worst list. An example of the CR-10 is provided in Figure 4 in the Appendix.

The final phase of the IEP requires "visualizing" or graphing the intensity estimates. The result of this procedure is the formal IZOF profile. An example profile is included in Figure 1. The graph includes four columned sections. Positive items (denoted P) are included on the right side, and negative items (denoted N) are on the left. Items associated with optimal functioning (denoted +) are located in the middle-two columns, with dysfunctional items (denoted -) on the outside columns. The columns therefore run (from left to right) as N-, N+, P+, and P-. Because functional (+) items are generally higher in intensity during optimal performances, and dysfunctional items are very mild, the resulting optimal-profile fits the traditional inverted-U or iceberg shape. Conversely, the dysfunctional-profile is typically U-shaped or concave.

The stepwise procedures balance the openness necessary to generate idiographic patterns with more efficient, structured procedures that permit interindividual comparisons that can generate nomothetic models. However, it is the most time-consuming method. Also, it is debatable how rigidly one should adhere to the protocols at each step of the process.

Self-generated metaphors. As metaphors are not included in the assessment procedures of this study, the description here will be brief. The use of metaphors to establish performance profile and to enhance performance is based on the Social Cognitive Theory (Bandura, 1986). Hanin has endorsed the potential value of metaphoric description (Hanin, 1997, 2000a) and has conducted three metaphor-studies with his colleagues (Hanin, 1997, 2000a; Hanin & Stambulova, 2002; Hanin, Stambulova, Lukkarila, & Tummavuori, 1997; Ruiz & Hanin, 2004). Athletes are asked to describe what it felt like (using a metaphor) prior to, during, and after their best and worst competitions. They are then asked to elaborate on each metaphor with the stem "in other words, you felt like…" When at their best, athletes might say they feel like: a lion, a calm breeze, an oak tree, a crouching red panther, etc. Descriptions of dysfunctional states may include Garbage, sloth, a robot, and a black bug. Metaphoric descriptions may not be effective for all personalities, but provide personally meaningful descriptions for many.

Narrative descriptions. Narrative data are simply stories, or accounts of experiences. A common example of narrative data is the self-story, which is a "first person narrative which defines identity based on memories and personal perceptions of history, present life, roles in various social and personal settings, and relationships" (Payne, 2000, p. 19). As with previous methods, narrative description is ultimately another means of describing factors that affect performance. In addition to very guided protocols, narrative descriptions can also be obtained through journaling (either during or after competitions).

Measurement Issues

The Positive-Negative Affect (PNA) scale. The PNA is an important component of the recently described IEP, but can also be combined with many of the other methods. The PNA was created for studies with elite Finish athletes that used the stepwise Individualized Emotion Profiling system (Hanin, 1993b; Syrja & Hanin, 1997). The Finish list was developed from Watson and Tellegen's (1985) 10 global affect scales. The English version includes 40 positive items and 37 negative items, each arranged in 14 synonymous rows. Examples of positive valence items include active, relaxed, happy, confident, exhilarated, thrilled, daring, motivated, pleasant, and fast. Examples of negative rows include afraid, aggressive, annoyed, worried, depressed, doubtful, unsafe, sluggish, fierce, sorry, tight, and tired. In addition to the 77 items in the list, participants are urged to include their own words. This allowance enhances the idiosyncratic capability of the PNA, and it promotes buy-in from athletes. Feelings such as attacking, pissed off, and tough do not appear on the list, but may be appealing to some athletes. The PNA-77 is shown in Figure 3 (See Appendix)—please refer to this figure for examples of items, and to see how synonyms are grouped in each row. The PNA has been translated into Spanish, Italian, German, and Russian (Hanin, 2003).

Syrja and Hanin (1997) compared the PNA-77 to popular anxiety inventories in sport and found 85% item overlap with the STAI (Spielberger, 1988a), 60% overlap with the PANAS, and 37% overlap with the POMS (Morgan, 1980; Morgan, O′Connor, Ellickson, & Bradley, 1988). While the PNA-77 accounts for a reasonable number of the items on these scales, the same cannot be said in reverse. Overlap ratings (similarity of items ranging from 0 to 1.0) revealed that the aforementioned scales fail to account for between 83% and 89% of the items on the PNA (Syrja & Hanin, 1997). A subsequent study with hockey players revealed that the CSAI-2 failed to account for 85% of the items identified by the PNA (Hanin, 2000d).

Extending Hanin's list. There is an interesting—albeit unpublished—study that contributes to our discussion of Hanin's PNA list (See Gould, et al., Date unknown). Two-hundred and eleven college athletes from a variety of male and female sports completed surveys that identified feeling states that were critical for individual performance. Affect was identified across eight categories based on combinations of three factors: context (practice and competition), time (before and during), and performance (good and poor). Because the authors used a very broad definition of emotion—"those specific positive and negative feelings, thoughts, physical reactions, and motivational tendencies" (Gould, et al., Date unknown, p. 8)—their results are consistent with the more holistic psychobiosocial feeling state underlying the PNA-77.

Consistent with Hanin's claim (Hanin, 2000d; Syrja & Hanin, 1997) that traditional measures of competitive affect underrepresented athlete's unique needs, Gould et al. (Date unknown) identified 5448 different raw items (almost 26 per participant across the eight contexts). Formal content analysis of the raw items yielded 65 general categories: of which only 18 were included among the 77 PNA items. Interestingly, nine of the top ten categories from Gould et al. are represented in the PNA. Gould et al. identified several new items that represent the broader psychobiosocial state and are not all true emotions.

Critique of the PNA/IEP. Hanin (2003) acknowledged two criticisms of the IEP system and of the PNA-77 list. First, the PNA-77 does not include pure emotions. There are items that might be better categorized as somatic (e.g., jittery, tense, tired), motivational (e.g., determined, willing, motivated), and cognitive (e.g., focused, alert). The PNA-77 could, accordingly, be considered a list of broader, performance-oriented psychobiosocial factors. As Hanin argued, "there is a clear need to extend the focus of individual profiling from emotions to other modalities of an athlete's state" (Hanin, 2003, p. 12). Anyone with experience working with athletes in real-world competitive settings cannot deny the validity of this broader inclusion of psychobiosocial feeling states. However, the PNA could be organized into emotions, somatic items, and so forth. Future research could combine Hanin's PNA-77 with Robazza et al.'s (2004) somatic item list, Gould et al.'s (Date unknown) grounded lists of items, and new research to provide a more comprehensive list that is organized into various types of feeling state.

Reversals. One other criticism of the PNA-77 is that valence is predetermined for each item. For example, anxiety is listed as a negative emotion and daring is presumed to be positive. Numerous studies have established that negative emotions can be helpful or harmful to performance (Edwards & Hardy, 1996; Hagtvet & Hanin, 2007; Hanin, 1993b, 1995; Hanin & Syrja, 1995, 1996; G. Jones, 1995; G. Jones, Hanton, & Swain, 1994; G. Jones, et al., 1993; Robazza, Bortoli, & Nougier, 1998). This finding is referred to as either a functional reversal or directionality of anxiety. Additionally, one could also argue that the hedonic tone of an emotion is determined by individual perceptions. If a person feels that anxiety is pleasant, or that daringness is unpleasant, then the conventional labeling of anxiety as having negative valence is arguable.

For instance, Robazza and Bortoli (2003) examined hedonic and functional (directionality) reversals in the CSAI-2, and in somatic and affect PNA scales. Based on their sample of 374 elite and non-elite Italian athletes, Robazza and Bortoli found evidence for both functional and hedonic reversals. Specifically, 72% of the 90 affect and somatic items included in this study were classified as both positive and negative. However, upon closer inspection, emotions conventionally deemed to be positive were perceived by participant to be positive 94% of the time, and unpleasant less than 6% of the time. Traditional negative emotions were identified as negative in 87% of cases and positive in only 13% of cases. Averaged together, hedonic reversals occurred in slightly fewer than 10% of the 5608 cases in this study. These results are supported by Bortoli and Robazza's (2002) study of 50 Italian volleyball officials which incorporated two PNA-style lists: one list with 64 affect items, and a second list with 24 physiological /

somatic items. Along with Robazza et al. (1998) these studies, supported Kerr's (1997) description of hedonic reversals.

Hedonic reversals are noteworthy, but in the view of this dissertation, the traditional assignment of valence to discrete feelings should not change because of a finding that occurs only rarely and lacks theoretical explanation. Functional reversals, on the other hand, have received nearly unequivocal empirical support. As such, these reversals should always be considered when studying valance and performance.

Validity of recall. One final measurement issue that is relevant for this study involves the validity of performance recall. There have been numerous studies that have examined the accuracy of both recall and prediction methods of assessing emotion. The issue of reflective assessment procedures is integral to the validity of the IZOF model, and any review of literature of this kind would be thoughtless to ignore it. However, because it is not an essential focus of this project, this section will be as brief as possible. Overall, recalling feeling states before and after performances is a method that is well supported (Hanin & Syrja, 1996; Jokela & Hanin, 1999; Tenebaum & Elran, 2003; Tenenbaum, et al., 2002).

Recall methods. Harger and Raglin (1994) assessed state anxiety in 34 college track and field athletes an hour before and two days after competition. The two values correlated at .97 for females, and .96 for males. Recall was consistent for high (r = .96) and for low (r = .97) performance ratings. Though not as high, other studies have supported Harger and Raglin. Hanin and Syrja (1996) had 17 Olympic men's soccer players complete individualized precompetition PNA scales 24 hours before competition (predicted), 40 minutes before competition (actual precompetition), and 30 minutes after competition. Results showed significant correlations for 14 of the 17 athletes' predicted-actual ratings, and for 13 of the 17 athletes' recalled-actual ratings. While prediction and recall were not reliable for all participants, the method, overall, was consistent for both predicting as well as recalling actual precompetition emotions.

More recently, Tenenbaum and Elran (2003) compared precompetitive anxiety reports 3, 7, and 14 days after competition using the CSAI-2 and the PNA-77. After a small change in reports from the actual to the three-day recall point, the authors noted that "correlations among the retrospective reports of emotions at Day 3, 7, and 14 were extremely high, higher than the ones between actual and the three day delay report correlations, indicating a high carryover effect from the first report procedure" (Tenenbaum & Elran, 2003, p. 283). On average, reported scores decreased only 2.37% in the 14-day recall. These results were supported by a similar study of 52 university athletes (Tenenbaum, et al., 2002). In studies of performance recall taken 3-22 months after competition, correlations ranged between .75-.82 (Imlay, Carda, Stanbrough, & O'Connor, 1995; Raglin & Turner, 1993; Turner & Raglin, 1996).

An alternative to recall assessments. Real time assessments can be too invasive (Hanin, 1995; Hanin & Syrja, 1995; Raglin & Hanin, 2000). Such methods can interfere with competitive routines and may be biased by the immediate moment. That is to say, that rather than describing the general state prior to competition, real time assessments are hyper-focused on a particular moment. Accordingly, researchers would be prudent to collect a large number of such direct, real time assessments. Also, these direct assessments are not as feasible or efficient as recall methods. Recall techniques avoid these potential problems, but can be undermined by outcome bias. For example, a successful outcome might bias recall of both emotions and of performance in a positive direction (Gould, Tuffey, Udry, & Lochbaum, 1993). Recall is also subject to fading effects in memory. In spite of these concerns, recall and even predictive methods of assessing emotion are strongly supported empirically.

Because the proposed dissertation will utilize online, or real time, procedures rather than recall methods, this section might appear to be irrelevant or even contradictory. However, it is not my position that real-time assessment is superior or that reflection is inferior. Predicted, real time, and reflective techniques are each valid and reliable—so long as they are executed precisely. The problem with IZOF research up to this point is not the use of recall designs, but the over-use of this method. The proposed method is especially significant to the body of literature not because it is better, but because it is most appropriate given the purpose of the study and because it fills a relative void in the literature with respect to online assessment.

Critique of IZOF Theory and Literature

While there are several possible criticisms of the IZOF model, our discussion will focus on the faults that will be examined in the proposed study. These criticisms include the failure to acknowledge moderate levels of performance, the failure to account for a complete range of emotional intensity, and related to these two problems, the IZOF theory does not account for overlap or gaps between optimal and dysfunctional profiles. Other criticisms pertinent to this dissertation are described briefly.

Exclusion of moderate performance. As described in the previous IZOF section, Hanin's stepwise procedure produces two zones. When an athlete is within his zone of optimal functioning (ZOF), the probability of optimal performance is at its highest for th

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that individual. The further "out of zone" the athlete is, the worse their performance is likely to be. The same principle applies for the zone of dysfunction (ZDy) and poor performance. Generating profiles for only optimal performance and poor performance leads practitioners and academics to an obvious question: why does the IZOF model exclude moderate performance? The failure of the IZOF model to consider a fuller range of sub-optimal performance levels is not trivial. The omission of moderate performance-levels is fundamental to the gaps and overlaps problems described later in this section.

Incomplete functional range of predictors. In conjunction with the previous concern that the IZOF model does not account for enough possible outcomes, the model does not account for the complete range of intensity for each feeling state (aka, each of the predictors). For example, reflecting on previous best and worst performances predicts an IZOF for 'aggression' between 7-9, and an IZDy between 2-4. While intuition allows us to reasonably assume that any level of aggression below 4 is likely to yield poor performance, the IZOF system cannot determine what the performance effects are when aggression is between 5-6 or above 9. If an athlete were to be a 5 or 6 for aggressiveness, would this result in optimal, average, or poor performance? Likewise, when the athlete exceeds a 9, is she able to sustain high performance, drop to moderate performance, or does she experience a catastrophic poor level of functioning? The limited ability to account for a complete functional intensity range on every predictor item and to describe all levels of performance is clearly interrelated to one another. These concerns are related to another, perhaps greater, problem with the IZOF model—gaps and overlaps.

Gaps and Overlaps. As a result of the above limitations, Hanin's approach can result in gaps and/or overlaps between ZOF and ZDy profiles. Gaps refer to the spaces in the c

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complete range of intensity that is not associated with either best or worst performance (e.g., the ZOF is 3-5, and the ZDy is 8-10, establishing a gap from 6-7). When there is overlap, some points on the intensity continuum are associated with both optimal and dysfunctional performance (e.g., the ZOF is from 5-9 and the ZDy ranges from 0-6, establishing an overlap from 5-6). These gaps and overlaps between ZOF and ZDy profiles are depicted in Figure 1. Gaps are ambiguous—there is no way to determine their meaning—but while gaps tell us nothing, overlaps tell us too much. Kamata et al. (2002) point out that "the larger the overlap, the less chance of predicting the quality of performance from emotional states" (p. 193). For example, if the athlete is within the overlapping range (e.g. 5-6 in the previous example), will they perform at an optimal or poor level? If the model cannot answer this question, it provides little value for researchers and practitioners. The IZOF model should resolve overlaps and must be able to explain the meaning of (if not eliminate) gaps within profiles.

Kamata et al. (2002) addressed these shortcomings with their IAPZ model. By establishing probabilistic estimates, IAPZ's account for performance effects throughout the entire range of valence, function, and emotional intensity—thus eliminating ambiguous gaps between optimal and dysfunctional profiles. Additionally, Kamata et al. recognized average performance outcomes—not just optimal and poor ones.

Brief aside: An anecdotal view on the overlapping phenomenon. Though empirical studies suggested that overlap between ZOF and ZDy profiles was rare (For reviews, see Hanin, 2000; 2007), the consulting experiences of the author in administering the IZOF system to hundreds of athletes provided contrary anecdotal evidence. In fact, overlap was so common that several practical solutions evolved. The solutions to this problem began e

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with reflection and explanation. Why is there overlap? Kamata et al. (2002) made an excellent point, which is that each level of an emotion is not going to elicit an exclusive 100-percent likelihood of poor, moderate, or optimal performance. At any level of intensity, the probabilities of poor, moderate, and optimal performances likely coexist at varying ratios. However, this is the only explanation offered by the IAPZ model.

Another reason for the overlap of intensity was that different items interact. The best way to explain this is with an example. Say there was overlap in anxiety: when Adolf is between 5-7 for anxiety, he experienced *both* best and worst performances. While anxiety does not discriminate performance cleanly, it was an important predictor of performance. The key in this example was the interaction between anxiety and confidence. Anxiety levels between 5-7 combined with low confidence predict poor performance; while the same anxiety levels combined with high confidence create optimal performances. In this sense, we can see how separate items could become feeling-conjunctions (i.e., confident-anxiety or relaxed-nerves). Interacting feelings and the notion of optimal emotional "recipes" are described in applied literature (Gould, et al., 2008; Hardy, et al., 1996).

An additional explanation for overlapping content is simply that the item does not effectively predict performance! Upon initial reflection of either a best or worst performance, an athlete might feel that an item (often a positive-harmful feeling such as calmness or energetic) is important. However, after monitoring several competitions, it became clear that calmness and feeling energetic are associated with both optimal and poor performance; these items did not differentiate functioning. The stepwise IZOF procedure can be considered analogous to backward linear regression in that you may intentionally start with too many items in an effort to be comprehensive while moving towa

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towards a model with only substantive non-redundant predictors. Researchers and practitioners should not be afraid to eliminate less helpful items. We should never allow orthodoxy and dogma to obscure our real experiences and special human insight.

Other Issues Addressed in this Study

The following section provides a compilation of smaller criticisms and shortcomings of the IZOF model. Each flaw is addressed in the design of the current study. Firstly, IZOF research has relied too heavily on recall of precompetition emotions. To balance this preference, direct assessments of emotion during competition will be acquired.

Secondly, most IZOF studies include relatively small numbers of total observations. By obtaining a larger number of repeated observations, more sophisticated statistical analyses can be conducted that account for more predictors and interrelated factors. Of the five dimensions of the PBS state, the context dimension is the most under-researched, yet perhaps the most intriguing. The proposed study involves tennis, which can be broken into two unique performing situations: returning serve and serving (where a player controls the point and has an advantage). By obtaining a large number of observations, intraindividual differences in profiles can be compared in each context.

Lastly, from an applied point of view, IZOF profiles are too big. It is important to be comprehensive, but great scientific models must have a parsimonious balance. It simply is not practical for an athlete to go into a competition with 16 or 20 emotional zones in his head. In an attempt to bring simplicity to the IZOF model, athletes will be asked to identify the two to four emotions that they feel are most important for their performance. These critical items will be compared to the complete model to determine which predicts performance more reliably.

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Extending the IZOF Model: Individual Affect-Related Performance Zones (IAPZ)

As explained in the introduction, this dissertation integrates the IZOF model with a newer IAPZ model. The following section describes the IAPZ model; ways in which it improves the IZOF model; and addresses shortcomings of the IAPZ method itself.

An Introduction to Individual Affect Performance Zones (IAPZ)

The IAPZ model was established in 2002 after collaboration between Akihito Kamata, IZOF creator Yuri Hanin, and Gershon Tenenbaum who has authored every published IAPZ study (Cohen, et al., 2006; Edmonds, et al., 2006; Golden, Tenenbaum, & Kamata, 2004; Johnson, Edmonds, Kamata, & Tenebaum, 2009; Johnson, Edmonds, Moraes, et al., 2007; Johnson, Edmonds, Tenenbaum, & Kamata, 2007; Kamata, et al., 2002; Medeiros Filho, et al., 2008; Tenebaum, et al., 2002; Tenenbaum, et al., 2008). IAPZ is not a completely original theory. It is a refinement of the IZOF model intended to correct specific limitations of its predecessor. Research on this idiographic model includes seven manuscripts and one conference proceeding. Of the nine manuscripts there are: five empirical field studies (two tennis, one golf, and two archery); one laboratory study (racing video game); two review article; and the preliminary article by Kamata et al. (2002), which introduces the probabilistic statistical procedure and compares IAPZ to IZOF using two hypothetical cases. Each of these papers is described in Table 1.

IAPZ research is at a pivotal juncture in that there is enough support to make the model credible; yet there is not enough research to identify IAPZ as a distinct theory from the IZOF model. IAPZ and IZOF are intimately related systems. As such, Tenenbaum's model will be contrasted with Hanin's IZOF theory, more so than it will be presented as a stand-alone model in the forthcoming section.

Table 1

Summary of Empirical Articles in the area of Individual Affect-Related Performance Zone

Authors (Year)	Sample	Task	Measures	Design / Analysis	Results
Kamata, Tenenbaum, & Hanin (2002)	2 [100]	None	Hypothetical Data using SAS measure	Hypothetical dataset; Tests 3 IAPZ models	This article introduces the IAPZ model
Golden, Tenenbaum, & Kamata (2004)	3 [226]	Tennis	Affect Grid; Function; FSS; PNA; Performance = 1-9	Timeline recall after matches; Bad moderate performance parameter	Introduces 2nd-order figures; Ind'l differences / similarities; Some flow
Cohen, Tenebaum, & English (2006)	2 [216]	Golf	Affect Grid; Function; TOPS; PNA; Performance = Modified Score Card	PST intervention; Season-long & Pre-/Post-Intervention; Online Assessment	Effects of interactions on performance; Mostly effects PST on performance (vs. IAPZ)
Edmonds, Mann, Tenenbaum, & Janelle (2006)	3 [180]	Racing Video Game	Affect Grid; HR; Skin; Immersion TQ; Performance = Time	Online assessment; Emphasis on multimodal assessment	Not much here; Value of multidimensional assessments
Johnson, Edmonds, Tenen-baum, & Kamata (2007)	4 [1473]	Tennis	Affect Grid; Performance = 1-9	Online assessment during changeovers	Changes during performance (momentum)
Johnson, Edmonds, Moraes, Medeiros Filho, & Tenenbaum (2007)	1 [348]	Archery	Affect Grid; HR; Performance = Shooting Accuracy	Online assessment; Assessed various distances	Flow; Context differences; Changes during performance (momentum)
Medeiros Filho, Moraes, & Tenenbaum (2008)	3 [720]	Archery	Affect Grid; HR; Performance = Shooting Accuracy	Online assessment; Assessed various distances	Context effect; Change over season; 2nd-order & Time graphs

Note. Values in brackets of 'Sample' column represent the total number of observations in each study.

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An example research study. However, before we explore these issues, and because some may not yet have read an IAPZ study, a typical study is described. Johnson et al. (2007) conducted a single-case study of an international female archer. The study included numerous observations over the course of one indoor and one outdoor competition. The competitions included five different shooting distances, with several rounds at each distance, and several shots in each round. There were 348 observations in this study. After each series of shots, the participant completed the affect grid (Russell, et al., 1989) which assessed general affect and arousal (or activation), and heart rate values were aggregated across the series. Functionality of affect was not rated.

Performance scores were based on accuracy of shooting in each series. Shooting scores one-half standard deviation above the mean were labeled as optimal, scores one-half standard deviation below the mean were labeled as poor, and all other scores reflected moderate performance levels. In accordance with the inverted-U theory (Yerkes & Dodson, 1908), poor and moderate performances were both split into two groups based on whether or not each affect score was above or below the average value associated with optimal performances. This resulted in five types of performance: poor-high affect, poor-low affect, moderate-high affect, moderate-low affect, and optimal.

In keeping with Kamata et al.'s (2002) probabilistic method, ordinal logistic regression was conducted separately at each competitive distance for each of the three predictor variables (i.e., heart rate, arousal, and pleasure). None of the predictors were combined or enabled to interact during the analysis. After the 15 graphs were developed, predictor scores were essentially recoded into one of the five possible performance labels, and placed in chronological order. This secondary analysis allowed the researchers to show

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show what zone the archer was in from one series of shots to the next. This figure showed how often and when she was in-zone. The authors were thereby able to compare profiles across distances (context analysis), and to provide a unique perspective on momentum.

How IAPZ Improves the IZOF Model

Because the IAPZ model is a relatively young model, and a comprehensive outline (i.e., book chapter or similar forum) has not been presented, it is difficult to define and describe characteristics of the IAPZ model. It is especially difficult to separate characteristics of IAPZ from the IZOF model. However, based on the five empirical studies conducted thus far, the following characteristics of the theory are available.

Probabilistic estimates. The defining feature of the IAPZ model is the use of probabilistic estimates of performance outcomes using logistic regression. Where the IZOF model confines itself to the intensity levels associated with two possible performance states (optimal and dysfunctional zones), IAPZ accounted for complete ranges of emotional intensity and three performance levels (poor, moderate, and optimal). A standard IAPZ graph is presented in Figure 5 (note that at any point along the intensity range (x-axis), the sum of the performance curves' probabilities (y-axis) each will always equal 1.0). Kamata et al. (2002) presented three different models (approaches) that each use logistic regression to identify optimal zones. Two sets of 50 hypothetical observations are presented so that probabilistic and traditional IZOF analyses may be compared. The results of these comparisons supported the probability-based method. One of the most interesting results compared how often observations associated with optimal and poor performances were correctly in- or out-of-zone (respectively). IZOF generated profiles were too narrow, and thus excluded too many optimal performances from being includ

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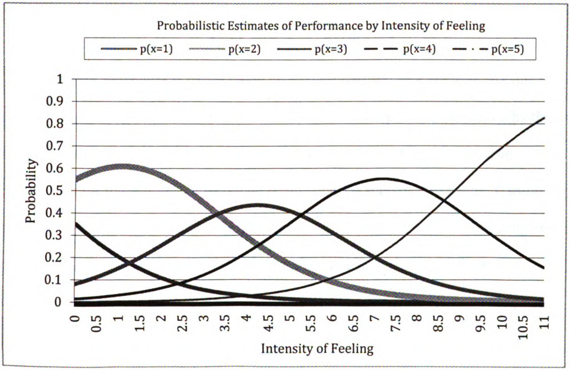
included in-zone. In other words, the IAPZ method more accurately identified helpful items as being associated with optimal performance. Likewise, the IAPZ method mislabels out-of-zone observations less frequently.

Figure 5

Example of a Typical IAPZ Graph of Probabilistic Curves



Note. This figure depicts the probability (y-axis) of various performance levels (represented by different curves) across the range of feeling intensity. Curves p(x=1) to p(x=5) represent the probabilities for poor-low intensity, average-low intensity, good, average-high intensity, and poor-high intensity outcomes (consecutively).

Splitting suboptimal performances. Tenenbaum and colleagues break moderate (and some times poor) performances into two categories based on a high-low split of emotional intensity. Although most IAPZ analyses have used this splitting procedure, the reaso

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reasons for this procedure were not explained in their introductory publication. Once data are collected, the mean of emotional intensity is calculated for optimal performances. Sub-optimal observations can then be designated as having intensities above and below the optimal mean threshold. A typical IAPZ analysis yields four curves that represent: poor performance (PP), moderate performance with above average-optimal intensity (M/A), moderate performance with below average-optimal intensity (M/B), and Optimal performance (OP). In some studies, this procedure has also been applied to poor performances (Johnson, Edmonds, Moraes, et al., 2007; Medeiros Filho, et al., 2008). The mean-split procedure is partly based on anxiety-performance theories, but due to the limited amount of published material in this area, it is difficult to understand why this method is included in most IAPZ analyses. Theoretical rationale aside, the true justification for the splitting of moderate results may be statistical in nature. Partitioning the data may enhance the fit of the model and thereby improve the overall quality of the results, while taking advantage of the disproportionate numbers of moderate observations.

Multimodal and online measurement. The following three characteristics are not explicit attributes of the model, but they are common features of nearly all IAPZ studies and are unique from nearly all IZOF research. From its inception, IAPZ research has emphasized the use of multiple types of measurements, including physiological measures (heart rate, skin conductance, etc.), immediate recalls (affect functionality, valence, arousal, and performance), and post-competition reflection (PNA-77, FSS, etc.). Psychophysiological measures have rarely been used in IZOF research, but are advocated strongly in IAPZ research. Not only do these assessments measure affect from a different perspective (explicit verbal versus implicit neurological), but they offer a measure that is unbiased by memory and perception. Also, physiological measures can often be monitored "online" while an athlete is performing. IAPZ research often combines online, immediate recall, and reflection 30-60 minutes post-competition (Johnson, Edmonds, Moraes, et al., 2007).

Of the five empirical research studies published by Tenenbaum and his colleagues, three have assessed psychophysiological markers such as heart rate and skin conductance during performance (Edmonds, et al., 2006; Johnson, Edmonds, Moraes, et al., 2007; Medeiros Filho, et al., 2008). Along with the many advantages of these objective biological markers of emotion, there are disadvantages to these measures (Lang, 2000). For instance, many of the necessary measurement devices cannot be utilized in competitive sport settings because they are too sensitive, cumbersome, or fragile. Additionally, physiological measures can be confounded in sport because physical activity can influence readings independently from affect. As examples of these limitations, IAPZ research has only measured neurophysiological factors during archery and a simulated racing game.

It should be noted that liberties have been taken in describing the IAPZ emphasis as being on multimodal measurement. This is not perfectly accurate. Authors have defined the issue as being one of multidimensionality. However, their terminology may be mistaken. Where multidimensionality conventionally refers to the evaluation of multiple unique forms of psychobiosocial content, IAPZ research focuses almost exclusively on one form: arousal. For instance, Edmonds et al. (2006) utilized several online and immediate recall measures, such as heart rate, skin conductance, and verbal report of both pleasantness and arousal. These are not four unique dimensions or forms of affect. More so, they are different perspectives on a single form of affect (arousal). As such, IAPZ research prefers to evaluate global affect using different measurement modalities, rather than truly assessing multiple unique dimensions of affect.

Intraindividual longitudinal and multi-context research. As we move further away from explicit, defining attributes of the IAPZ model and closer to trends in this line of research, we arrive at the final two features. More so than in IZOF literature, IAPZ research has emphasized more long-term (season-long) repeated measures designs. Researchers have also excelled in comparing APZ's for individual athletes across different contexts/tasks (e.g., shooting distance in archery). These studies have offered unique information about the dynamics of emotions during a competition, across different tasks within a competition, and between competitions over the course of a season.

For instance, in their case study of an international-level female archer, Johnson et al. (2007) collected 348 observations over five shooting distances in two competitions. Each shooting distance was associated with a unique APZ profile. Generally, optimal zones and related probabilities decreased as shooting distance increased. Medeiros Filho et al. (2008) conducted a similar study of three archers over a 10-month season. At least 40 observations were collected at each distance for all three participants. Results supported Johnson et al.'s conclusion that APZs fluctuate within individuals across various distances and during the duration of the season as well. Specifically, optimal zones narrowed as distance increased (i.e., task difficulty increased). Their study did not reveal momentum for optimal performances (i.e., optimal performance did not increase the probability of subsequent optimal performance). It is worth noting that this study and all other IAPZ research have confirmed the basic premise of idiosyncratic zone theories: that individuals have unique optimal zones of functioning and vary from athlete to athlete.

Critique and Shortcomings of IAPZ

Compared to the up to 20 items assessed through Hanin's procedure, IAPZ measures are simpler and less invasive. By reducing the assessment of affect to only two or three questions (rating valence, intensity, and functionality), measurement is less invasive. However, important information is lost (or never acquired). The criticisms of IAPZ can be considered a product of IAPZ's methodological catch-twenty-two. In summary, the IAPZ model may be less ecologically valid; it has abandoned discrete emotional items in favor of a broader focus on global affect; and does not examine the interactions between discrete items (i.e., how confidence, anxiety, and focus interact).

Deemphasized ecological validity. Because it is early in the development of the IAPZ model, much of the preliminary research has involved more controlled experimental designs (e.g., video racing games and archery). This methodology is not a problem at this point in the IAPZ's development. However, it is very important to remember that these idiosyncratic models originated from the applied realm, and should continue to remain ecologically valid. IAPZ must use experimental tasks that are generalizable to popular competitive sports that are emotionally intense—like hockey, football, and basketball.

Global dimensions versus discrete categories. Since its inception, and in every study since, researchers have assessed IAPZ within the framework of Russell's (1980) circumplex model of affect. In keeping with this perspective, researchers have consistently used the affect grid to measure feeling states. The affect grid (Russell, et al.,

1989) is a 9 X 9, 81-square graph. The two axes of the graph represent pleasure (from "displeasure" to "highly pleasurable") and arousal (from "sleepiness" to "highly aroused"). The grid can be deployed in a number of ways, such as by: having participants respond to two separate nine-point likert scales (Cohen, et al., 2006); having participants respond verbally while performing (Edmonds, et al., 2006); or in the traditional manner of checking the one square of the 81 that describes their feeling state. Some studies have included a third axis to assess the functionality of the person's state (from very unhelpful to very helpful).

Weaknesses of continuous dimensions. As mentioned previously, IAPZ research has favored Russell's circumflex model, which focuses on global measures of affect. IAPZ authors have presented this as an effort to achieve "parsimony and idiosyncratic generalizability" (Johnson et al., 2007, p.318) by shifting the focus from emotions to affect. However, this move towards parsimony neglects important information about the emotions. The distinction between discrete categorical and continuous descriptions of affect is a complex issue in psychology. This debate is ongoing and a review of the literature on this topic suggests that both approaches are relevant (Lazarus, 1991; 2000). It is not a question of determining which is right, but of understanding the strengths and weaknesses of each. Though its parsimony makes the affect grid convenient for field research, it does provide a comprehensive representation of emotion. Lazarus (1991) explained the difference succinctly:

> Conceiving of emotions as discrete *categories*, each of which can be placed on a dimension from weak to strong, is very different from thinking of them as

overlapping dimensions, in which many categories are reduced to a few and their distinct qualities lost or blurred. (p. 59-60)

Consider the following example of sadness and anger, two very different emotions. A person could perceive sadness and anger as being equally unpleasant, and thus give them the same valence score. Furthermore, each might be considered equally helpful (or harmful). As such, measuring only valence and functionality will not distinguish between unique emotions if those emotions are similar in terms of valence and functionality, but differ in every other parameter of affect.

Watson (2002) recommends that global dimensions of affect be assessed in combination with lower-level assessments of specific affect categories. Not only does this approach evade the conflict between the discrete and continuous positions in science, but it allows researchers to capture more information—which is the ultimate goal of scientific inquiry. Specifically, this dual-method approach accounts for both a simplified depiction of higher-order characteristics (e.g., valence and functionality), as well as the unique personal significance of discrete emotions (e.g., sadness, joy, confidence, anxiety, etc). While IAPZ research has focused almost exclusively on global measures of affect, the traditional (PNA-based) stepwise method is more flexible. Hanin's method assessing IZOF meets Watson's recommendations because discrete emotions are categorized by their valence and functionality (e.g., N-, N+, P+, and P- form categories). Despite citing Watson's work, IAPZ researchers neglect Watson's call for multilevel representation of affect in favor of only global descriptions.

Deemphasizing interactions between feeling states. Along with the disadvantages mentioned in the previous paragraph, there is a second disadvantage of depicting affect along continuous axes. When you chose a point on an axis, you are saying that in that given moment, the person had a single feeling state—that they can only experience one type of affect at a time. This constraint is substantial: IAPZ does not consider the interaction of multiple feeling states at a given moment (i.e., being confident yet anxious, or angry but focused).

Furthermore, and more frustratingly, IAPZ researchers have chosen not to have their predictors (e.g., pleasantness, arousal, and functionality) interact. Pleasantness (valence) scores could be combined with functionality ratings to identify affective content similar to that in the IZOF model. Currently, by separating these indices, researchers often find that more pleasant and more functional emotions are associated with optimal performance. The problem with his approach is that it does not differentiate between relevant combinations such as negative-functional and negative-dysfunctional feeling states. This is just one differentiation that has been neglected in IAPZ studies up to this point. In particular, Cohen et al. (2006), Edmonds et al. (2006), Golden et al. (2004), Johnson, Edmonds, Tenenbaum, et al. (2007) and Johnson, Edmonds, Moraes, et al., (2007) could have coded pleasantness ratings below the midpoint as "negative" and above the midpoint as "positive," repeated the procedure for functionality ratings, and then combined these to establish four groupings similar to Hanin's N-, N+, P+, and P-.

Misrepresenting IZOF research. Unfortunately, there have been instances where IAPZ authors have misrepresented the IZOF model in such as way a to favor IAPZ during comparison. These critiques of IAPZ do not represent problems with the IAPZ model itself, but are important considerations nonetheless.

The first example comes from Kamata et al. (2002), who only presented one method of estimating IZOF profiles. Not only are there numerous IZOF methods, but the method presented was the most outdated (e.g., recall of optimal states using questionnaires, +/- either ¼ or ½ of a standard deviation). Also, while IZOF research has over-utilized recall procedures, Kamata et al. present this as the only method used in IZOF studies.

Golden et al. (2004) seem to overstate the reliance of IZOF research on best-/worst-ever reflections. Again, while many studies have asked participants to reflect on previous best and worst performances, some IZOF studies established optimal zones by monitoring repeated competitions. Golden et al. also exaggerated the focus on pre-competitive states and failed to acknowledge IZOF studies that have assessed emotions during performance.

In addition to these flawed statements, Golden and colleagues made a rhetorical comment that cannot be ignored. The authors explained that "the purpose of [their] study was to replace Hanin's (2000) concept of affect-performance linkage by deploying a probabilistic method" (Golden, et al., 2004, p. 37). The notion that IAPZ is a sufficient model to replace IZOF is highly overstated. IAPZ is arguably insufficient to justify even being considered unique from IZOF. This concern is explained in the following section.

Conclusion: Is IAPZ a method or a model?

Considering the above review of IAPZ literature, and in spite of high regards for Tenenbaum's research on the topic, one must ask if the IAPZ is truly a unique affect-performance theory? Does the IAPZ separate itself sufficiently from the IZOF model? It is the position of this dissertation that the IAPZ is a method of assessing individual zones of optimal functioning. The IAPZ method lacks unique procedures for determining individual profiles, does not have a unique theoretical or conceptual foundation, and simply does not sufficiently distinguish itself from the work of Hanin.

Though there is greater emphasis on the use of multiple methods of assessing optimal zones, the IAPZ does not present a unique set of procedures for collecting performance data. IAPZ provides an excellent alternative method for analyzing this data once obtained, but little more. Also, with the exception of three brief paragraphs describing the Individual Psychological Crisis Theory (IPCT, See Tenenbaum et al., 2008), IAPZ does not have a unique theoretical foundation. Tenenbaum et al. (2008) introduced the IPCT only recently—describing it as "conceptually linked to the main assumptions of the IZOF" (p. S18). The IPCT also recognizes the probabilistic nature of phenomenon. However, very little else is offered about how this theory explains IAPZ's, and there is no comparison between IZOF and IAPZ models with respect to the predictive and explanatory ability of the IPC Theory.

IAPZ's use of logisitic regression to determine probabilistic estimates is an important contribution to IZOF research. In fact, Tenenbaum and colleagues' IAPZ is one of the most important contributions to the IZOF model. However IAPZ is only minimally unique from IZOF. The differences in methods supplement, but do not supplant the work of Hanin, Robazza, and others. Furthermore, the use of OLR to determine individual profiles is not something that all practitioners are capable of computing due to the statistical complexity and the amount of data necessary for this analysis. Consequently, even this most-beneficial aspect of IAPZ cannot replace the IZOF model completely.

Summary: Integrating the IZOF and IAPZ Frameworks

The literature review has thus far provided a foundation for the primary purpose of this study: to examine the effects of feeling states on tennis performance by integrating and contrasting the IZOF and IAPZ frameworks. Among the various types of feeling states, emotions are the most researched, most relevant to individual performance profiling, and have the strongest theoretical foundations. Accordingly, special emphasis was placed on the role of emotions and related theories. By their very nature, emotions are important performance variables because they influence goal-achievement, cognitive processing, and motor functioning. However, the focus of this dissertation is not limited from other important performance factors. Feelings of confidence, vitality, speed, and focus (etc.) are important to athletic performance, and generally function in a similar manner as emotions (recall Hanin's mobilization-utilization hypothesis).

The first and most fundamental hypothesis of this study is that the IAPZ's OLR method will identify idiosyncratic probabilistic estimates for each function-valence category of each athlete's individual profile. Testing this hypothesis requires a large number of observations that are relatively balanced across a range of performance-levels, along with a variety of emotional feelings and intensities.

Because the complete IEP-based IZOF profile can include 16-20 items—which is not sufficiently simple for applied practice—a small number of "critical" trigger emotions will be determined by each athlete, and compared to the predictive accuracy of the four function-hedonic categories. Thus, a second hypothesis will compare the accuracy of each trigger item and the four valence-function categories to determine how accurately each item/category predicts poor, average, or best performance based on feeling intensity.

For the final hypothesis, the dynamic context component of the five-dimensional psychobiosocial model will be examined by comparing service games to service return games. More specifically, means and variances of feeling intensity for three performance-levels and four feeling categories will be compared across the two contexts within each participant. While intraindividual differences are expected due to the different demands of serving and returning serve, the outcome of this hypothesis is not as important as the mere fact that it is being assessed. In order to understand the dynamics of feeling-performance relationships, all dimensions of the psychobiosocial model must be tested.

CHAPTER THREE

METHOD

This investigation was designed to assess the effects of feeling states on performance during competitive tennis matches for the purpose of contrasting and integrating the IZOF and IAPZ models of emotions and performance. Also, intraindividual differences in performance-zones were compared between serve and return of serve context. Finally, a complete profile with four feeling categories (based on functionality and valence) were compared to four simple idiosyncratic discrete feeling states identified by each player as being critical for his performance.

Ten male NCAA tennis players were recruited and provided informed consent to participate in the study without compensation. Participants created individualized profiles that describe the relationship between performance and the intensity of various feeling items they experience during poor and good performances. Based on these individual profiles, monitoring forms were created for each player. The form also assessed the outcome, context (service/return), set score, performance rating, perceived challenge and skill, and intensities of individual emotions. The challenge and skill ratings of the form were used to assess flow (Csikszentmihalyi & Larson, 1987; Csikszentmihalyi, Rathunde, & Whalen, 1993; Jackson & Csikszentmihalyi, 1999), and were not pertinent to the purposes of this dissertation. Participants completed the monitoring form during the changeovers of each intra-squad challenge match. Each participant played between 5-8 (M = 6.90) matches and completed 52-138 forms (M = 91.8). An average of 13.3 observations were recorded for each match. The IAPZ method was used to determine bandwidths of feeling intensities for individual zones of poor, average, and good performance. Upon establishing individual zone profiles, hypotheses were tested.

Participants

Ten male players from an NCAA Division I tennis team were recruited to participate in this study. The study and its purpose were described to the head coach of the team, and his approval was obtained before requesting consent from each player.

The players in this study represented an ideal sample because they were experienced, highly trained and relatively elite athletes. On average, participants were 20.1 years of age (SD = 1.66), had 13.7 years of tennis experience (SD = 2.58), and 2.5 years of college tennis experience (SD = 1.27). They also had previous experience working with a sport psychology consultant, although none of the participants had experience with the IZOF model prior to this study. Because of these characteristics of the sample, it was expected that participants would reflect a high level of emotional self-awareness and tennis experience. Both of these attributes are essential when assessing individual zones of functioning because the method and the theory are based on elite athletes (Hanin, 2000b) and individuals who are aware of their emotions. Hanin explains that experienced, competitive athletes offer more reliable recall and emotional awareness than do novice or inexperienced athletes (Raglin & Hanin, 2000).

Also, tennis represented an ideal sport for the purposes of this study. Players compete alone on court, so team dynamics and social factors do not have a strong influence within the psychobiosocial model—those dimensions are essentially controlled for by choice of sport. Tennis is a difficult sport where momentum shifts regularly, so there is generally a great deal of variability in terms of emotion and performance. There are two unique tasks, or contexts in tennis—serving and returning serve—that require different skills, strategies, and perhaps different optimal feeling states. These differences permitted comparisons of the context dimensions of the psychobiosocial model. Finally, the rules of tennis require intermissions in each set in order to change sides after every odd-numbered game. Intermissions during sets are approximately 90 seconds and breaks between sets are approximately three minutes in duration. These changeover breaks were used to self-assess performance without interfering with the normal conduct of play, as each observational form required only 25-40 seconds to complete.

Measures of Feeling

The foundation of the current methodology involved the development of individual profiles of optimal (IZOF) and dysfunctional (IZDy) performance zones. IZOFs and IZDys are identified through stepwise procedures known as Individualized Emotion Profiling (IEP; Hanin, 1997, 2000c, 2003). The current study slightly modified the stepwise procedures based on the applied experiences of the investigator, and integrated them with Hanin's narrative-interview method (Hanin, 2003). The stepwise procedures for the identifying and measuring individual profiles will be described in further detail in the procedure section.

Positive-negative affect list. The Positive and Negative Affect List (PNA-77; Hanin & Syrja, 1995, 1996) was established by Yuri Hanin as part of his stepwise procedure of assessing individual profiles. The PNA is a list of feeling items, which athletes chose from to describe their experiences. The PNA-77 is depicted in Figure 3 of the Appendix. With respect to hedonic tone, there are 40 positive and 37 negative items. Items on each line / row are synonyms, so participants were permitted to choose no more than one item from any row. In addition to the 77 items in the PNA, participants were urged to include their own adjectives or key word items.

Borg CR-10. Borg's Category Ratio scale (CR-10; Borg, 1998) has been used to describe the intensity of feeling states in the IZOF model since the model's revision in 1997. The CR-10 allows athletes to identify the intensity of feeling states, and thus, to establish zones of optimal functioning and of dysfunction. In spite of its title, the CR-10 is a 12-point scale that includes 0 ("nothing at all") and 11 ("maximal possible"—sometimes coded as '#' or '10*'). The scale begins at 0, 0.5, and 1, increasing by integers of 1, up to 10, and ends with the value 10* which is identified as 11 in the current study. The descriptive anchors for each level on the continuum are described in Figure 4 (See Appendix) as part of the monitoring form for participants during matches.

The traditional CR-10 scale was modified slightly by Hanin and his colleagues (Hanin & Syrja, 1995; Tummavuori & Hanin, 2000). The reliability of the CR-10 scale in IZOF research was established by Hanin and Syrja (1996). In a later study of 200 athletes providing 46,934 intensity ratings, the distribution of verbal anchors along the intensity continuum were confirmed to be appropriate (Tummavuori & Hanin, 2000).

Monitoring form. The primary source of data for this dissertation was the monitoring forms completed during competition (See Figure 4). The monitoring forms included three sections. The first section identified the context (service or return), outcome of the game (won / lost), and score in the set. Next, perceptions of performance, challenge, and skill were assessed across three separate 11-point likert scales (from 0-10). The descriptive words "poor," "average," and "good" were used to anchor the likert scale at 0, 5, and 10 respectively. The likert scale was partitioned into three groupings to represent each anchor (e.g., 0-3, 4-6, and 7-10). The third and most important set of information on the form was the intensity ratings for each content item. Discrete items were self-selected, and intensity was determined based on the Borg CR-10 scale—these content and intensity dimensions were described in the previous sections. Participants were urged to limit their monitoring form to only 10-14 items, with at least two items in each of the four content categories (e.g., helpful-positive, harmful-negative, etc.). Participants chose 12-13 items.

Procedure

Michigan State University's Internal Review Board (IRB) for ethical and legal research conduct approved the study protocol. The primary investigator met with the head coach of an NCAA Division I Men's Tennis program prior to recruiting participants. The NCAA tennis season begins with a semester-long preseason in the autumn. In the first week of the preseason, players attended an orientation meeting at which time informed consent was provided and IEP's were developed.

Adaptations to Hanin's procedures. The traditional stepwise procedures for identifying IZOF profiles were modified slightly based on the applied experiences of the primary investigator, who had used Hanin's method for hundreds of athletes prior to conducting this study. Three changes were made, which increased the number of performances recalled, reduced the number of items in each profile, and refined each profile based on face-to-face interviews. Rather than reflecting on a single best- and worst-ever performance, participants were asked to identify two or three such 'poor' and 'good' experiences. Also, rather than identifying as many as 20 unique content items, participants were only permitted to include 10-14 relevant items. After completing the stepwise procedures, individual profiles were further reduced to 12 items—including at least two, but no more than four items in each of the four categories described in Chapter 2 (e.g., positive-helpful, negative-helpful, etc.). One participant preferred to have a 13-item profile. Although the full stepwise process utilizes 16-20 items in each athlete's profile, Hanin recommends that field research reduce profiles to only 12 items (Hanin, 2000d). Also, more recent studies have used the PNA-10, a list of the 10 most prominent items based on previous research (Hagtvet & Hanin, 2007; Hanin & Syrja, 1995; Lukkarila & Hanin, 2001). As such, it is acceptable to simplify athletes' profiles.

Stepwise procedure. Given the aforementioned modifications to the traditional stepwise procedures, the following process was employed in order to develop individual profiles. Participants began by identifying and describing their best and worst performances in the previous 2 years (more recent performances were preferable). Next, based on these performances, participants used the PNA to identify helpful positive and negative emotions (based on previous best performances), and harmful positive and negative emotions (based on previous worst performances). Thirdly, the Borg CR-10 scale was used to estimate the intensities of each discrete content item (the positive and negative feeling states from the PNA) during each best and worst performance. It is important to note that, given the purpose of the current study, participants were asked to recall intensities *during* competition—rather than pre-competition and post-competition states. Fourthly, the intensities of each content item were combined across best-ever performances to create a bandwidth, or zone, of optimal functioning (IZOF). Intensities were also combined across worst-ever performances to create a zone of dysfunction (IZDy). IZOF and IZDy profiles were depicted on the same graph and compared (See

Figure 1). The graphic representation, or "visualization," of the profiles was the final procedure before individual meetings were conducted to refine the profile.

Interviews. A final revision of the stepwise procedures involved individual interviews. During these interviews, players were allowed to refine intensity estimates and eliminate erroneous items. This is important because by the end of the procedure, many athletes felt that some of the initial items were not predictive of, or important for performance, or that the original zone estimates (based on previous performances) should be raised or lowered by a point or two. Participants also identified four critical "trigger" items from among the 12-13 in their final profile during their interviews.

Data collection: monitoring forms. Having established and refined each IZOF profile, identified trigger items, and explained the in-vivo data collection procedures; the next stage of the procedure involved monitoring feelings and performance during competitive intra-squad matches. Every player on the team played a round-robin of matches against his teammates. These challenge matches were important because they partly determined rankings within the team (only the top six players play singles matches in the NCAA). Because of the importance of these matches, and the relative parody within the team, these challenge matches were highly competitive.

In a post-study survey of players, the average rating of how important the challenge matches were was 7.05 (on a scale from 1-10; SD = 1.32), and the average rating of how competitive the matches were was 6.40 (SD = 2.31). Six of the 10 ratings of competitiveness were between 7-8. There were two 'outliers' of sorts who rated competition as a 2-3: neither player performed as well as he had hoped. One participant rated the importance of the matches lower than the rest of the team (i.e., a 4 out of 10).

The challenge matches were played as typical NCAA matches, which included changeovers with a 90 second break after every odd service-game of each set (note that there is no break after the first game, only a changing of ends). Though a 90-second break is not permitted during the first changeover (after the first game of each set), participants completed forms during the first changeover in order to collect more data. Also, without this procedure, the first game of each set would likely have been forgotten by the end of the third game and therefore either lost to the dataset records or recalled less accurately.

In tennis, players alternate service games. Serving to start each point of a game is an advantage in tennis. When a player is not serving, he/she is said to be "returning serve." As such, with the exception of the first changeover of each set, there is one service game and one return game played between each changeover. Participants were asked to monitor one of the two previous games during each changeover. Specifically, participants were asked to complete the monitoring form for the game that they felt had the extreme (very positive or very negative) performance. If both games had comparable performances, then participants were urged to choose the context (service or return) that they had least often monitored. If both games had extremely good or poor performances, players were urged to complete a form for both, so long as two forms could be completed without excessively distracting the player or delaying the conduct match. Occasionally, players felt that the previous service and return games were identical in their feelings and performance. This was more common for tiebreakers (where the two players alternate serves every two points). In these cases, players circled both serve and return on their forms—data were entered accordingly.

In both pilot testing and in the actual data collection, forms were completed in 25-40 seconds, and were considered to be minimally distracting. In a post-study survey of players, the average rating of how distracting the forms were from their performance was 4.05 (on a scale from 1-10; SD = 2.813). Two players found completing the form to be quite distracting, rating it as a 7.5 and a 9. The participant who provided the latter rating withdrew from the study after five matches. Though moderately-to-very distracting for some players, all participants felt that they completed the forms very accurately (M = 8.2; SD = 1.42). In fact, the attention to detail and desire to be accurate was the primary cause of the negative, distracting effects identified by the aforementioned two players. Both of these participants described very high accuracy, and showed throughout the data collection process that they were reporting their feelings and performance ratings as accurately as possible. These participants may have essentially been trying too hard. All players were told to complete the forms quickly, so as not to over-think or distract from performance. The primary investigator attended all challenge matches to ensure that forms were available and that participants' concerns could be addressed.

Ethical Considerations

The principal investigator had a dual-relationship with the team as both researcher and mental training consultant. Right to refuse was especially important because the investigator was in his third year as the team's mental trainer and while positive rapport and trust had been developed over the years, it was important that players not feel forced to participate. It is clearly unethical to force or coerce people to participate in a research study. Furthermore, coercing participation is likely to result in untrustworthy data. The investigator was considerate of the effects that the monitoring procedure had on the participants' performance—particularly because of the importance that the matches could have on each player's ranking. As such, all players on the tennis team were given the opportunity to exclude themselves from the study at any time. Also, in order to ensure that players were not coerced into participating, an independent party met with the participants without the researcher or coaches being present. The independent party reminded participants that players could withdraw at any time. Due to frustration over his performances and several injuries, one player withdrew after his fifth match (one match before the final round of play).

Measures were also taken to make the collection of data less intrusive. Each player was given his own binder and pen with copies of the monitoring form. Binders were set on each player's bench / chair to make it easier to write. The investigator reviewed forms during each match to make sure that players had not made mistakes (e.g., incomplete data, etc.). Most importantly, when participants chose not to complete a form after very frustrating points, the investigator did not force players to comply. This occurred very rarely, and when it did so, it was most often at the end of a match after a loss.

CHAPTER FOUR

RESULTS

Treatment of Raw Data: The Basics

Performance levels. Participants rated their performance on an 11-point scale from 0-10. By convention and for the sake of simplicity, these ratings were converted to ordinal data by defining ratings between 0-3 as 'poor' performances, 4-6 as 'average' performances, and 7-10 as 'good' performances. For two participants, the ordinal parameters were modified due to extreme distributions of 'good' performances. Specifically, Player 1 originally had only nine good performances (out of his 97 observations). Contrarily, Player 3 rated 70 out of 101 observations as good performances. Player 3 also had an extremely low number of poor performances (e.g., only five). After consulting with each player, both agreed that their standard were excessively high or low. Player 1's standard for good performances was adjusted to 6-10; and Player 3's parameters were set at 0-4, 5-7, and 8-10. The revised distributions of poor, average, and good performance for each participant are described in Table 2.

Aggregated feeling categories. Each of the 12-13 discrete feelings identified by participants was grouped into one of four possible categories based on the functionality and valence of the item. These categories were determined through the Individual Emotion Profiling process that included the PNA-77 list of feelings (described in the previous chapter). Rather than conducting analyses for each discrete item for each player, analyses were conducted for the aggregated value of items in each category. Aggregating items within categories helped to create parsimony in the models: as developing individual curves for all 121 discrete items selected by the 10 players would not be productive. For example, Player 2's ratings for energetic, confident, and determined, and Player 5's selection of relaxed, quiet, alert, and overjoyed were aggregated into the positive-functional category. This not only simplified each player's profile, but it also made it possible to compare individuals because while few players selected the same discrete items, every player had the same aggregated function-valence categories.

Analyses were also performed for the four discrete items identified by each player as being most important for his performance (i.e., trigger items). As such, the raw values entered by players were not directly considered in the results. Ultimately, feeling intensities were represented by eight categories: positive-functional, negative-functional, negative-dysfunctional, positive-dysfunctional, and Triggers 1-4.

Table 2

Distribution [and Percentage Proportion] of Performances for Each Participant

	Performance Levels				
Participant	Poor	Average	Good	Missing	Observations
1	32 [33.0]	31 [32.0]	34 [35.1]	0	97
2	37 [36.6]	44 [43.6]	20 [19.8]	0	101
3	8 [7.9]	38 [37.6]	55 [54.5]	0	101
4	11 [14.7]	42 [56.0]	22 [29.3]	0	75
5	13 [13.4]	67 [69.1]	17 [17.5]	1	98
6	22 [42.3]	14 [26.9]	16 [30.8]	0	52
7	60 [58.8]	26 [25.5]	16 [15.7]	0	102
8	16 [20.0]	53 [66.3]	11 [13.8]	3	83
9	20 [29.0]	44 [63.8]	5 [7.2]	2	71
10	21 [15.2]	83 [60.1]	34 [24.6]	0	138
Totals	240 [26.3]	442 [48.5]	230 [25.2]	6	918

Descriptive Data

The total number of valid observations collected for this study was 918. Fewer than 10 observation forms were deemed unreliable. Such forms were excluded due to excessive incomplete data, or because the intensity ratings for every item were identified with a single circle (out of frustration). If a player circled both 'serve' and 'return' on the same form, the observation was entered into the dataset twice. This occurred very rarely: most often for tiebreakers. There were very few tiebreakers, and even fewer were double-coded. The total number of observations for each participant ranged from 52 to 138.

Player 6 had only 52 observations because he missed three matches due to an injury and then asked to be removed from the study before the final round of matches due to frustration from under-performing. Completing the forms did not cause his frustration, but did exasperate it. All players completed nearly every possible form. The range in observations per player was simply due to the number of games and sets played in each match. Participants sometimes failed to complete the last form of the match after a loss. Given the extraordinary compliance and quality of data provided by participants—as well as the disappointment associated with many losses—the investigator did not follow up on these missing forms. Descriptive data for performance levels and intensity ratings of feelings are described in the subsections below.

Distribution of performance. As described in Table 2, there was a relatively normal distribution of performance ratings across participants. In terms of the statistics, the ratio of skewness to standard error was 0.198 (0.016 / 0.081), and kurtosis ratio was -6.531 (-1.058 / 0.162) well above the conventional threshold of 2.0 (Raykov & Marcoulides, 2008). While significant negative kurtosis was observed for the ordinal performance variable, this was reflective of the parameters established before the study. That is to say that, in order to conduct reliable logistic regressions, a larger number of extreme performances (i.e., non-average ones) were necessary. As such, more poor and good performances were desirable, and thus a flat kurtosis distribution. This violation of normality does not implicate the subsequent analysis as nonparametric statistics do not require normality (Mueller & Hancock, 2008; Pallant, 2009), and ANOVAs are robust enough to overcome negative kurtosis (Vincent, 1999). Also, many of the ANOVAs that were conducted accounted for each performance level separately.

In total, 240 (26.3%) of the 918 performances were poor, 442 (48.5%) average, and 230 (25.2%) were good (See Table 2). This distribution varied slightly among players, including the following noteworthy exceptions: Player 3 had very few poor performances (7.9%); Player 6 had more poor (42.3%) and fewer average (26.9%) performances; and Player 9 had relatively few good performances (7.2%).

The frequency of raw performance scores across all participants is of less consequence to the study's purpose and hypotheses, but worthy of a brief description. Each performance rating from 0-10 had the following percentage distribution: 0 (9.5%), 1 (3.8%), 2 (4.8%), 3 (7.8%), 4 (10.0%), 5 (21.3%), 6 (18.9%), 7 (11.5%), 8 (7.7%), 9 (3.7%), and 10 (0.9%). The very low occurrence of extremely high performance levels may have some consequence on the results and will be discussed in the next chapter.

Intensity of feelings. Feeling intensities are described separately for each of the four feeling categories in Tables 3-6, which are organized into the three performance levels for each participant. Figures 6-9 (See Appendix) depict the distribution of intensity scores aggregated across participants for each feeling category. These raw descriptive tables and figures are not critical to the objectives of the study, but do provide interesting background information for the interindividual comparisons.

Of particular interest are the variability of means and standard deviations within each column (i.e., within performance levels between participants). For the most part, means appear to be different across performance levels for each player, but formal ANOVAs were not conducted to examine this as it is neither relevant to the study's purposes, nor is it required by convention.

Table 3

Individual Means and Standard Deviations for Positive-Functional Feeling Intensities across Performance Levels

	Poor		Average		Good	
Players	Mean	SD	Mean	SD	Mean	SD
1	4.83	1.34	5.62	1.08	6.86	0.67
2	0.82	1.09	4.39	1.75	6.13	2.22
3	4.84	1.97	6.50	1.71	8.70	1.27
4	5.36	1.06	6.10	1.55	6.71	1.76
5	3.10	1.28	5.80	1.64	6.67	1.30
6	1.66	1.51	4.43	0.79	5.22	0.27
7	1.39	1.78	5.55	1.32	8.59	0.78
8	3.61	1.89	5.74	1.53	7.65	1.49
9	6.30	0.65	7.14	0.80	8.27	0.28
10	3.63	2.29	6.31	1.07	8.03	0.87

Table 4

Individual Means and Standard Deviations for Negative-Functional Feeling Intensities across Performance Levels

	Poor		Average		Good	
Players	Mean	SD	Mean	SD	Mean	SD
1	2.27	2.66	2.32	2.50	1.19	0.95
2	0.56	0.94	3.83	2.30	5.20	2.95
3	6.56	0.94	6.71	1.79	7.17	1.27
4	5.97	0.86	6.23	0.96	6.23	0.85
5	5.28	2.18	3.51	1.33	3.51	0.58
6	6.16	1.25	4.55	1.38	3.89	0.79
7	1.48	1.88	5.67	1.36	8.44	1.03
8	6.52	3.09	2.65	2.50	2.39	3.94
9	5.18	0.82	5.75	0.91	8.27	0.41
10	3.16	1.82	5.92	1.09	7.39	0.62

Table 5

Individual Means and Standard Deviations for Negative-Dysfunctional Feeling Intensities across Performance Levels

	Poor		Average		Good	
Players	Mean	SD	Mean	SD	Mean	SD
1	2.14	1.80	3.10	1.73	2.26	1.31
2	4.94	2.34	2.94	1.87	1.89	1.85
3	5.11	2.60	2.65	2.10	0.91	0.96
4	3.30	0.35	2.61	0.58	2.24	0.52
5	6.38	1.98	4.05	1.18	3.49	1.04
6	7.20	1.18	4.81	1.18	5.20	1.35
7	1.09	1.39	0.71	0.69	0.51	0.19
8	2.86	1.98	0.96	1.03	0.38	0.64
9	4.49	2.24	2.81	1.38	3.20	1.02
10	5.98	2.51	2.63	1.23	2.95	0.59

Table 6

Individual Means and Standard Deviations for Positive-Dysfunctional Feeling Intensities across Performance Levels

	Poor		Average		Good	
Players	Mean	SD	Mean	SD	Mean	SD
1	4.34	1.11	4.90	1.13	3.97	1.73
2	6.09	1.49	4.27	1.58	3.48	1.44
3	4.88	2.60	3.71	1.96	3.70	1.72
4	2.36	1.01	2.35	1.04	2.70	0.91
5	1.54	1.18	4.63	1.69	6.47	1.30
6	5.55	1.32	5.77	0.89	5.60	0.63
7	0.01	0.07	0.10	0.32	0.00	0.00
8	1.02	1.92	2.75	2.50	3.61	2.89
9	0.58	0.63	0.69	0.72	1.00	1.00
10	5.33	2.55	2.49	1.41	1.85	1.07

Treatment of Raw Data: Ordinal Logistic Regressions

Ordinal logistic regressions. As the foundation for the IAPZ method and this dissertation, ordinal logistic regressions (OLR) were conducted on the four feeling categories and four trigger items. Parameter estimates from the regressions were used to establish performance curves (probabilistic estimates of performance across feeling intensity), which were then used to identify poor, average, and good performance zones. These performance zones were used to predict performance based on feeling intensities for each category or trigger.

Mean splitting performance levels. Initially, OLR was conducted using three dependent measures of performance described earlier. However, because none of the IAPZ graphs identified a typical catastrophe-type result (e.g., performance decrements occur at the highest levels of intensity) the OLR and curves were conducted again with five outcome variables. As described more thoroughly in the method, poor and average performances were each split into two subgroups: based on feeling intensities above and below the mean intensity for good performances. The resulting five performance levels acted as dependent measures in the OLR and included the following performances variables: poor-low, poor-high, average-low, average-high, and good.

Conducting ordinal logistic regression. For each participant, eight separate OLRs were conducted for the four feeling categories and four trigger items. Within each regression, as many as five dependant variables were included to establish an independent set of parameter estimates. Five parameter estimates were identified from each regression, including intercepts for performance outcomes one through four (the fifth dependent measure acted as a control), and the slope for the overall output. The probability of each performance (θ_i) is depicted mathematically below with α representing the intercepts, β_x the slope, and IV represented feeling intensity from 0.00 to 11.00 increasing by 0.01 for precision:

$\theta_1 = 1 / [1 + \exp(\alpha_1 + \beta_x * \text{IV})]$

$\theta_2 = 1 / [1 + \exp(\alpha_2 + \beta_x * \text{IV})] - \theta_1$

$\theta_3 = 1 / [1 + \exp(\alpha_3 + \beta_x * \text{IV})] - \theta_1 - \theta_2$

$\theta_4 = 1 / [1 + \exp(\alpha_4 + \beta_x * \text{IV})] - \theta_1 - \theta_2 - \theta_3$

$\theta_5 = 1 - \theta_1 - \theta_2 - \theta_3 - \theta_4$

Note that the probability of the fifth outcome (good performance) is established as the remaining probability (e.g., 1.0 minus the sum of average- and poor-performance thetas).

Establishing individual profile curves. A screenshot of one of the 80 spreadsheets is provided in Figure 10. In the top row, θ_1 to θ_5 are represented correspondingly by p(x=1) to p(x=5). Parameter estimates α_1 to α_4 were inserted in the second row with the final cell in the row representing the slope (β_x). The first column of the figure included feeling intensities (the independent variable). To interpret the spreadsheet: at the intensity-level of 0.0, the probability of poor-low performance was 0.4%, poor-high was 5.7%, average-low was 11.0%, average high was 39.0%, and good performance was most likely at 43.9%. As such, 0.0 is clearly part of the good performance zone. However, the zone of good-functioning is short-lived for this individual, as average-high performance is more likely than good performance above the intensity level of 0.43 (circled in Figure 10). The values inside of the box inserted at the bottom of the figure show that good performance moves from being more-to-less probable than average-high performance from 0.43 to 0.44. Each spreadsheet was represented with visual graphs (See Figures 11-18 in text for examples of probabilistic curves).

Performance prediction parameters. In total, 80 curves were generated with three to five performance outcomes on each graph. Figures B6-B13 display examples of unique IAPZ curves. Each curve was visually inspected to identify a rough approximation of each performance zone, or bandwidth. From these approximations, the original spreadsheets were consulted to identify the precise parameters of each zone (See Figure 10). This process was repeated for each performance zone of the 80 probabilistic curves, then manually programmed into SPSS to establish performance predictions for each category and trigger item. The performance prediction variable is described in the forthcoming accuracy section of the results.

Figure 10

Example of an Excel Spreadsheet used to Generate OLR Performance Curves

IV	p(x=1)	p(x=2)	p(x=3)	p(x=4)	p(x=5)
	-5.4629	-2.727712942	-1.57666	0.246188383	-0.32945
0	0.00422	0.057134616	0.109911	0.389969724	0.438762
0.01	0.00424	0.057310751	0.110189	0.390312713	0.437951
0.02	0.00425	0.05748739	0.110467	0.390654356	0.43714
0.03	0.00426	0.057664536	0.110746	0.39099465	0.43633
0.04	0.00428	0.057842187	0.111026	0.391333588	0.43552
0.05	0.00429	0.058020347	0.111306	0.391671166	0.43471
0.06	0.00431	0.058199016	0.111586	0.39200738	0.4339
0.07	0.00432	0.058378195	0.111867	0.392342224	0.433091
0.08	0.00434	0.058557886	0.112148	0.392675694	0.432283
0.09	0.00435	0.05873809	0.11243	0.393007784	0.431474
0.1	0.00436	0.058918807	0.112712	0.39333849	0.430666
0.35	0.00474	0.063607363	0.119915	0.401142507	0.410598
0.36	0.00475	0.063801874	0.120209	0.401435585	0.409801
0.37	0.00477	0.063996932	0.120504	0.401727155	0.409004
0.38	0.00478	0.064192538	0.120798	0.402017212	0.408208
0.39	0.0048	0.064388694	0.121094	0.402305753	0.407413
0.4	0.00482	0.064585401	0.121389	0.402592772	0.406617
0.41	0.00483	0.06478266	0.121685	0.402878266	0.405823
0.42	0.00485	0.064980473	0.121982	0.403162231	0.405029
0.43	0.00486	0.06517884	0.122279	0.403444662	0.404235
0.44	0.00488	0.065377763	0.122576	0.403725554	0.403442
0.45	0.00489	0.065577243	0.122874	0.404004905	0.402649

Note. This image is a screen shot of an actual data set (Player 10's Positive-Dysfunctional curve). The image was modified to include the circle and box located at the bottom of the figure, indicating a change in zone. Also, the plane of the spread sheet was frozen after the independent value 0.1 to save space. The 'IV' column represents feeling intensity from 0.0 to 11.0, increasing by one-hundredth of a point. Columns 'p(x=1)' to 'p(x=5)' represent the parameter estimates (in row 2) and probabilities (in all subsequent rows) for poor-low, poor-high, average-low, average-high, and good performances respectively.

Interindividual Differences

Four methods were deployed to assess interindividual differences in feeling-performance profiles. These methods included: qualitative comparisons of the feeling items chosen by players; visual inspection of individual graphs; and statistical comparisons of the means and variances of each zone.

One of the core hypotheses of this dissertation is that there are individual differences in performance-feeling profiles. By nature of these profiles, there are two ways in which profiles can vary—in either location or in width—and thus two possible tests of individual differences. First, zones can vary in terms of their location on the continuum. For instance, Kurt's optimal zone for positive-functional feelings may be higher than Krist's. The second method compares the width, or size, of each zone. For example, Kurt's optimal zone might range from 8-10, while Krist's ranges from 5-9—thus differing in both size and location.

Differences in the location of each zone can be represented by assessing differences in central tendency (e.g., ANOVA's and post-hoc t-tests). There is no conventional method to assess whether or not the bandwidth of one player's zone is different from another's. Without an established statistical procedure to follow, the variances of intensity ratings were assessed simultaneously for all participants. Twelve such separate tests were conducted for each feeling category and performance level. Variances for each player were compared by dividing the one player's variance score by the other's, and referring to the standardized F-Tables using the number of observations for each player (i.e., n-1) to determine the critical value ("Comparing Variances," 2001).

Before presenting these statistical methods, there are two qualitative means of assessment of examining individual differences. Firstly, the variety of discrete items selected by each participant to represent each feeling category can be examined. Secondly, visual comparisons of probabilistic performance profiles can be made.

Qualitative differences in individual profile items. The most idiosyncratic element of feeling-performance profiles may be the choice of discrete feelings. Recall that while participants shared four common feeling categories (e.g., positive-functional, etc), the exact items within each category were self-selected and unique across participants. The question is: how often did participants choose the same discrete feeling states. It would be unreasonable to consider one player's choice of 'angry' as being different from another's choice of 'furious' to be substantively different. As such, before conducting this comparison, synonymous items were grouped and compared to unique groupings. The grouping of items adhered to the presentation of the PNA-77 (Hanin, 1993a; Syrja & Hanin, 1997) in the Individual Emotion Profiling system (EIP; Hanin, 1997, 2000a). Both positive and negative items are presented in Table 7.

For each set of positive and negative feeling items, there are 14 rows from which to choose. A majority of players (five or more) supported six rows from the positive list and eight rows from the negative list. While some rows received very strong support and could be generalized as being important for most players, the distribution of player support shown in Table 7 supports the notion of idiosyncratic differences in players' choices of critical performance-related feelings. The rows that received strong support (i.e., seven or eight players) included being satisfied, confident, aggressive, and irritated. Surprisingly, rows with items like relaxed, fast, energetic, determined, nervous, intense,

Table 7

Player Support for each Row of (Synonymous) Positive and Negative Content Item Descriptors

Positive Items	Support	Negative Items	Support
glad, pleased, satisfied, contented	8	angry, aggressive, furious, violent	7
confident, certain, sure	7	annoyed, irritated, distressed	7
relaxed, comfortable, easy	6	afraid, fearful, scared, panicky	6
determined, set, settled, resolute	6	discouraged, dispirited, depressed	6
quick, rapid, fast, alert	6	doubtful, uncertain, indecisive, irresolute	6
lighthearted, carefree	5	intense, fierce	6
active, dynamic, energetic, vigorous	4	jittery, nervous, uneasy, restless	5
calm, peaceful, unhurried, quiet	4	tense, strained, tight, rigid	5
delighted, overjoyed, exhilarated	3	anxious, apprehensive, worried	4
excited, thrilled	3	helpless, unsafe, insecure	3
nice, pleasant, agreeable	2	inactive, sluggish, lazy	3
brave, bold, daring, dashing	2	tired, weary, exhausted, worn out	3
inspired, motivated, stimulated	2	concerned, alarmed, disturbed, dissatisfied	1
cheerful, merry, happy	1	sorry, unhappy, regretful, sad, cheerless	1

Note. Maximum player support value was 10. Rows of synonymous items were arranged based on Hanin's PNA (2000) and discouraged were not the most strongly supported themes. Finally, all 28 rows of positive and negative items were chosen by at least one player.

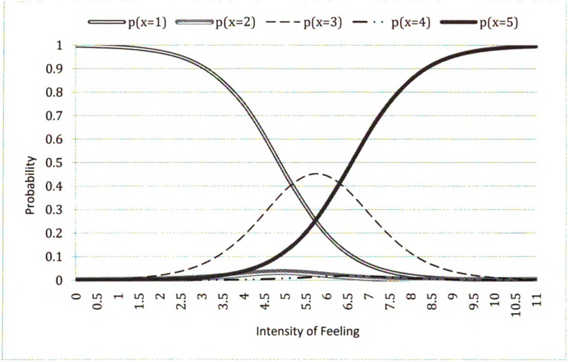
Visual comparisons across performance and category. In keeping with how Tenenbaum and colleagues have typically displayed IAPZ results, each player's unique probabilistic curves (Figures 11-18 later in text) were combined to produce simplified performance zone profiles (Figures 19-22 later in text). The disadvantage of the simplified figures is that they do not describe the probability of each performance level across intensity. Rather, the most probable performance level at each level of intensity is given absolute recognition. For example, rather than showing a 10% chance of poor performance, a 40% chance of average performance, and a 50% likelihood of good performance at a certain level of intensity, that point would be described as being a part of the player's good-performance zone. The advantage of these figures is that they allow researchers to see a parsimonious comparison of all 10 players on a single figure.

Probabilistic IAPZ curves. The importance of these figures is to first show that the study was successful in combining IZOF and IAPZ methodologies to create probabilistic feeling-performance profiles. The second objective of these figures is to represent the idiographic nature of these differences.

Figures 11-13 are included to show how individual profiles can vary in terms of the location and/or the width of each zone. Figure 11 shows a typical probabilistic profile with a relatively high (in terms of location of the x-axis) and small (in terms of bandwidth) average zone. As was often the case in this dissertation, two of the five performance curves had very low probabilities (e.g., the curves associated with poor-high and average-high performance-intensities). Note that the legend describes each curve in

Figure 11

Positive-Functional IAPZ Curves for Player 1

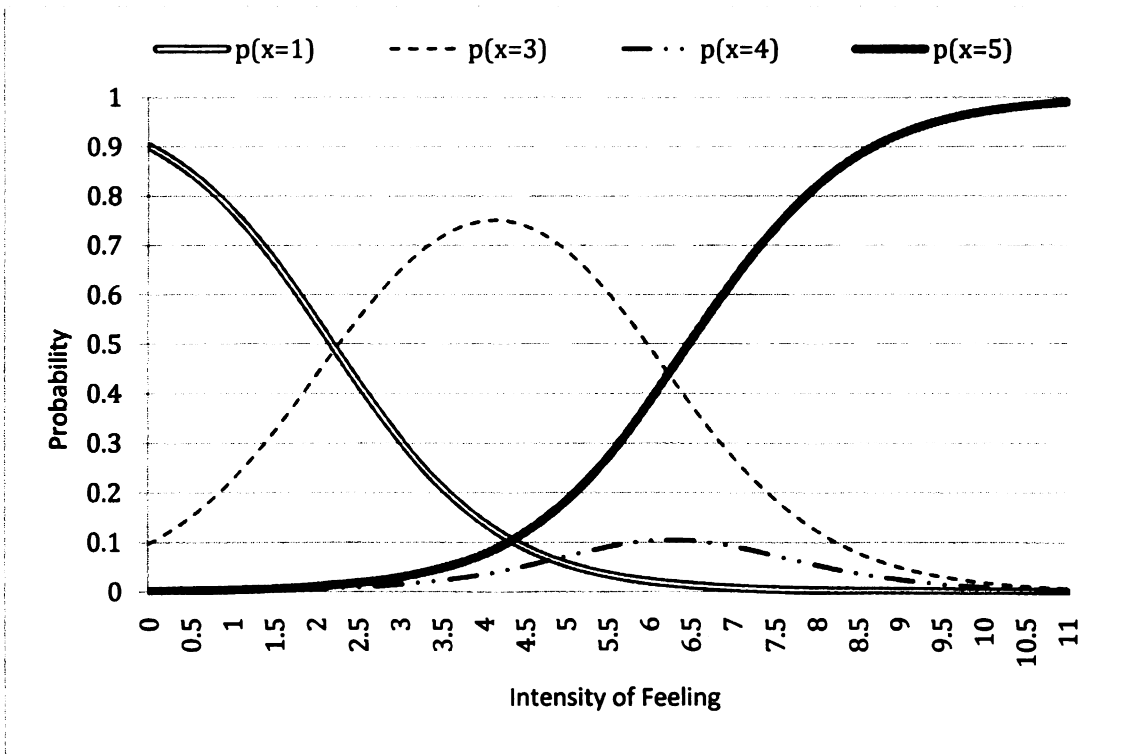


Note. Curves labeled p(x=1) and p(x=2) represent the probabilities of poor performances with low and high intensity ratings (respectively). The curves p(x=3) and p(x=4) represent average performances in the same way; and p(x=5) is the good-performance curve. The purpose of this curve is to illustrate a typical IAPZ profile. Note that only three of the five performance curves are prominent.

statistical notation: with p(x=1) representing poor-low performance, through p(x=5) representing the probability of good performance. Figure 12 has a much wider and lower average performance zone. From an applied perspective, this is generally a preferable profile because the range for poor performance is smaller, the good-zone is larger, and there is a nice buffer between the two where performances are average—which mean that the athlete does not drastically slip from good to poor performance. Figure 13 is actually quite similar to Figure 12. The means for average performance in both figures are approximately 4.25. If the only method of assessing individual differences were to compare mean values, the zones would likely be deemed equal. This would clearly be a wrong assessment. As such, assessing the mean location and width of each zone are necessary.

Figure 12

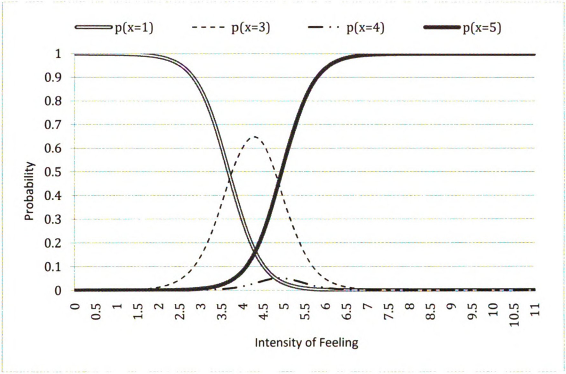
Positive-Functional IAPZ Curves for Player 2



Note. The curve labeled p(x=1) represent the probabilities of poor performance. The curves p(x=3) and p(x=4) represent average performances with low and high intensity ratings (respectively); and p(x=5) is the good-performance curve. The purpose of this curve is to illustrate how 'normal' profiles can vary from one another. Note that the location and breadth of each zone varies from the previous profile.

Figure 13

Positive-Functional IAPZ Curves for Player 6

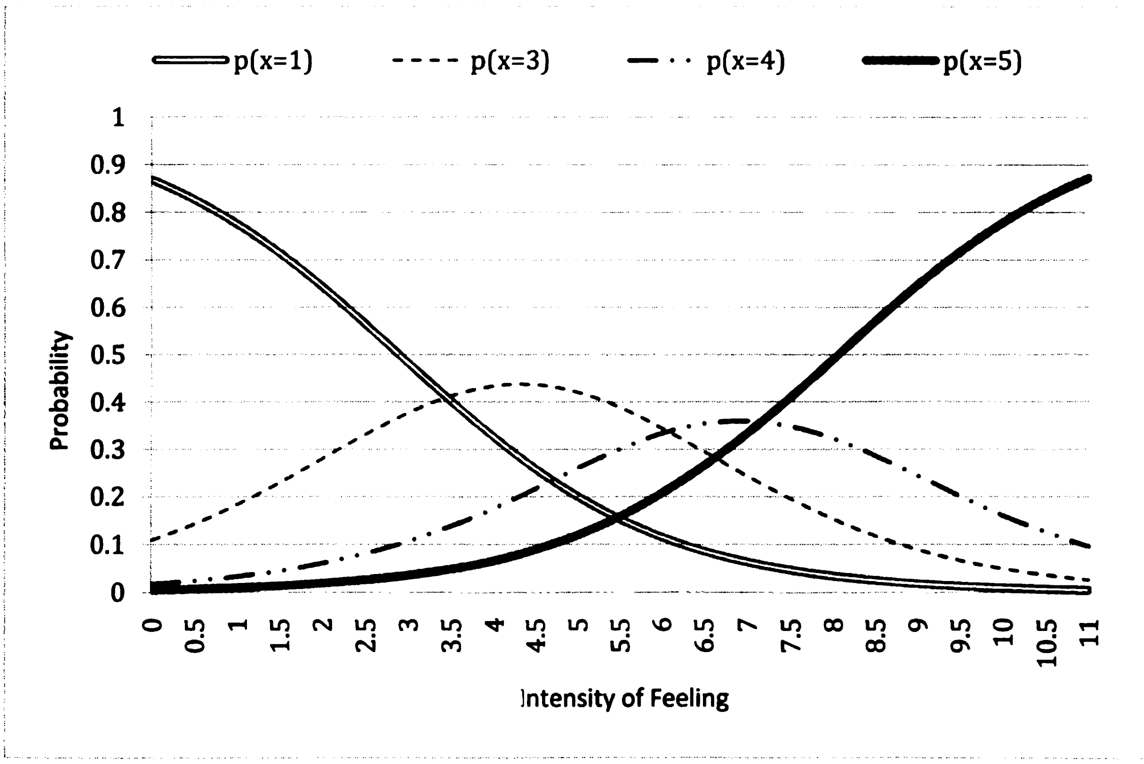


Note. The curve labeled p(x=1) represent the probabilities of poor performance. The curves p(x=3) and p(x=4) represent average performances with low and high intensity ratings (respectively); and p(x=5) is the good-performance curve. The purpose of this curve is to illustrate that idiographic differences can occur with the location (central tendency) or bandwidth (variance) of zones. As with the previous profile (Figure 13), the mean of the moderate zone at approximately 4.25, however, the width of this zone is clearly much narrower.

Figure 14 is interesting because it shows four prominent performance curves rather than three. In this case, there are two influential average-performance curves. It is uncommon to the established literature in this field that the probability of good performance increases through the intensity continuum—yet this result was common for this study. Figure 14 presents the issue clearly. Rather than the average-high performance curve being to the right of the good performance curve, it is only barely to the right of the average-low performance curve. There were not significant distributions of sub-optimal performances at high intensity levels of functional profiles.

Figure 14

Positive-Functional IAPZ Curves for Player 4

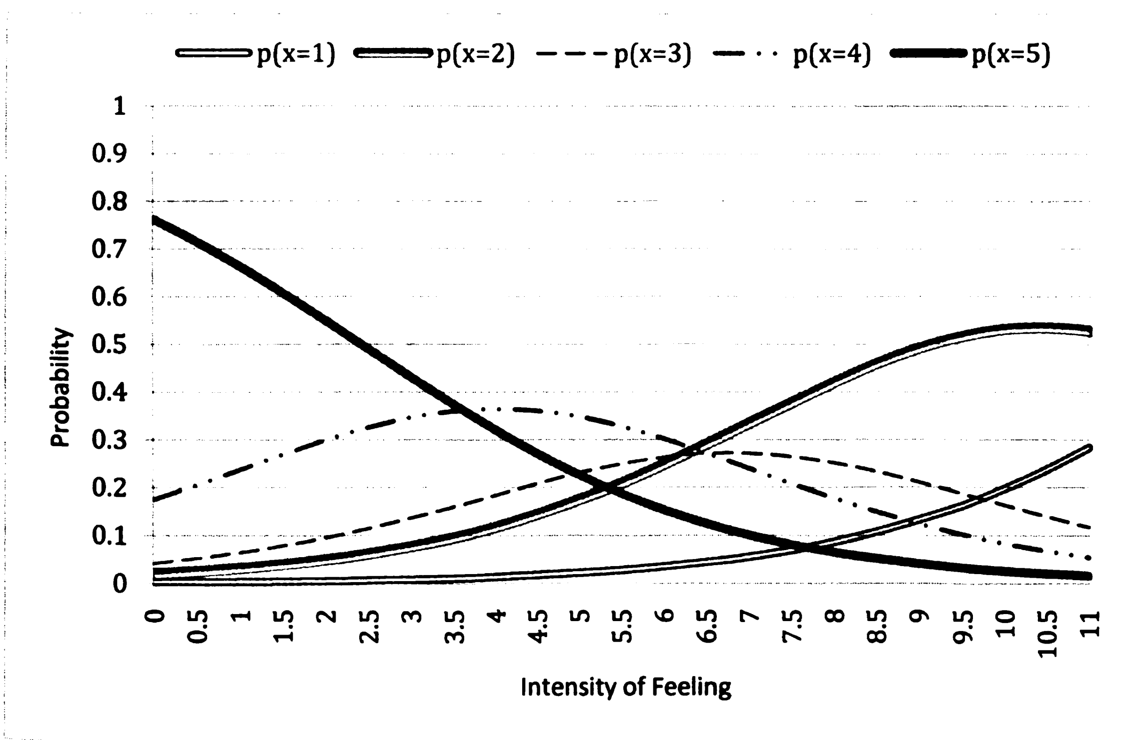


Note. The curve labeled p(x=1) represent the probabilities of poor performance. The curves p(x=3) and p(x=4) represent average performances with low and high intensity ratings (respectively); and p(x=5) is the good-performance curve. The purpose of this curve is to illustrate a large bandwidth for average performance, with both high- and low-intensity average performance curves featuring prominently. It is also an example of how the high- and low-intensity average-curves are generally in close proximity.

Figures 15 and 16 provide examples of typical dysfunctional profiles. The probability of poor performance increases as feeling intensity increases. Though each of these Figures has only three prominent performance curves, the influence of the other two performance curves is greater than in Figure 11. It is interesting to note, for instance, that the probability of poor performance appears to decrease beyond the intensity of 10.0 in Figure 15. However, the true probability of poor performance is actually the combination of poor-low (p(x=1)) and poor-high (p(x=2)) curves. Consequently, the probability of poor performance at the intensity-level of 11.0 is approximately 81% (0.52 + 0.29). For applied interests, it should be noted that the bandwidth for poor performance in Figure 16 is very large (approximately 3-11). Keeping negative-dysfunctional emotions very low would be critical for this type of player.

Figure 15

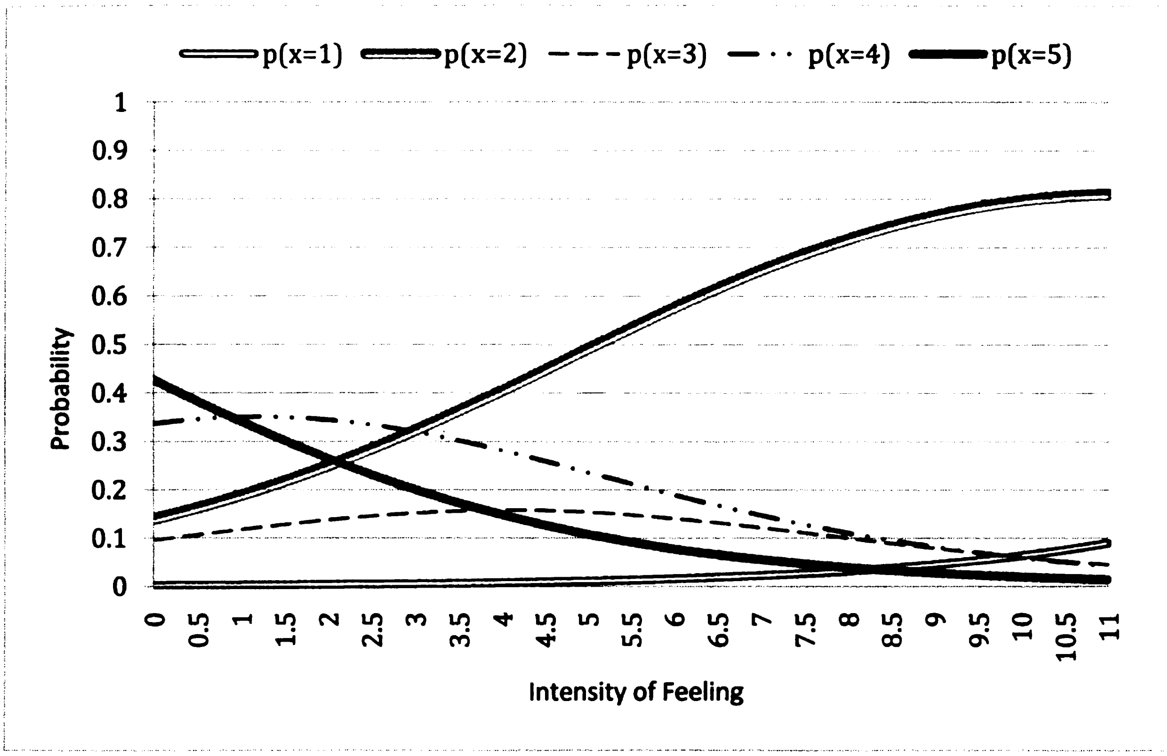
Negative-Dysfunctional IAPZ Curves for Player 3



Note. Curves labeled p(x=1) and p(x=2) represent the probabilities of poor performances with low and high intensity ratings (respectively). The curves p(x=3) and p(x=4) represent average performances in the same way; and p(x=5) is the good-performance curve. The purpose of this curve is to illustrate good-performance being most probably at lower intensity levels. There is also an interesting interaction and influence from all five performance curves.

Figure 16

Negative-Dysfunctional IAPZ Curves for Player 2

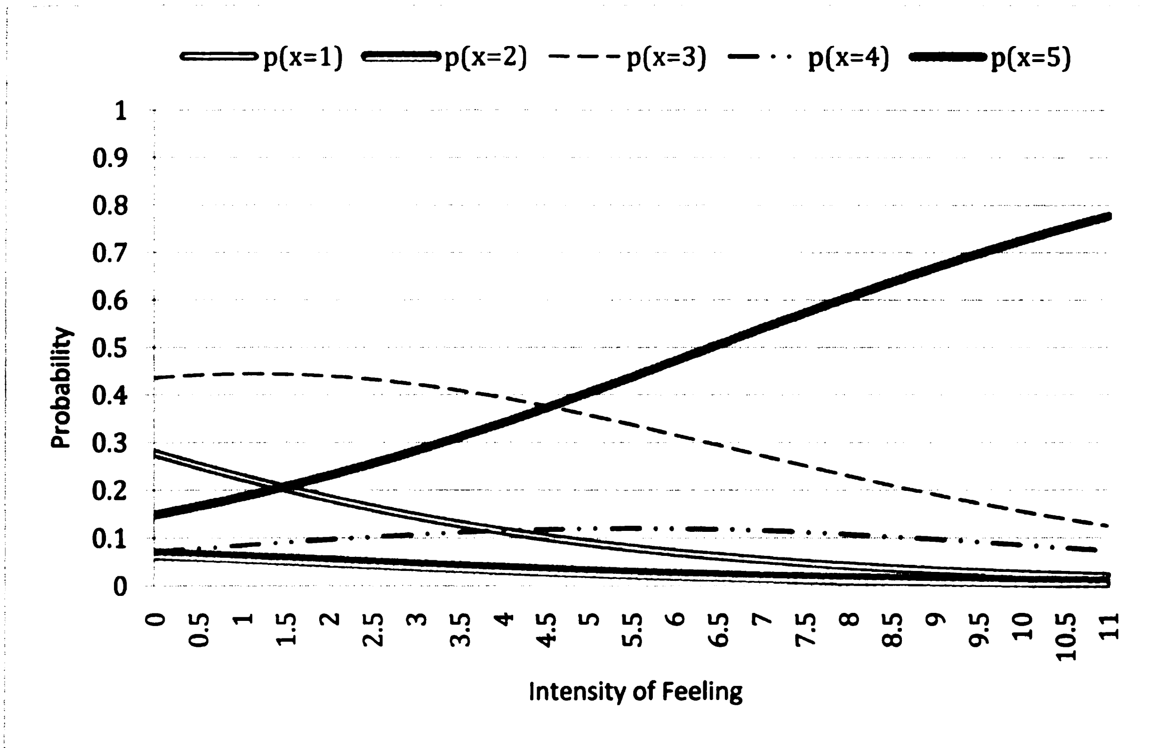


Note. Curves labeled p(x=1) and p(x=2) represent the probabilities of poor performances with low and high intensity ratings (respectively). The curves p(x=3) and p(x=4) represent average performances in the same way; and p(x=5) is the good-performance curve. The purpose of this curve is to illustrate an example of good performance being most probably at lower intensity levels. Also note that this profile has a very large bandwidth for poor performance (i.e., p(x=1)).

Figures 17 and 18 display linear curve profiles. It is rarely, but not unheard of for the IAPZ method to result in linear profiles (See Edmonds, et al., 2006). Particularly for Figure 18, this type of an output had a negative impact on the subsequent accuracy analysis because Player 1's zone profile predicted good performance at all levels of intensity. As such, every observation for Player 1 that was not rated as a good performance would result in an inaccurate prediction score. Fortunately, there were very few profiles like Figure 18.

Figure 17

Negative-Functional IAPZ Curves for Player 3



Note. Curves labeled p(x=1) and p(x=2) represent the probabilities of poor performances with low and high intensity ratings (respectively). The curves p(x=3) and p(x=4) represent average performances in the same way; and p(x=5) is the good-performance curve. The purpose of this curve is to illustrate a rare linear relationship between intensity and probability for p (x=5). Also note the absence of a poor performance zone.

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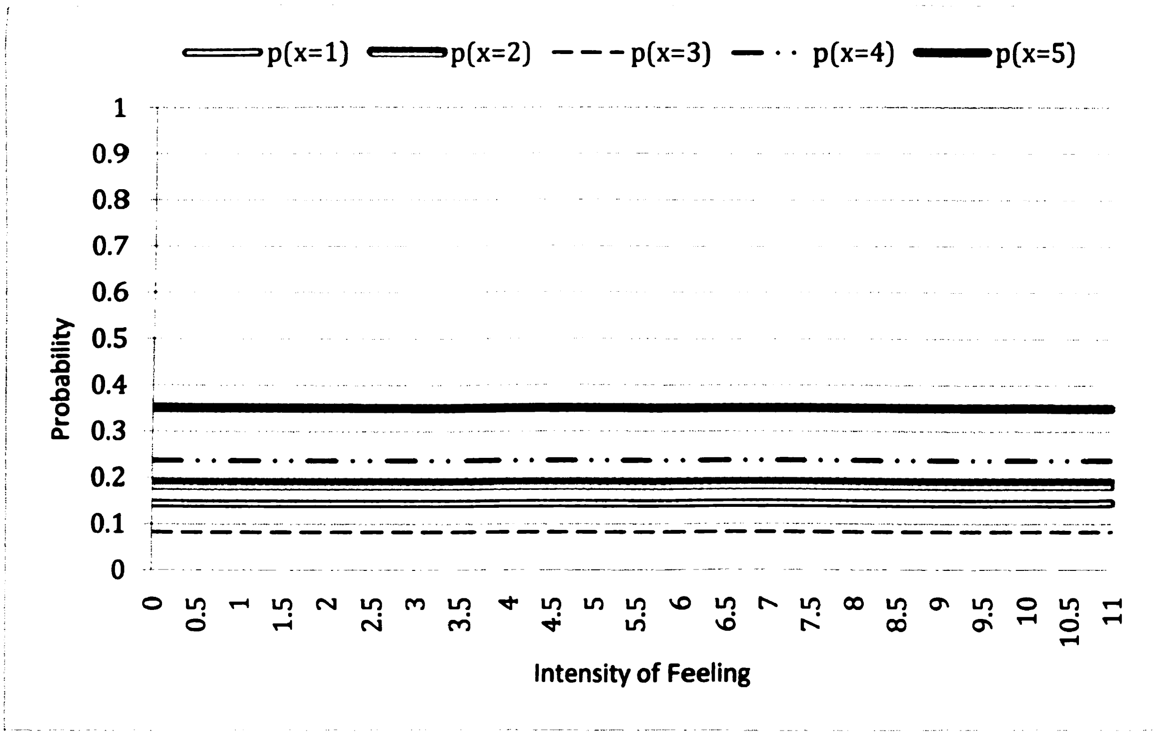
Figure 18

Positive-Dysfunctional IAPZ Curves for Player 1



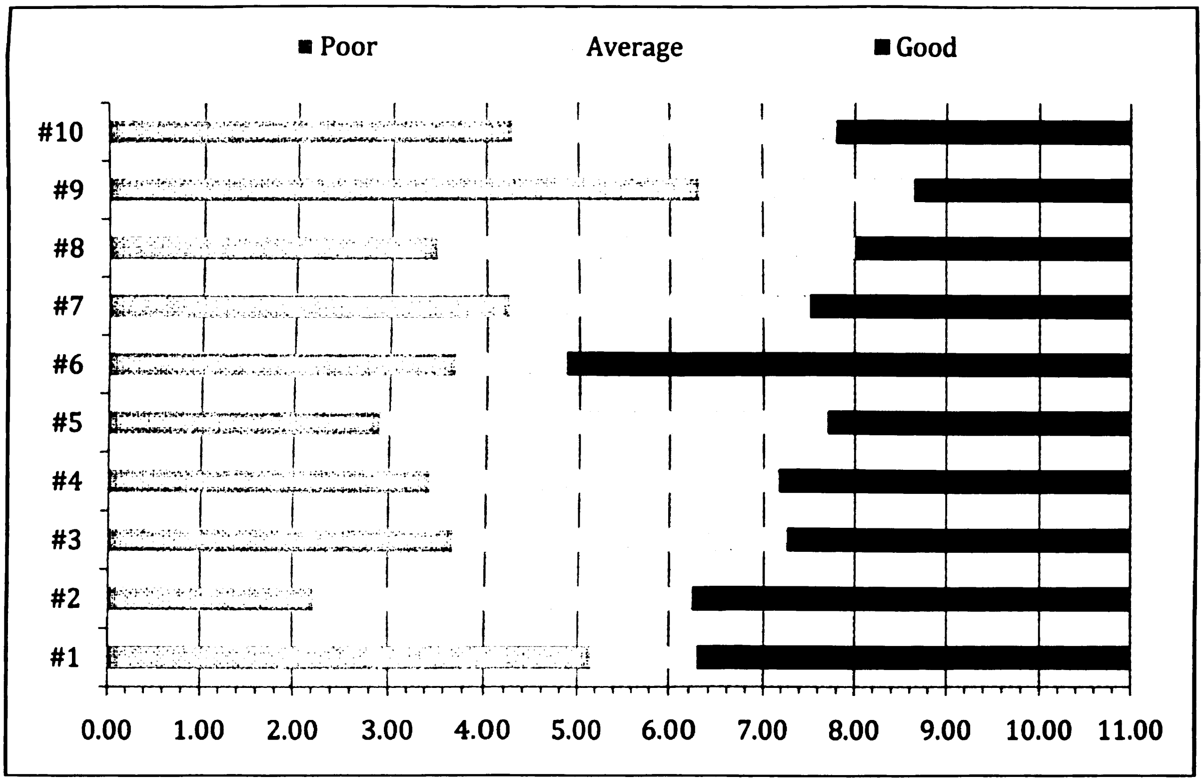
Note. Curves labeled p(x=1) and p(x=2) represent the probabilities of poor performances with low and high intensity ratings (respectively). The curves p(x=3) and p(x=4) represent average performances in the same way; and p(x=5) is the good-performance curve. The purpose of this curve is to display a unique profile where only one performance level is predicted across the entire range of intensity. Outcomes are also linear, rather than curvilinear.

For personal interest, readers can connect the probabilistic profiles in Figures 11-18 to the zone profiles in Figures 19-22. For example, the summary zone profile for Figure 18 can be found at the bottom of Figure 22. These figures support the ideographic nature of feeling-performance relationships and the related hypothesis (Hypothesis #1).

Performance zone figures. Figures 19-22 are more meaningful to the study's purpose. The performance zone profile for positive-functional feelings were identical in that all players went from poor to average to good performance levels as intensity

Figure 19

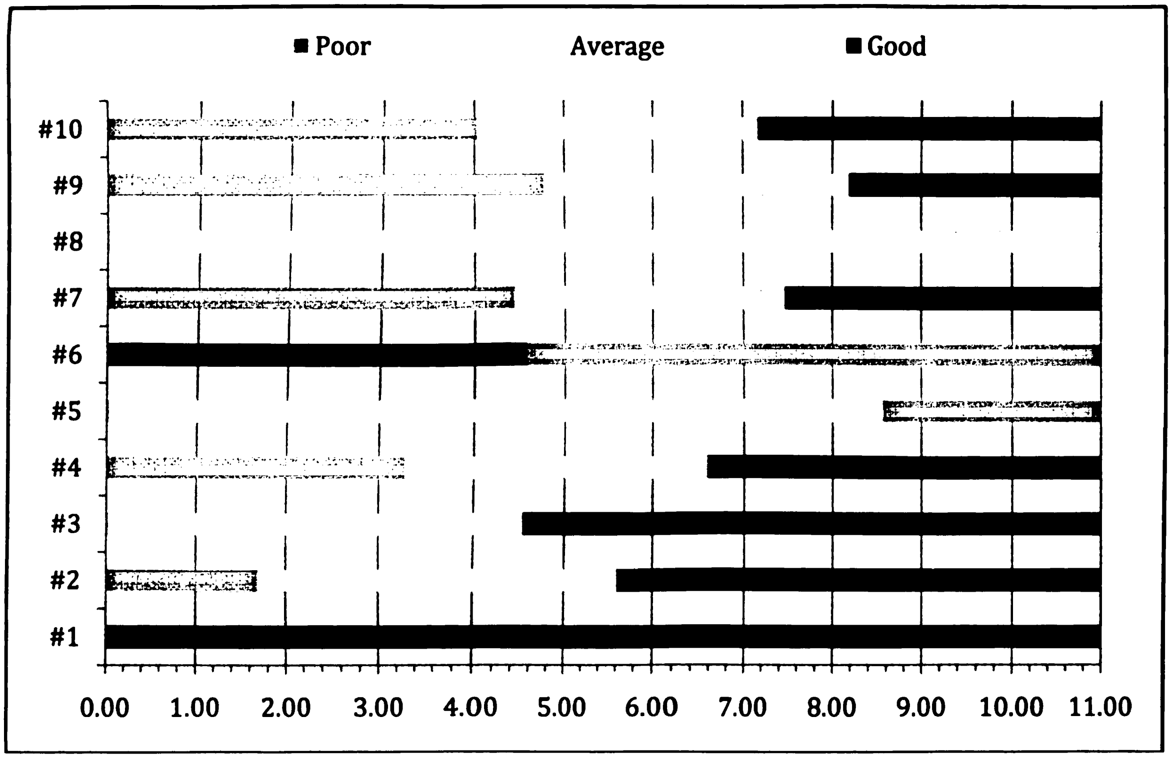
Positive-Functional Affect Performance Zones for Each Participant



Note. Participants are displayed as rows assigned to the y-axis. The x-axis represents the intensity of positive-functional feelings. Performance levels are assigned in grey-scale, with: good-zones in black, poor-zones in dark grey, and average-zones in light grey.

Figure 20

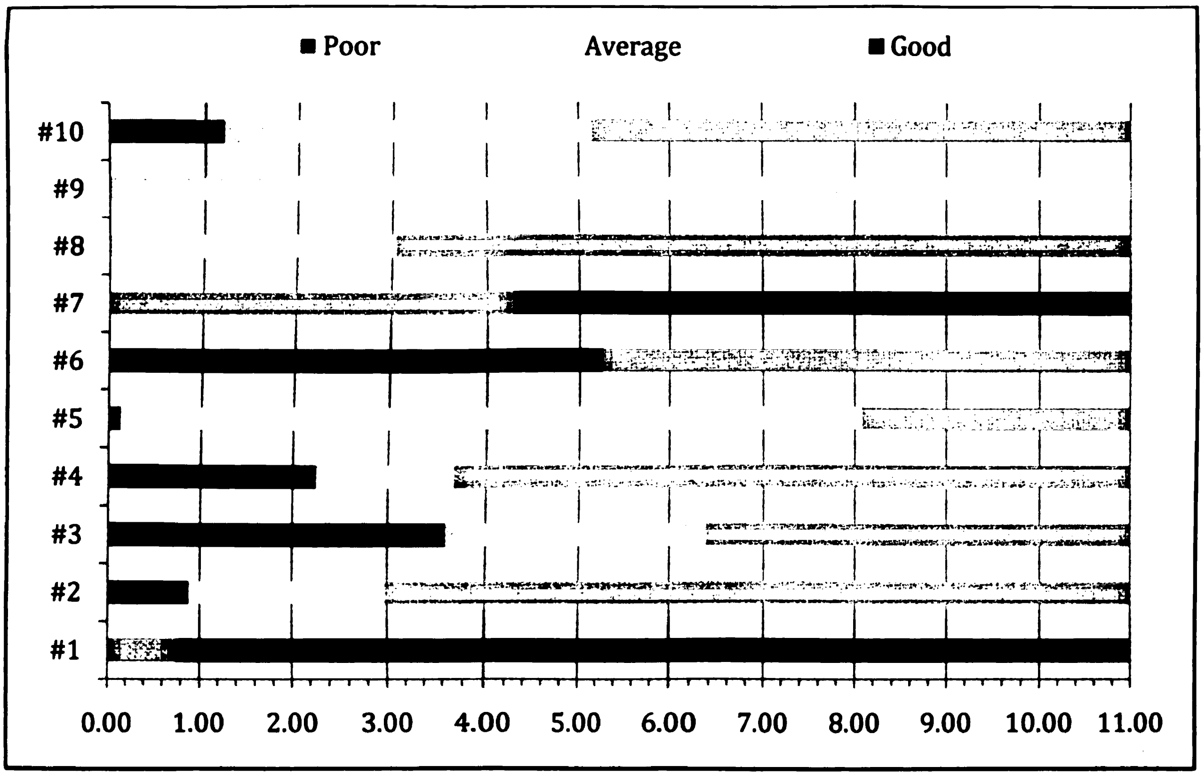
Negative-Functional Affect Performance Zones for Each Participant



Note. Participants are displayed as rows assigned to the y-axis. The x-axis represents the intensity of negative-functional feelings. Performance levels are assigned in grey-scale, with: good-zones in black, poor-zones in dark grey, and average-zones in light grey.

Figure 21

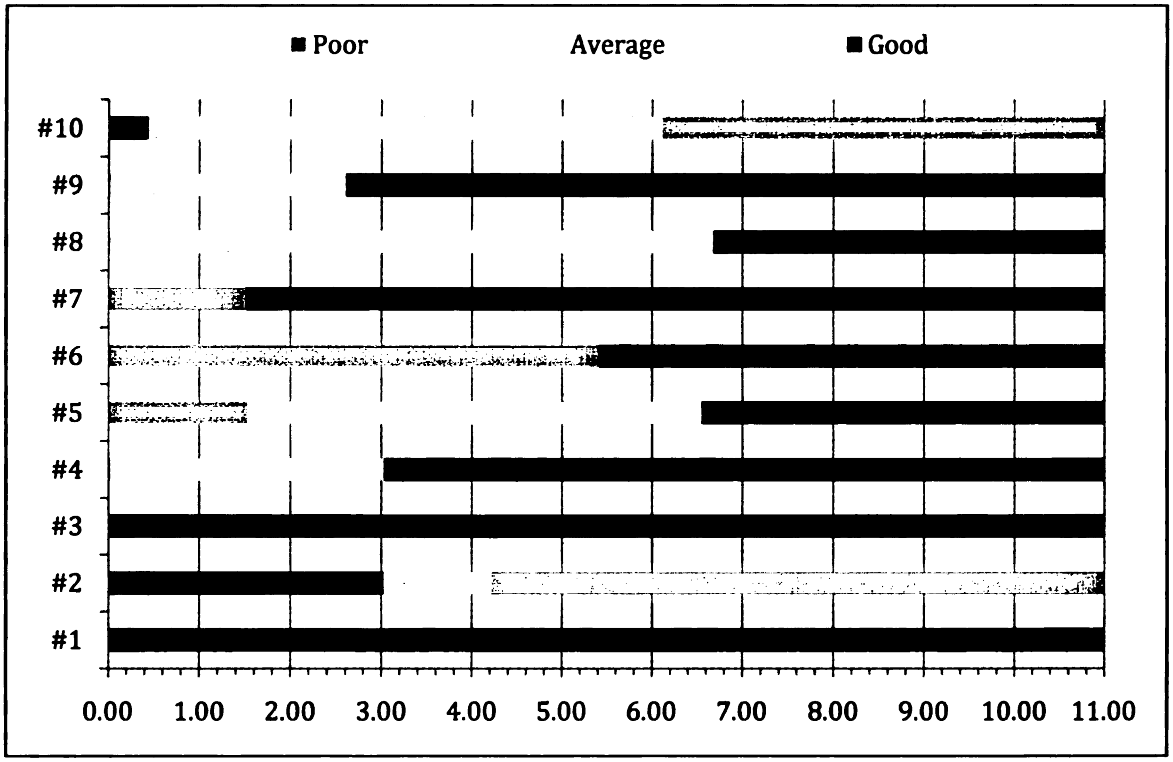
Negative-Dysfunctional Affect Performance Zones for Each Participant



Note. Participants are displayed as rows assigned to the y-axis. The x-axis represents the intensity of negative-dysfunctional feelings. Performance levels are assigned in grey-scale, with: good-zones in black, poor-zones in dark grey, and average-zones in light grey.

Figure 22

Positive-Dysfunctional Affect Performance Zones for Each Participant



Note. Participants are displayed as rows assigned to the y-axis. The x-axis represents the intensity of positive-dysfunctional feelings. Performance levels are assigned in grey-scale, with: good-zones in black, poor-zones in dark grey, and average-zones in light grey.

increased (Figure 19). In no case was there a "catastrophe effect" wherein the highest intensity levels were associated with performance decrements. This result is unique from profiles presented in both IZOF and IAPZ literature. Beyond these two similar patterns, individual profiles appear to differ in terms of the location and/or bandwidth of each zone. However, it is also worth suggesting that some players' profiles are quite similar. For instance, Player 3 and 4 are alike, as are Players 7, 10, (and to some extent) 5, and 8.

Performance zone profiles for negative-functional feelings displayed more idiosyncratic patterns (Figure 20). Most players' performances improved as intensity increased. However, Players 1 and 8 only had one performance zone; and Players 3, 5, and 6 only had two performance zones in their profiles. Performance decreased as intensity increased for Players 5 and 6. This result is atypical because functional feelings of greater intensity normally improve performance—whether they are positive or negative in terms of valence. Once again, while most participants' profiles were unique, Players 7, 9, and 10 were relatively similar.

Performance zone profiles for negative-dysfunctional feelings displayed even more idiosyncratic patterns (Figure 21). Player 9 had only one performance zone. Players 1, 5, 6, 7, and 8 had only two zones (Players 5's good-zone is so small that there were effectively only two likely outcomes). Players 2, 3, 4, and 10 had three zones, and each of their profiles appears to be different. Performance diminished as intensity increased for most participants. Atypically however for dysfunctional emotions, Players 1 and 7 displayed improved performance over intensity gains.

Performance zone profiles for positive-dysfunctional feelings displayed erratically idiosyncratic patterns (Figure 22). Player 1 and 3 had only one performance zone. Players 4, 6, 7, 8, and 9 had only two zones. Players 2, 5, and 10 had three zones, and each of their profiles appears very different. What makes these results especially peculiar is that all but two players displayed improved performance with increased intensity of dysfunctional feelings—including Players 1 and 3 whose lone zones predicted good performance. Only Players 2 and 10 performed better with lower intensity. Of the four categories, the positive-dysfunctional set had the most unique—if not strange—results.

Although visual-qualitative comparison of individual profiles does not provide objective statistical comparisons, there are clearly many advantages to this method. In fact, in much of IZOF and IAPZ research, visual comparisons are the lone method of comparison. Because of the large number of observations collected in this study, it was possible to complement these qualitative comparisons with the forthcoming statistical analyses.

Central tendencies across performance. Understanding what the individual profiles look like, and how probabilistic curves profiles translate into zone profiles, a quantitative assessment of the location and breadth of zones is now presented. As described in the introductory paragraph of this section describing interindividual differences, two statistical tests were conducted in order to assess differences in the location (central tendency) and width (variance) of zones. The results from these analyses are presented in Tables 8-19 (See Appendix) and summarized in a later table.

Twelve separate one-way ANOVAs were conducted for each feeling category and performance level, with feeling intensity as the dependent measure and participants as the nominal predictor. Each of these ANOVAs revealed significant differences between participants' mean intensity values. For all 12 analyses, Levene's Test for homogeneity of variances was violated ($p < .001$). The second value listed in the degrees of freedom for each ANOVA vary considerably between performance-levels for each of the valence-feeling categories because the number of poor, average, and good performances varied.

Based on these violations of homogeneity of variances, post-hoc comparisons were made between each participant using Dunnett's C. This test was selected because it accounts for unequal variances (violations of homogeneity), unequal samples, and is more conservative than comparable tests (e.g., Games-Howell) and thus controls the alpha level more effectively and reduces the chance of Type I error (Pallant, 2009).

Furthermore, the critical p-value for variance analyses were adjusted to a more conservative .01. Forty-five comparisons were made between the 10 players for each of the 12 feeling-category and performance level combinations (See Tables 8-19 in the Appendix for each comparison). In order to assess every possible interindividual comparison, these large numbers of t-tests were necessary.

Clearly, this many t-tests increases the likelihood of Type I error. It is important to note that—unlike most post-hoc tests—this dissertation was not concerned with any one particular t-test. To study the extent of idiosyncratic variability, a general representation of the proportion (percentage) of significant interindividual differences was required. A Bonfferoni correction for the 45 tests would require an alpha level of < .001, which was not practical. After consulting with a statistical advisor from Michigan State University, it was recommended that a .01 alpha-level and the choice of the Dunnett's C provided sufficiently reliable post-hoc results. As such, results should be interpreted as a general index of idiosyncrasy resulting from a balance of pragmatism and conservative rigor.

Performances across positive-functional feelings. A one-way between subjects analysis of variance was conducted to explore inter-player differences in feeling intensities during poor performances. Significant individual differences in zone-intensities were identified at a $p < 0.05$ level: F (9, 230) = 36.57, $p < .001$. An identical ANOVA was conducted for average performances that revealed significant differences: F (9, 432) = 13.41, $p < .001$. Analysis of good performances also revealed significant individual differences: F (9, 219) = 18.43, $p < .001$. Mean differences from Dunnett's C post-hoc analyses are presented in Tables 8-10 with significant values ($p < 0.01$) in bold. Of the 45 post-hoc tests for each figure (or ANOVA), there were 23, 19, and 23 significant comparisons across poor, average, and good performance levels respectively—meaning that zones were slightly more similar across individuals during average performance-levels.

Performances across negative-functional feelings. A one-way between subjects analysis of variance was conducted to explore inter-player differences in feeling intensities during poor performances. Significant individual differences were identified at a $p < 0.05$ level: $F(9, 230) = 37.19, p < .001$. An identical ANOVA was conducted for average performances that revealed significant differences: $F(9, 432) = 38.01, p < .001$. An analysis of good performances also revealed significant individual differences: $F(9, 219) = 60.96, p < .001$. Mean differences from Dunnett's C post-hoc analyses are presented in Tables 11-13 with significant values ($p < 0.01$) in bold. Of the 45 post-hoc tests for each figure (or ANOVA), there were 26, 24, and 28 significant comparisons across poor, average, and good performance levels respectively.

Performances across negative-dysfunctional feelings. A one-way between subjects analysis of variance was conducted to explore inter-player differences in feeling intensities during poor performances. Significant individual differences were identified at a $p < 0.05$ level: $F(9, 230) = 33.16, p < .001$. An identical ANOVA was conducted for average performances that revealed significant differences: $F(9, 432) = 27.40, p < .001$. An analysis of good performances also revealed significant individual differences: $F(9, 218) = 33.55, p < .001$. Mean differences from Dunnett's C post-hoc analyses are presented in Tables 14-16 with significant values ($p < 0.01$) in bold. Of the 45 post-hoc tests for each figure (or ANOVA), there were 21, 27, and 25 significant comparisons across poor, average, and good performance levels respectively.

Performances across positive-dysfunctional feelings. A one-way between subjects analysis of variance was conducted to explore inter-player differences in feeling intensities during poor performances. Significant individual differences were identified at a $p < 0.05$ level: F (9, 230) = 87.59, $p < .001$. An identical ANOVA was conducted for average performances that revealed significant differences: F (9, 432) = 45.22, $p < .001$. An analysis of good performances also revealed significant individual differences: F (9, 217) = 28.57, $p < .001$. Mean differences from Dunnett's C post-hoc analyses are presented in Tables 17-19 with significant values ($p < 0.01$) in bold. Of the 45 post-hoc tests for each figure (or ANOVA), there were 28, 34, and 26 significant comparisons across poor, average, and good performance levels respectively.

Unlike most research analyses, no particular post-hoc comparison was critical for the hypotheses. Rather, the sum total of significant paired differences was used as an indicator of how much interindividual variability there was in the location of zones within the sample. For each of the four feeling categories and three performance levels, 12 separate analyses were conducted between the 10 participants (i.e., 45 interindividual comparisons per analysis). Of these 540 total comparisons, 304 significant differences were identified—meaning that 56.3% of the possible comparisons were statistically unique. Before examining this degree of idiosyncratic difference, differences in the width of zones must be considered, and are in the following section.

Variance across performance. Before conducting interindividual comparisons to determine how many individuals differ from one another in terms of the variability (or bandwidth) of their zones, Levene's test of homogeneity of variances was assessed. Just as the F-test of an ANOVA provides an overall assessment of mean differences while accounting for family-wise error, Levene's test offers a big-picture perspective on the homogeneity of variance (i.e., that the squared standard deviations of each participant are statistically equal. The Levene statistics for poor performances across feeling categories were 4.59 (positive-functional), 8.56 (negative-functional), 4.66 (negative-dysfunctional), and 15.11 (positive-dysfunctional). The Levene statistics for average performances across feeling categories were 6.95 (positive-functional), 11.84 (negative-functional), 10.068 (negative-dysfunctional), and 15.83 (positive-dysfunctional). The Levene statistics for good performances across feeling categories were 10.43 (positive-functional), 18.33 (negative-functional), 6.41 (negative-dysfunctional), and 9.173 (positive-dysfunctional). All 12 of these tests were significant ($p < .001$ for all), meaning that there were meaningful differences in variance scores across participants.

Once more, the sum of Dunnett's C tests were used as an indicator of general variability in the size of zones across players. Like the comparisons of central tendencies, 540 comparisons of variance were conducted. Of these comparisons, 289 significant differences were identified—meaning that 53.5% of the possible comparisons were statistically unique. In other words, approximately half of the individual zones were significantly bigger or smaller than one another.

Summary of individual differences. Of the possible interindividual comparisons across feeling categories and performance levels, 76.3% showed significant differences in central tendency, variance, or both (See Table 20). Good performance zones displayed the most idiosyncratic tendencies (averaging 82.2%), followed by average (75.6%) and poor performances (71.1%). Zone profiles for positive-dysfunctional feelings had the most significant individual differences (83.0%), followed by negative-functional (80.7%), negative-dysfunctional (73.3%), and positive-functional (68.1%) feelings. In summary, players displayed greater individual differences across good-performance zones and reversal categories (positive-dysfunctional and negative-functional combinations). Likewise, players were more similar to one another for poor-performance zones across non-reversal feelings.

Table 20

Summary of Individual Differences across Performance and Feeling-Category.

	Performance			
Feeling Category	Poor	Average	Good	Subtotal
Positive-Functional	28 [62.2]	29 [64.4]	35 [77.8]	92 [22.3]
Negative - Functional	36 [80.0]	32 [71.1]	41 [91.1]	109 [26.4]
Negative-Dysfunctional	27 [66.0]	36 [80.0]	36 [80.0]	99 [24.0]
Positive-Dysfunctional	37 [82.2]	39 [86.7]	36 [80.0]	112 [27.2]
Subtotal	128 [31.1]	136 [33.0]	148 [35.9]	412 [76.3]

Note. This table indicates the degree of interindividual idiosyncrasy in feeling-performance zones. Values represent the number of inter-individual differences in central tendency or variance. The total possible number of comparisons was 45 (for non-subtotal cells), 135 for the feeling-category subtotal column, and 180 for the performance subtotal row. Values in brackets represent the percentage of significant individual differences based on the potential number for that cell. The percentage value in the bottom-right cell is based on a total number of 540 comparisons.

The performance-feeling grouping with the highest variance was good-zone for negative-functional feeling (91.1% different). Meaning that, more so that for any other area of the profiles, the tennis players in this sample were most unique from one another when playing well in terms of negative-functional. The two groupings with the least number of individual differences were the poor- and average-zones for positive-functional feelings (with 62.2% and 64.4% differences respectively). Meaning that the players in this study were most similar to each other in their suboptimal performances in the positive-functional category.

Given that the number of participants and the limited range of feeling intensities for zones to distribute across, the fact that 76.3% of interindividual comparisons showed differences in either the location or the size of zones was surprisingly high. Though idiographic differences are limited (i.e., there are not 100% differences between each player), these analyses provide strong support for the notion of idiosyncratic feeling-performance relationships across different players.

Intraindividual Context Differences

The second major objective of this study was to compare individuals' profiles across two separate tennis contexts: serving and returning serve. It was hypothesized that there would be significant differences in feeling-performance zones across service and return of service contexts. To test this statistically, means and variances for feeling intensity were compared within individuals across category and performance level. Like the previous comparison between players, zones were compared in terms of the location (central tendency) and breadth (variability). However, where as the predictor in the previous analysis had 10 levels (i.e., 10 players), the independent factor in the current analysis of context had only two levels. Accordingly, post-hoc comparisons were not necessary to determine where differences in significant F-tests occurred within the predictor.

Central tendencies across performance. The ecological design of the study did not permit for service data to be paired with return of serve data across observations. As such, while each ANOVA was conducted within subjects, the analysis had to be unpaired (not a repeated measures analysis). One analysis of variance was conducted for each participant, performance level, and feeling category. Tables 21-23 present the *F*-values for each of the 120 ANOVAs. Significant differences ($p < .01$) between service and return zones are expressed in bold.

There was only one significant *F*-test within the positive-functional category; one significant *F*-test within the negative-functional category; two significant *F*-test within the negative-dysfunctional category; and two significant *F*-tests within the positive-dysfunctional category. These six significant tests represent a mere 5.0% of the total context comparisons—an especially low proportion given the decision to not make a full Bonfferoni adjustment to the alpha-level (to $p < .001$). Though not essential for the objectives of this dissertation, it is worth noting that the six differences were evenly split among poor and good performances.

Variance across performance. Because the predictor variable had only two levels, the Levene's Test to assess family-wise inequality of variances across context was not necessary. Rather, the same method of comparing variances used in the interindividual analysis was repeated here. These values are reported in Tables B20-23 as the "s^2 *F* Ratio" with significant differences ($p < 0.01$) expressed in bold.

Table 21

Intraindividual Comparisons of Central Tendency and Variance F-Ratios across Return and Serve Contexts for the Positive-Functional Feeling Category

	Poor		Average		Good	
Player	Mean F	s^2 F ratio	Mean F	s^2 F ratio	Mean F	s^2 F ratio
1	0.53	1.88	0.95	1.62	0.53	1.26
2	0.02	1.35	0.00	1.70	0.14	2.86
3	0.07	3.05	0.45	1.26	0.89	1.59
4	0.98	5.51	0.01	1.01	**4.83**	2.10
5	0.02	1.01	1.26	1.16	0.60	**11.99**
6	0.04	1.09	0.05	**6.47**	0.79	1.29
7	0.05	1.64	0.46	2.46	0.04	1.34
8	1.13	1.13	1.20	1.19	0.18	2.20
9	2.98	1.63	0.98	1.45	0.20	4.00
10	0.20	1.14	0.20	1.02	0.04	1.01

Note. Mean values are represented by F-Ratios across context. Significant values at a $p < .05$ level are represented in bold. Variance values are represented by the F-Ratio of variances in each context. Significant values at a $p < .01$ level are represented in bold.

Table 22

Intraindividual Comparisons of Central Tendency and Variance F-Ratios across Return and Serve Contexts for the Negative-Functional Feeling Category

	Poor		Average		Good	
Player	Mean F	s^2 F ratio	Mean F	s^2 F ratio	Mean F	s^2 F ratio
1	0.11	2.86	0.70	**3.55**	0.29	1.62
2	0.31	1.70	0.03	1.07	0.77	2.54
3	0.25	1.14	0.15	1.53	0.56	1.10
4	0.35	3.60	2.29	1.02	2.29	1.45
5	5.20	1.96	1.93	1.46	0.11	4.44
6	0.79	1.04	0.69	1.12	0.99	3.12
7	0.03	1.46	0.07	1.39	0.06	1.65
8	**5.22**	1.22	3.67	1.13	3.01	**69.02**
9	2.95	2.00	0.42	1.62	0.11	**0.00**
10	0.07	1.07	0.01	1.00	0.05	1.01

Note. Mean values are represented by F-Ratios across context. Significant values at a $p < .05$ level are represented in bold. Variance values are represented by the F-Ratio of variances in each context. Significant values at a $p < .01$ level are represented in bold.

Table 23

Intraindividual Comparisons of Central Tendency and Variance F-Ratios across Return and Serve Contexts for the Negative-Dysfunctional Feeling Category

	Poor		Average		Good	
Player	Mean F	s^2 F ratio	Mean F	s^2 F ratio	Mean F	s^2 F ratio
1	0.02	2.54	0.01	1.74	0.18	2.57
2	0.00	1.02	0.57	1.69	0.29	1.09
3	**6.80**	**19.28**	3.92	1.85	0.00	1.05
4	1.38	2.50	0.47	1.75	1.46	2.63
5	1.05	1.79	2.90	1.40	0.79	1.55
6	0.14	3.60	0.04	2.59	0.36	2.14
7	0.09	1.01	0.17	1.22	1.44	1.13
8	0.03	1.35	1.93	**3.57**	0.01	1.87
9	1.74	2.96	0.02	1.23	0.05	1.86
10	0.06	1.05	0.12	1.04	0.00	1.00

Note. Mean values are represented by F-Ratios across context. Significant values at a $p < .05$ level are represented in bold. Variance values are represented by the F-Ratio of variances in each context. Significant values at a $p < .01$ level are represented in bold.

Table 24

Intraindividual Comparisons of Central Tendency and Variance F-Ratios across Return and Serve Contexts for the Positive-Dysfunctional Feeling Category

	Poor		Average		Good	
Player	Mean F	s^2 F ratio	Mean F	s^2 F ratio	Mean F	s^2 F ratio
1	0.86	1.24	0.60	1.59	0.00	2.29
2	0.41	1.48	0.30	1.46	0.51	**3.36**
3	0.01	8.17	0.55	1.29	**5.23**	1.72
4	1.07	2.25	0.01	1.84	1.41	1.77
5	1.82	**8.08**	0.51	1.19	0.08	1.04
6	**4.50**	1.39	0.66	3.41	3.55	1.56
7	0.58	**11.00**	0.56	2.20	0.00	0.00
8	1.92	**24.68**	1.41	1.97	0.35	4.43
9	0.34	1.25	2.95	1.48	0.20	4.00
10	0.32	1.13	0.00	1.01	0.54	1.16

Note. Mean values are represented by F-Ratios across context. Significant values at a $p <$ .05 level are represented in bold. Variance values are represented by the F-Ratio of variances in each context. Significant values at a $p < .01$ level are represented in bold.

There were only two significant *F*-tests within the positive-functional category; three significant *F*-tests within the negative-functional category; one significant *F*-test within the negative-dysfunctional category; and four significant *F*-tests within the positive-dysfunctional category. These 10 significant tests represent a mere 8.33% of the total context comparisons. Though not essential for the objectives of this dissertation, it is worth noting that four differences existed for poor performances, three for average performances, and three for good performance levels.

Summary of context differences. Especially compared to the interindividual analysis that explored the degree to which idiosyncratic differences existed in performance-feeling profiles, the current analysis of context effects showed very little variability. While 76.3% of individuals' zones were different, only 15 out of the 120 context comparisons (12.5%) were different. This result does not support the notion that individuals have unique feeling-performance profiles for serving compared to returning service. Players' zones were generally stable across each tennis context.

Though differences were few, poor (17.5%) and good (15.0%) performance zones were more variable than average (7.5%) performance zones. With only 16 total differences, each player could be said to have 1.6 differences across the 12 comparisons. Based on that average, Player 3 (three context differences) and Player 8 (four context differences) had relatively more differences. As such, it may be possible that the context effect was at least somewhat applicable for two of the ten tennis players in this study.

Accuracy of Discrete Categories versus Trigger Items

The third major objective of this dissertation was to determine if a small number of critical trigger items (feelings) could be as effective as a full profile of 12-13 items representing four fundamental categories of feeling. To answer this question, the accuracy of eight variables (four feeling categories and four trigger items) were determined and compared. After conducting OLRs on all eight variables, parameters were identified for each performance level. These performance zones were used to predict performance ratings. Accuracy was determined by comparing the predicted level of performance to the actual performance rating for each observation. The process of determining accuracy and comparisons of accuracy results are presented below.

Creating performance prediction variables. Performance predictions were generated from the OLR curves and zone bandwidths depicted graphically in Figures 19-22. The process of establishing this data was described earlier in the section titled "Treatment of Raw Data: Ordinal logistic regressions." Continuing from where this section finished, eight new variables (columns) were created in the SPSS file. These variables combined the bandwidth parameters from each player's four feeling categories and four trigger items with the actual aggregated intensity value in each category and trigger. From this process, performance predictions were established for each observation. For example, Player 5's zones for positive-functional feelings were poor (0.0-3.70), average (3.71-4.87), and good (4.88-11.0). If the average positive-functional (PF) intensity rating was 3.0 for a certain observation, that observation's PF performance prediction would be 'poor,' if the aggregated feeling intensity was 4.5, the prediction would be for 'average' performance, and 'good' performance would be predicted if the rating was a 5.0 or a 10.0, etc.

Determining accuracy of OLR-based zones. Determining accuracy was a simple process of comparing the predicted performance values in each of the eight columns to the actual performance level for that observation. Continuing from the previous example, If the actual performance rating was 'average,' than only positive-functional scores between 3.71 and 4.87 would be coded as accurate predictions. When the predicted and actual performance levels were identical, the accuracy column for that category/trigger was coded as a 1 (accurate), if not, it was a 0 (inaccurate).

Comparing accuracy results. The accuracy of the traditional feeling categories and the idiographic trigger items are described in Table 25. The analyses of accuracy ratings

Table 25

Accuracy of Performance Predictions for Feeling Categories and Trigger Items

Category / Item	Rank	Accuracy	Z value	Significance
Positive-Functional	1	73.2%	1.84	0.066
Trigger 2	1	71.4%	0.08	0.938
Trigger 1	1	71.1%	**2.19**	**0.029**
Trigger 3	4	67.6%	**2.85**	**0.004**
Negative-Functional	5	63.4%	**2.09**	**0.037**
Negative-Dysfunctional	6	60.2%	**2.18**	**0.030**
Positive-Dysfunctional	7	56.9%	1.03	0.303
Trigger 4	7	55.7%	-	-

Note. '*Z* value' and 'Significance' columns describe the comparisons between that row and the subsequence row in the rank-ordered list based on Wilcoxon Signed Rank Test. Significant differences at the $p < .05$ level are in bold.

were one of the few statistical tests that were conducted across all participants simultaneously. While each player had unique feeling items and emotion-performance profiles, the accuracy of the zone-based predictions could be collapsed across individuals. Because the outcome variable in this analysis was nominal with only two possible outcomes (accurate or not), a non-parametric equivalent of a one-way repeated measures ANOVA was used (Pallant, 2009). This non-parametric option is called a Friedman Test. Because each participant's observations were combined, and non-parametric analyses are conditional on the assumption of independent observations, it was very important to use the Friedman Test rather than the Kruskal-Wallis between-groups test. Table 25 depicts the eight feeling categories and items, their ranking, percentage accuracy, Z score for the difference between each row and the row below it (less accurate), and the p-value for the paired Z score comparison at the critical alpha level of .05.

The results of the Friedman Test indicate significant differences in the accuracy scores of the eight variables, χ^2 (7, n = 903) = 247.060, $p < .001$. Just as a significant F-Test in an ANOVA justifies post-hoc t-tests, the non-parametric equivalent tests (the Wilcoxon Signed Rank Test) were conducted. Seven paired comparisons were made along the ranked order of the eight variables, such that the most accurate variable was compared to the second most, and the second most was compared to the third most accurate, etc. As Table 25 shows, the three most accurate variables were statistically equal ranging from 71.1% to 73.2% accurate. To explain each row, the positive-functional category was accurate in predicting performance 73.2% of the time, but not statistically more accurate than the Trigger 2 variable (71.4%), $z = 1.84$, $p = .066$, at a critical alpha level of 0.05. As Table 25 shows, Positive-Functional feelings, Trigger 2, and Trigger 1 were the most accurate; Trigger 3 (67.6%) was next; Negative-Functional feelings (63.4%) were less accurate; Negative-Dysfunctional feelings (60.2%) were less accurate; and Positive-Dysfunctional feelings (56.9%) and Trigger 4 (55.7%) were equally least accurate.

Simply stated, the trigger items were significantly more accurate than the aggregated traditional feeling categories. Three of the top four most accurate variables were trigger items. It should be noted that functional categories were more accurate than dysfunctional ones; and that most individuals would probably benefit from three, rather than four, critical trigger items.

CHAPTER FIVE

DISCUSSION

This investigation was designed to assess the effects of feeling states on performance during competitive tennis matches for the purpose of contrasting and integrating the IZOF and IAPZ models of emotions and performance. Secondly, intraindividual contextual differences in performance-zones were compared within individuals. Thirdly, four discrete 'trigger feelings' were compared to a complete profile with four valence-function categories of feeling to determine which predicted performance most accurately. Each hypothesis is briefly reviewed in the following paragraph, and expanded upon through the discussion chapter.

The first hypothesis predicted that discrete feelings organized into four valence-function categories would form idiosyncratic feeling-performance profiles that accurately predict performance. This hypothesis was supported by the results. The second hypothesis predicted that idiographic profiles would vary between serve and return of serve contexts for each player. The results failed to support this hypothesis. The final hypothesis proposed that the simplified "trigger" items would be comparable to a complete profile in terms of predictive ability. This assumption was not only met but was clearly exceeded, based on the results of this study.

Integrating Elements of IZOF with IAPZ

The essential objective of this dissertation was to test whether or not valuable elements of the IZOF model could be integrated with the IAPZ method. Based on the successful production of probabilistic idiographic curves and the reasonable accuracy performance predictions, it appeared from this study that Tenenbaum and colleagues'

IAPZ model (Johnson, et al., 2009; Kamata, et al., 2002; Tenebaum, et al., 2002; Tenenbaum, et al., 2008) can accommodate discrete feeling states. Results supporting this conclusion are presented.

Establishing accurate probabilistic curves. Based on the results of this study, OLR analysis was clearly capable of identifying performance zones from aggregated groups of discrete feelings (See example Figures 6-13). Overall, the zones depicted in Figures 19-22 were 65.0% accurate (valence-function categories were 63.5%; and zones for trigger items were 66.4%). Accuracy results were more than twice the likelihood of chance (i.e., 33.3% based on three possible outcomes), and therefore considered to be strong. Ideally, these accuracy scores would be compared to accuracy reported in previous IAPZ research. However—with the exception of the introductory paper, by Tenebaum et al. (2002), which used a theoretical data set to compare the accuracy of the proposed IAPZ model to the established IZOF model—no subsequent research has reported the accuracy of predictive profiles. It would benefit this field of study to consistently report the accuracy of the profiles to predict performance.

Individual differences. The identification of individual differences offered further statistical support that discrete feeling items can be used with IAPZ methods to develop probabilistic models. Both qualitative and quantitative support for the idiosyncratic nature of feeling-performance relationships were presented. Statistical comparisons of zone locations and bandwidths supported traditional visual comparisons (See Figures 19-22). This is an important result because IAPZ and IZOF studies have often relied on visual comparisons without producing statistical evidence in support. While idiographic differences were identified, these differences should not be overstated. As the description of Figures 19-22 showed, some players had effectively similar profiles. There certainly was not complete, 100% uniqueness across participants. In the same way that the Transtheoretical model of physical activity groups people into five motivational categories (e.g., pre-contemplative, maintenance), perhaps athletes' feeling-performance relationships can be grouped into a parsimonious number. As robust as the visual and statistical evidence was, differences in individual selection of items appeared to be the greatest source of idiosyncratic differences.

Discrete items. Hanin (2000c, 2007), Lazarus (1991, 2000b), Pekrun (1992, 2000; Pekrun, Elliot, & Maier, 2006) and others have argued that discrete emotions (e.g., anxiety, relaxation, anger, etc.) that are grouped by similar valence and functionality (e.g., as being either helpful or harmful to performance) act in similar ways. They further contend that different valence-function groupings have unique mechanistic effects on functioning (i.e., see Hanin's Energy Mobilization-Utilization hypothesis described in Chapter 2). As such, there are valuable theoretical reasons to study discrete feelings that can be organized into valence and function categories.

There are also practical benefits to using discrete emotions, rather than measuring affect using the continuous, two-dimensional construct of the affect grid (Russell, et al., 1989). People do not identify their feelings in terms of continuous valence and arousal / intensity. They can, but they do not do it naturally. Athletes likely relate better to an individual profile with personalized, familiar, and meaningful items like confidence, relaxed, aggressive, fast, than they do to describing the hedonic tone of their state.

In addition to being more tangible and meaningful to the athlete, discrete items provide another advantage to the traditional IAPZ method. No IAPZ study published up to this point has developed profiles based on integrated valance-functionality feeling states. In fact, only two studies have even assessed functionality of feelings (See, Cohen, et al., 2006; Golden, et al., 2004). In other words, IAPZ studies have developed separate individual profiles for valance ratings, activation ratings, and functionality ratings—but have not integrated these measures. By failing to combine measures, IAPZ research has not compared reversals (positive-dysfunction and negative functional categories). Reversals have provided important sources of idiosyncratic feeling-performance information. Most noticeably for example, practitioners now appreciate the benefits of at least moderate levels of negative feelings like nervousness and aggression; while being mindful of the potential detriments of positive states (e.g., being too relaxed or overjoyed). Hence, negative feelings in particular should always be organized into helpful and harmful subclasses.

Intraindividual Context Differences

With only 12.5% of the context comparisons reaching statistical significance, the data from this study fails to support the notion that individuals have unique zones of functioning (or IAPZs) across the context dimension of the psychobiosocial model in terms of serving and returning serve. This finding supports the idea that tennis players want to remain centered during matches—with a consistent, stable focus. Aside from each player's first shot of the point (the actual serve or return), both players are required to execute the same skills: groundstrokes and volleys. In other words, beyond the serve or return that starts the point, rallies require the same skills from each player. The differences between serving and returning serve are not as physically or mentally unique as the differences in playing offense and defense in basketball or hockey, for instance. The differences in task demands between serve and return of serve may be quite subtle.

It is possible that there are differences—but that they are quite subtle, and that they may exist for only some tennis players. Because each feeling item was aggregated into one of four feeling categories, the precise impact of each item (with the exception of the trigger items) was not identified. Here is an example of how the limited sensitivity of the aggregated analysis might hide a subtle effect. Player 8 identified 12 discrete items in his profile, including four negative-dysfunctional items. Of these four, three may have identical effects when serving as when returning serve. However, the fourth feeling (indecisive) may be critically important for serving well. The differences in optimal zones for this one item across context could be hidden by the statistical 'noise' created by the other three items. Likewise, an item like 'determination' might be most relevant when returning serve—which is generally a more defensive posture—while other positive-functional feelings may not vary across context. This hypothesis could be tested by using the same method to analyze the four feeling-categories; but doing so separately for each discrete item. This hypothesis and potential analysis are, however, beyond the objectives of this study.

Based on their psychological make up or playing style, some players might find that a shift in their zones or their mental focus will benefit their performance as they transition from dictating the point with their serve to counter-punching and defending on return. However, based on the results of this study, coaches and sport science practitioners may consider each task to require the same mental/emotional approach. However, other types of contextual comparisons are possible within the psychobiosocial framework (Hanin, 2000), such as being down/up a break (the score), their previous record against the current opponent, or the importance of the match. These comparisons may yield substantive findings.

Simplified Feeling-Performance Profiles

In developing scientific models, there is a constant struggle to balance comprehensiveness with parsimony. In structural equation modeling, factor analysis, and other statistical methods, researchers have to make somewhat arbitrary decisions about how many factors should be included in a model. A researcher may find that six things are statistically significant, but that only three of them are substantively meaningful. Does that researcher present a more complete model, or a more succinct, powerful model?

The results from this dissertation clearly argue that most tennis players can self-identify three critical trigger items that have a strong influence on their performance. Moreover, these three items are more accurate at predicting performance than the complete profile with four valence-function categories (e.g., 70.0 % compared to 63.5%). With the exception of the positive-functional category, the top three trigger items were more accurate than all of the other feeling categories. This result was surprising. It was expected that accuracy would have to be sacrificed in order to simplify the model. This was not the case: a simple profile with three or four discrete, self-selected items is more accurate than completing a 12-item profile. This result is particularly relevant for consultants, coaches, and athletes—as well as for scientists interested in less intrusive methods of collecting data.

It is worth noting that 'complete' profiles in this study included 12-13 items rather than the typical 16-20 originally proposed by Hanin (2000). An even bigger profile would likely include some less impactful items, and therefore be even less accurate overall.

The value of categories. The results from this study should not be considered as an exclusive endorsement of simple trigger-item performance modeling. There is considerable value in more comprehensive profiles. Firstly, although the trigger items were statistically more accurate, the four categories from the full profile were not drastically less accurate. Based on the values in Table 25, the average accuracy of trigger items was 66.45% and the mean accuracy of the feeling categories was 63.43%.

More importantly, a complete profile with valence-function categories presents theoretical value for both practitioners and to researchers. Both researchers and practitioners can benefit from being able to organize emotions and other feeling states into valence-functionality categories. Feelings have different performance effects based on their pleasant/unpleasant (or attraction/avoidance) and functional/dysfunctional nature. As such, negative-dysfunctional feelings may be more important when studying athletes in slumps; and positive-dysfunctional feelings may be more important when examining periodized training—two issues not examined in this study (See, Hanin, 2002).

Considering both functional and dysfunctional feelings is beneficial because coaches and consultants are able to identify what players should strive towards, as well as what they should avoid—e.g., barriers to optimal performance. While it is well known that athletes should strive to achieve specific goals, or ideal performance states (IPS; Orlick, 2008), the ability to be aware of and to avoid barriers to self-actualized performance is foundational to humanistic consulting paradigms (Hill, 2001; Rogers, 1980). For instance, as much as Jean may want to be confident, calm, and aggressive, she may *not* want to be irritated and worried. Developing strategies and routines that prevent irritation and worry may be more helpful to Jean than only striving to be confident, etc. If the theoretical and practical benefits of organizing feelings into valence- and functionality-based categories are important to a scientific study or to an applied intervention, then trigger items, alone, may not suffice.

With all of those points in mind, the results of this study suggest that all categories are not equal. Some categories appear to influence performance more strongly or more clearly than others. For instance, positive-functional feelings were less idiosyncratically unique across participants and were more accurate at modeling (predicting) performance ratings. On the contrary, positive-dysfunctional feelings were relatively poor predictors of performance. It could be concluded that, for some participants in this study, positive-dysfunctional feelings were not relevant or helpful to their idiographic profile.

An interesting question might be to investigate if the trigger items selected by each player were, in fact, their most accurate discrete predictors. Although the trigger items were more accurate than the complete profile, they were not necessarily the most accurate (i.e., the most effective predictor) of the 12 self-selected items. This could be determined by conducting separate OLRs on each of the 12 items in each player's profile, establishing the bandwidth zones, and examining the accuracy of each zone. Again, however, such an analysis was not necessary for the objectives of this dissertation.

Strengths and Limitations

Strengths of the study. Before discussing the critical limitations of this dissertation, it is worth acknowledging its strengths. Most importantly, the data collected was reliable.

There were times when a player's frustration made completing the forms impossible, and in those rare cases, the participant's frustration was always respected. The rapport between the researcher and player-participants helped to ensure data of the highest quality. It is also important to the study that an exceptionally large number of observations were collected.

Finally, the theoretical and practical foundation for the study seems to have been supported. For instance, understanding relevant theories (i.e., IAPZ, IZOF, CMRT, etc) led to the integration of probabilistic analysis (OLR) with discrete items that could be combined into valence-function categories. The researcher's practical experience in applying the IZOF model was foundational to the interest in more parsimonious trigger-item methods. The real value of this dissertation is in the contributions in bridging the IZOF and IAPZ frameworks. From an IZOF perspective, the study offers a very large dataset, assessments taken during performances rather than upon reflection, better statistical analyses (including the use of OLR), and the alternative of simplified trigger-item profiling. From an IAPZ perspective, it is clear that discrete items from the PNA-77 could be used as an alternative to the Affect Grid. Perhaps most importantly of all, interactions of valence and function were studied, which recognized the effects of reversals (e.g., the different effects of negative-helpful and negative-harmful feelings). The study also provides another tennis context to the IAPZ literature (which is more transferable than the laboratory-based and aiming sport contexts used in nearly all IAPZ research.

Limitations. All forms were completed during intra-squad challenge matches. These matches were very competitive—more competitive than practices, and many exhibition matches. However, challenge matches were likely not as competitive as conference matches or major tournaments. This likely reduced the frequency of very extreme feeling intensities. Though there inevitably would have been more intensity, it is impossible to know if the relationship between performance and intensity of feelings would have changed. The intensity of feelings was also less extreme because of the culture of tennis—which participants had been socialized in for a long time. In tennis, extreme displays of emotion are frowned upon. Compared to hockey, basketball, football, and many other sports, tennis players generally strive to be more centered. That said, tennis players generally express more emotional intensity than athletes in aiming sports such as curling or small bore, as well as some track and field events.

The design of this study generated an unavoidable degree of dependency within the dataset. Specifically, since both players in each match completed forms, the performance and feelings of one participant were interrelated to the other participant's data in that match. If, for instance, if Bob was to play a near-perfect game with intense emotion, Dylan (his opponent) is more likely to report poor performance, and his feelings may have been influenced by Bob's intensity. With this limitation in mind, there is no reason to think that interindividual dependency would influence the relationship between feelings and performance *within* individuals. Additionally, while there is total dependence for variables like outcome (i.e., if one player wins, the other must lose), outcomes were not considered in the analysis of this dissertation—performance was analyzed. Performance ratings were thoroughly described for participants. This measure enabled participants to focus on process, rather than results, which is influenced less by what one's opponent is doing. Also, since participants often had two games to chose from when completing the monitoring form, each player in a match did not necessarily chose the same game. This would have also reduced the dependency within the dataset.

Another limitation—or more so, a difference from previous literature—is that 'good' performances were analyzed rather than 'best-ever,' 'optimal,' or 'excellent' levels of functioning. Comparing good performances with poor and average performances is less drastic than if the study had examined more extreme performance levels. If a greater frequency of very high performance ratings had been collected, a separate analysis could have grouped performances differently. Perhaps, for instance, four performance levels could have been studied (e.g., poor, average, good, and great). Such a nuanced breakdown of performance has not been conducted in previous studies.

Finally, while the participants in this study qualify as expert tennis players with more than 10 years of experience in the sport, they are not world-class athletes. Hanin (2000a, 2007) has argued that emotion-performance modeling is more effective with more experienced, self-aware, ultra-elite athletes. Relative to many of the IZOF and IAPZ studies in the field, the current sample could be considered less elite. A more elite sample might have improved the accuracy of the models, and provided more very high performance ratings.

Dual-role: investigator and consultant. The primary investigator and author of this dissertation worked with most of the participants in this study as the tennis team's mental training consultant for two years prior to data collection (the study began in the author's third year with the team). Over the years, a variety of sport psychology topics were discussed and skills were developed. It should be noted that none of the participants had previous experience in developing feeling-performance profiles. It is, nevertheless, important to acknowledge the duel-role that the investigator held in this study. The rapport between the players and the consultant/investigator certainly improved the buy-in and dedication of the participants. However—in spite of instructions by the investigator to provide the most accurate and honest responses possible—the duel-role of the investigator may have also increased the chances of socially desirable responses.

In keeping with the integrated, applied-research, nature of this study, it is interesting to note that the process of collecting data also acted as a sort of a sport psychology intervention for many players. Upon completion of the study, most of the participants explained that completing the forms (i.e., monitoring their performance and their feelings) forced them to be more emotionally self-aware. For all but one player, this was a beneficial thing, as it helped them to correct harmful feelings and to focus more on helpful feelings. From a research perspective, this confound is neither rare, nor is it overwhelmingly problematic. Measuring variables—whether by interview, psychometric assessment, force plate, or respirometer—often has some affect on the participant. In the case of this dissertation, this influence was unavoidable. However, it should be acknowledged that monitoring feelings and performance during matches may have influenced the actual feelings and performance of players during those matches. Future studies should assess participants' emotional regulation skills and emotional intelligence before and after the monitoring process.

Future Research Directions

Future analyses of this data set. The data collected for this dissertation has the potential for a great deal of further analysis. Extensive 'data mining' provides a dubious foundation for the development of generalizable theories due to the possibility of capitalizing on chance. This study offers a unique sample size that is sufficient for more elaborate statistical analyses. In addition to the future directions identified throughout the discussion chapter, other analyses with the current data set are described below.

For instance, it may be possible to nest feelings states within players or within valence-function categories using multilevel models or latent variable models. Additionally, researchers interested in momentum could conduct time series analyses within matches (combining participants). Does being in-zone in one game influence the probability of being in-zone or of performing well in the subsequent game? How long does being in-flow, in-zone, or performing exceptionally well, have a positive influence on subsequent performances?

Most of all, because each observation assessed challenge and skill ratings (standard indices of challenge-skill balance (See, Csikszentmihalyi & Larson, 1987; Csikszentmihalyi, et al., 1993; Jackson & Csikszentmihalyi, 1999)) a number of flow-related studies could be conducted. This could include a direct comparison of how feeling states and flow states influence performance. For example, which predicts performance better, being in-flow, or being in-zone. Comparing effect sizes of flow and feeling data would be particularly interesting from a statistical perspective. Another important line of inquiry includes the relationship between flow and affect. Based in Csikszentmihalyi and colleague's (Csikszentmihalyi, 1994, 1997; Csikszentmihalyi & LeFevre, 1989; Jackson & Csikszentmihalyi, 1999) descriptions of flow, it is clear that flow is a positive state that may be associated with performance, but is not required to. Flow is a state of optimal experience, not optimal functioning—though Jackson seems to favor the performance benefits of flow more than Csikszentmihalyi (Gould, Eklund, & Jackson, 1992; Jackson, 2000; Jackson & Kimiecik, 2008; Jackson & Roberts, 1992). Consequently, flow should correlate: positively with positive valence; negatively with negative valence; and the relationship with valence should not vary based on functionality of feelings. In short, if flow is a positive, optimal experience and not about functioning, flow should correlate more strongly with valence than function.

Future research beyond this study. It would be interesting to study context effects in a sport where the contrast between contexts are greater than in tennis. Offense-defense comparisons in basketball, or comparing high school football players who play multiple positions would make for excellent samples. However it is executed, more should be known about the context dimension of the psychobiosocial state.

Nearly all studies published in the area of emotion-performance relationships have focused on establishing zones and comparing the size and location of zones. While valuable, these questions may be ignoring much more important questions about how the zones are controlled. Researchers ask, 'how big is the zone?' but they should also be asking: 'how often are you in-zone?' and 'how much control do you have over each feeling?' Does it matter how small the zone is if the player is able to get into that zone almost all of the time? How much control an athlete has over each feeling in his or her profile may be more important in designing an intervention or psychological skills training program. From an applied perspective, athletes would benefit most from research that can: (a) determine which items are most influential; (b) how much control athletes have over those items; (c) and then developing skills and routines that facilitate self-regulation of these critical performance factors.

Future publications in this area of research should consider the benefits of establishing standard descriptive statistics for IZOF/IAPZ models. Such data might include the distribution of performance ratings in either scale or ordinal form. Another valuable statistic would be the percentage of significant interindividual differences in zone shapes (i.e., intensity and size). This statistic would offer a general index of the degree to which idiographic differences exist. Finally, it is critically important for this field of research to develop individual models that accurately predict performance. There is little value in establishing individual zones if the profiles cannot accurately predict performance. To this end, it is surprising and frustrating that the accuracy statistics from this dissertation cannot be compared to other published studies. Such a statistic would likely over-estimate the accuracy of each profile because the zones were estimated from the same sample of performances that the accuracy of the model was tested against. Regardless, this is an important statistic, which helps to validate the models in each study. In future studies, such a capitalization on chance could be assessed by developing individual profiles from a series of initial performances before testing the accuracy of the zones against a series of subsequent performances for each participant.

Applied Implications

The tennis laboratory. Tennis is an excellent sport to conduct research in. It requires both athleticism and skill. There are long intervals of play (tennis points are longer than the average play in football and baseball, or a shift in hockey), followed by short breaks between points and longer breaks between games and sets. It is an individual sport, so participants' performance levels and feelings are more "controlled for" than in team sports. Although tennis is not as "emotionally intensely" as rugby, hockey, football, and many other sports, it is more emotional than typical aiming sports, track and field, etc. Also, tennis is a long rollercoaster. A player can be performing at his absolute best in one set, and then drop the next set at love (0-6). A player may go from flow to frustration in a matter of just one or two games. Accordingly, tennis is a sport that provides an excellent laboratory for feeling-performance research.

However, if a researcher has sufficient buy-in from a team, many other sports could provide unique insight into the relationship between feeling states and athletic functioning. For instance, hockey players could monitor performance and feelings between shifts; football players could do so between possessions; and volleyball and basketball players could complete forms while sitting on the bench after substitutions. More researched should be conducted in a variety of sports. Such information might challenge existing theories of emotion and feeling in athletic competition.

What these results mean for practitioners. What, do the results from this dissertation mean for coaches, athletes, and sport science consultants? Feeling-performance profiling is a fascinating area of research because it is highly theoretical, complex, and it requires advanced statistical analyses—yet it also has enormous practical implications and must be disseminated in basic, straightforward terms for practitioners. Four very important results could be disseminated to coaches, athletes, parents, and administrators such as coaching educators and league officials.

Idiosyncrasy. First, there is further support for the essentially unequivocal finding that individuals differ in their feeling-performance profiles. Not only do the size and intensities of idiographic zones vary, but so to do the choice of discrete feeling items. In fact, individuals may vary more in terms of the factors that they feel are most influential to their performance, than they do in the shape of their idiographic profiles. Everyone in sport should understand that emotions are not barriers to optimal performance: they are essential for optimal performance. Athletes are better served by understanding and working *with* their feelings than from trying to ignore them.

Discrete feelings. In addition to being an important result for researchers, the fact that discrete feelings can be used to develop probabilistic profiles is important in a practical sense. First, discrete descriptions of feeling states are more personally meaningful to people than valence and arousal ratings. Second, the development of probabilistic profiles has a very simple and profoundly important meaning. Though Hanin has always emphasized such probabilistic relationships, his profiles and in-/out-of zone hypothesis reinforce a more black-and-white relationship between zones and performance. The beauty of probabilistic profiling is that it promotes an important truth for practitioners: preparation gives athletes a better *chance* to perform well—but *nothing* can be certain. As such, the more we do to prepare and be 'in zone,' the more likely we are to succeed.

Can an athlete have multiple zone profiles? The results from this study clearly support the notion that athletes have similar profiles for when they serve compared to when they return serve. Tennis players want to remain in a fairly stable zone during a match. However, athletes from all sports should identify when they may benefit from adjusting their feelings, emotional constellations, or emotional thermostats. Are their times when a player should be a little more aggressive, try to be extra-confident, or very relaxed? Basketball provides a clear and indisputable example. Even the most intense players must shift their attitude and feeling while shooting free-throws. A football player might benefit from breaking the huddle and surveying the defense (before the start of the play) in a more relaxed state so as to make the right reads and decisions—then raise his intensity during the play. Athletes should not only know what feelings comprise their individual profiles, but also know how to adjust their feelings in certain situations. To some degree, athletes may need different attitudes for different contexts (e.g., playoffs versus regular season, rivalry games, starts of matches versus the second half).

Keep it simple. The final implication for practitioners in sport is to keep it simple. Based on the results of this study, a combination of three personally meaningful, athlete-selected, discrete feelings will more accurately predict performance than a compete Individual Emotion Profile. Coaches are responsible for an incredible number of things. They are stretched in every possible direction by parents, administrators, sport scientists, and most of all, by their players. As such, sport science consultants must be careful not to overwhelm coaches with every possible sport psych, biomechanics, or nutritional topic on earth. Emotional profiling offers two essential things for coaches: it is important and it can be simple. Simply stated, coaches and athletes get a great bang for their buck. Profiling does not demand too much time, yet the information gained is truly essential to optimizing performance. All coaches, players, teammates, and consultants should know the 2-4 factors that most strongly influence each athlete's performance within a team/training group. If I know that Judy needs to be calm and confident, and that Harold needs to be aggressive but not be angry, I am better informed to help Judy and Harold reach their performance goals. I recommend that athletes share this information with their coaches and teammates. This discussion of applied information for coaches continues in the final section of this dissertation.

What coaches can do. Though highly theoretical, this research can be useful to coaches. In fact, while the full procedure used in this study may not be pragmatic, the *process* of developing profiles is a useful tool for coaches and parents. Developing profiles with athletes involves reflecting on previous best and worst performances, considering the importance of various feeling states, and sharing beliefs about what it takes to perform at one's best. This process improves emotional and metacognitive awareness in athletes. But more importantly, it can help coaches to understand their players better while also building rapport. In my view, rapport between coaches and their players is the single most important factor in effective coaching. Talking about how athletes feel shows athletes that their coaches care about them as people. Along with the necessary discussion about emotions, these profiling activities can segue into teaching emotional-regulation and life skills to athletes. Finally, coaches and athletes can use the information gained from this process to develop more effective and individualized precompetition routines and coping strategies (See Gould, et al., 2009).

Not only does developing individualized feeling-performance profiles provide coaches, mental trainers, and athletes with important information about how athletes perform at their best, but the process of acquiring this knowledge also helps practitioners to build closer relationships and better routines within teams. There are so many unanswered questions in sport psychology! Sport psychologists must continue to work more closely with coaches and athletes in order to share their knowledge, as well as to learn from their more applied counterparts. In my experiences, working with athletes will also help researchers to identify new and important questions. Our future is very bright.

APPENDIX

Figure 2

Example of the First Form from the Stepwise Individual Emotion Profiling (IEP) System

IZOF-Based Emotion-Profiling: Step-Wise Procedures

You are asked to complete a series of forms that will help to identify your individualized zone of optimal functioning in sport. The first form has you reflect on your best- and worst-ever performances over the past year or two. If possible, try to focus on more recent performances. When reflecting these competitions, focus mostly on what you thought, did, and felt during the performance. Please do not reflect on post-match events; we want to focus our assessment on feelings during and before competition. Subsequent forms will help to describe your zone of optimal functioning in terms of the descriptors that matter for you, and the intensity range that is related to best and worst performances! Finally, we will create a visual figure that describes the zones that are associated with your most functional and dysfunction performance states.

Step 1: Identify BEST EVER and WORST EVER Performances

BEST EVER Competition:	***WORST EVER Competition:***
Date: Location:	Date: Location:
Competition:	Competition:
Result:	Result:
Details: (environment, opponents, feelings, etc)	Details: (environment, opponents, feelings, etc)
Date: Location:	Date: Location:
Competition:	Competition:
Result:	Result:
Details: (environment, opponents, feelings, etc)	Details: (environment, opponents, feelings, etc)
Date: Location:	Date: Location:
Competition:	Competition:
Result:	Result:
Details: (environment, opponents, feelings, etc)	Details: (environment, opponents, feelings, etc)

Figure 3

The Positive-Negative Affect (PNA-77) Scale: The second IEP form

Step 2: Identify HELPFUL-Positive and HELPFUL-Negative Emotions

Go over the list of HELPFUL-positive (pleasant) emotions below and select from the list 2-4 words that describe the emotions you felt before your **best ever** match in the recent past. You may **select only one word on the same line.** Circle the words you select. If you don't find a word describing an emotion that is important to you, **you may add you own word** to the list. Follow the same procedure for HELPFUL-Negative emotions: these are normally unpleasant emotions that you feel help you. Please select at least two (2) items for each positive and negative list.

<u>HELPFUL-POSITIVE FEELINGS (P+):</u>

active, dynamic, energetic, vigorous
relaxed, comfortable, easy
calm, peaceful, unhurried, quiet
cheerful, merry, happy
confident, certain, sure
delighted, overjoyed, exhilarated
determined, set, settled, resolute
excited, thrilled
brave, bold, daring, dashing
glad, pleased, satisfied, contented
inspired, motivated, stimulated
lighthearted, carefree
nice, pleasant, agreeable
quick, rapid, fast, alert
Your own emotion: ________________

<u>HELPFUL-NEGATIVE FEELINGS (N+):</u>

afraid, fearful, scared, panicky
angry, aggressive, furious, violent
annoyed, irritated, distressed
anxious, apprehensive, worried
concerned, alarmed, disturbed, dissatisfied
discouraged, dispirited, depressed
doubtful, uncertain, indecisive, irresolute
helpless, unsafe, insecure
inactive, sluggish, lazy
intense, fierce
jittery, nervous, uneasy, restless
sorry, unhappy, regretful, sad, cheerless
tense, strained, tight, rigid
tired, weary, exhausted, worn out
Your own emotion: ________________

Step 3: Identify HARMFUL-Negative and HARMFUL-Positive Emotions

Follow the same procedure as for step 2, select between two to five (2-4) words to describe the HARMFUL-Negative and HARMFUL-Positive emotions you felt before your WORST EVER competition. **When complete, you should have between 12-16 items.**

<u>HARMFUL-NEGATIVE FEELINGS (N-):</u>

afraid, fearful, scared, panicky
angry, aggressive, furious, violent
annoyed, irritated, distressed
anxious, apprehensive, worried
concerned, alarmed, disturbed, dissatisfied
discouraged, dispirited, depressed
doubtful, uncertain, indecisive, irresolute
helpless, unsafe, insecure
inactive, sluggish, lazy
intense, fierce
jittery, nervous, uneasy, restless
sorry, unhappy, regretful, sad, cheerless
tense, strained, tight, rigid
tired, weary, exhausted, worn out
Your own emotion: ________________

<u>HARMFUL-POSITIVE FEELINGS (P-):</u>

active, dynamic, energetic, vigorous
relaxed, comfortable, easy
calm, peaceful, unhurried, quiet
cheerful, merry, happy
confident, certain, sure
delighted, overjoyed, exhilarated
determined, set, settled, resolute
excited, thrilled
brave, bold, daring, dashing
glad, pleased, satisfied, contented
inspired, motivated, stimulated
lighthearted, carefree
nice, pleasant, agreeable
quick, rapid, fast, alert
Your own emotion: ________________

Figure 4

Example of the Monitoring Form used by Participants

Type of Game: Serve / Return **Result:** Won / Lost **Set Score:** ___ - ___ (you / him)

Rate your feelings about...

My performance was:	Poor				Average						Good
Performance:	0	1	2	3	4	5	6	7	8	9	10
The challenge of the game (task) was:	Poor				Average						Good
Challenge:	0	1	2	3	4	5	6	7	8	9	10
My skills to meet my goals for the game were:	Poor				Average						Good
Skill:	0	1	2	3	4	5	6	7	8	9	10

Intensity Scale

0	nothing at all
0.5	very very little
1	very little
2	little
3	moderate
4	
5	much
6	
7	very much
8	
9	
10	very very much
11*	maximal possible

Emotional Intensity

(P+)	________	0	.5	1	2	3	4	5	6	7	8	9	10	11*
(P+)	________	0	.5	1	2	3	4	5	6	7	8	9	10	11*
(P+)	________	0	.5	1	2	3	4	5	6	7	8	9	10	11*
(P+)	________	0	.5	1	2	3	4	5	6	7	8	9	10	11*
(N+)	________	0	.5	1	2	3	4	5	6	7	8	9	10	11*
(N+)	________	0	.5	1	2	3	4	5	6	7	8	9	10	11*
(N+)	________	0	.5	1	2	3	4	5	6	7	8	9	10	11*
(N+)	________	0	.5	1	2	3	4	5	6	7	8	9	10	11*
(N-)	________	0	.5	1	2	3	4	5	6	7	8	9	10	11*
(N-)	________	0	.5	1	2	3	4	5	6	7	8	9	10	11*
(N-)	________	0	.5	1	2	3	4	5	6	7	8	9	10	11*
(N-)	________	0	.5	1	2	3	4	5	6	7	8	9	10	11*
(P-)	________	0	.5	1	2	3	4	5	6	7	8	9	10	11*
(P-)	________	0	.5	1	2	3	4	5	6	7	8	9	10	11*
(P-)	________	0	.5	1	2	3	4	5	6	7	8	9	10	11*
(P-)	________	0	.5	1	2	3	4	5	6	7	8	9	10	11*

Comments (Not necessary, but please include if there is something you would like to note):

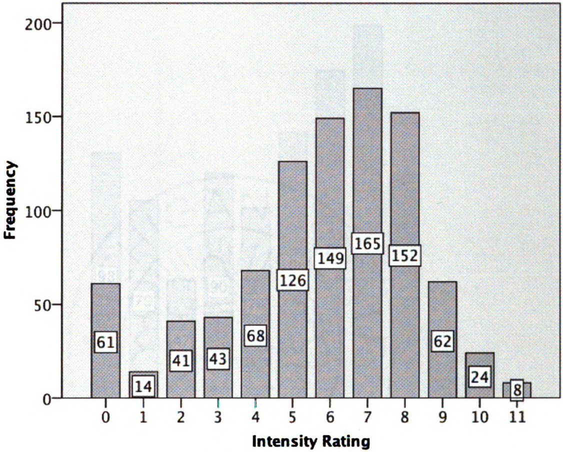
____

____

____

Figure 6

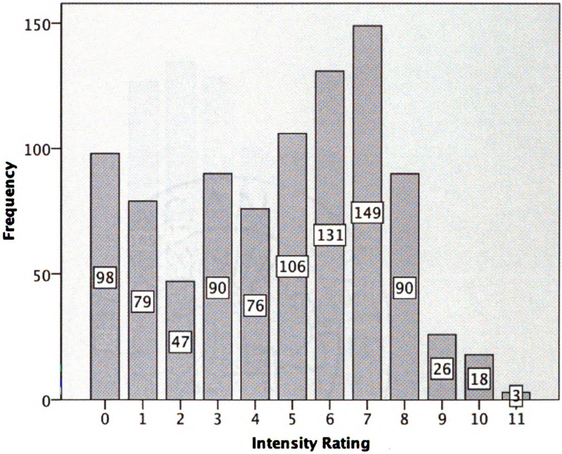
Frequency of Combined Positive-Functional Intensity Ratings for All Participants



Note. Values within each column represent the number of observations across feeling intensity. The distribution of intensity ratings includes poor, average, and good performances.

Figure 7

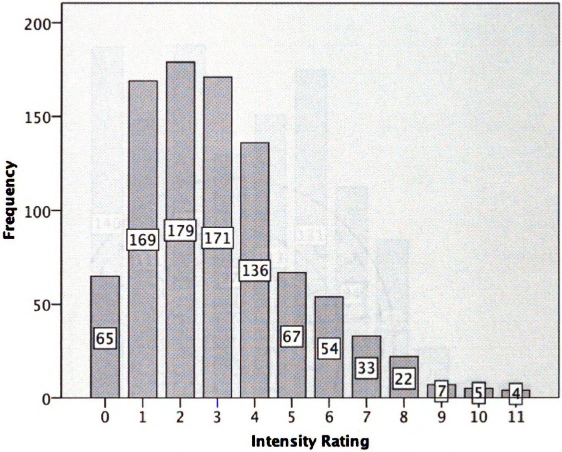
Frequency of Combined Negative-Functional Intensity Ratings for All Participants



Note. Values within each column represent the number of observations across feeling intensity. The distribution of intensity ratings includes poor, average, and good performances.

Figure 8

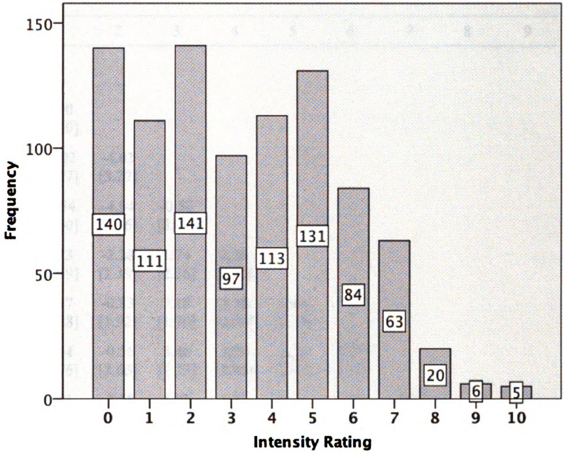
Frequency of Combined Negative-Dysfunctional Intensity Ratings for All Participants



Note. Values within each column represent the number of observations across feeling intensity. The distribution of intensity ratings includes poor, average, and good performances.

Figure 9

Frequency of Combined Positive-Dysfunctional Intensity Ratings for All Participants



Note. Values within each column represent the number of observations across feeling intensity. The distribution of intensity ratings includes poor, average, and good performances.

Table 8

Interindividual Comparisons of Mean Difference [and Variance] for Positive-Functional Feeling Intensities during Poor Performances

	1	2	3	4	5	6	7	8	9
1	-								
2	**4.00** [1.50]	-							
3	-0.02 [2.17]	**-4.02** **[3.27]**	-						
4	-0.54 [1.60]	**-4.54** [1.06]	-0.52 [3.47]	-					
5	**1.73** [1.09]	**-2.28** [1.39]	1.74 [2.36]	**2.26** [1.47]	-				
6	**3.17** [1.28]	-0.83 [1.92]	3.18 [1.70]	**3.70** [2.04]	1.44 [1.39]	-			
7	**3.44** [1.76]	-0.56 **[2.65]**	**3.46** [1.23]	**3.98** **[2.82]**	**1.72** [1.91]	0.27 [1.38]	-		
8	1.21 [1.99]	**-2.79** **[3.00]**	1.23 [1.09]	1.75 [3.18]	-0.51 [2.16]	-1.96 [1.56]	**-2.27** [1.13]	-	
9	**-1.47** **[4.27]**	**-5.48** **[2.84]**	-1.75 **[9.27]**	-0.94 [2.67]	**-3.20** **[3.93]**	**-4.64** **[5.46]**	**-4.91** **[7.52]**	**-2.69** **[8.50]**	-
10	1.19 **[2.92]**	**-2.81** **[4.39]**	1.21 [1.34]	1.73 **[4.67]**	-0.53 **[3.17]**	-1.98 [2.28]	**-2.25** [1.66]	-0.02 [1.47]	**2.67** **[12.46]**

Note. Mean differences (player on left column subtracted from player on top row) are represented by Dunnett's C post-hoc comparisons. Significant values at a .05 level are represented in bold. Variance values are represented by the F-Ratio of each player's variance. Significant values at a .01 level are represented in bold.

Table 9

Interindividual Comparisons of Mean Difference [and Variance] for Positive-Functional Feeling Intensities during Average Performances

	1	2	3	4	5	6	7	8	9
1	-								
2	1.23 **[2.62]**	-							
3	-0.88 **[2.51]**	**-2.11** [1.05]	-						
4	-0.48 [2.06]	**-1.72** [1.27]	0.40 [1.22]	-					
5	-0.18 **[2.30]**	**-1.42** [1.14]	0.70 [1.09]	0.30 [1.11]	-				
6	**1.19** [1.87]	-0.04 **[4.90]**	**2.07** **[4.69]**	**1.67** **[3.86]**	**1.37** **[4.30]**	-			
7	0.07 [1.49]	-1.16 [1.76]	0.95 [1.68]	0.56 [1.39]	0.26 [1.54]	-1.12 **[2.78]**	-		
8	-0.12 [2.00]	**-1.35** [1.31]	0.76 [1.25]	0.36 [1.03]	0.06 [1.15]	**-1.31** **[3.75]**	-0.19 [1.35]	-	
9	**-1.52** [1.84]	**-2.76** **[4.82]**	-0.64 **[4.62]**	**-1.04** **[3.80]**	**-1.34** **[4.23]**	**-2.72** [1.02]	**-1.60** **[2.74]**	**-1.40** **[3.69]**	-
10	-0.68 [1.01]	**-1.92** **[2.65]**	0.19 **[2.54]**	-0.20 **[2.09]**	-0.50 **[2.32]**	**-1.88** [1.85]	-0.76 [1.51]	-0.57 **[2.03]**	**0.84** [1.82]

Note. Mean differences (player on left column subtracted from player on top row) are represented by Dunnett's C post-hoc comparisons. Significant values at a .05 level are represented in bold. Variance values are represented by the F-Ratio of each player's variance. Significant values at a .01 level are represented in bold.

Table 10

Interindividual Comparisons of Mean Difference [and Variance] for Positive-Functional Feeling Intensities during Good Performances

	1	2	3	4	5	6	7	8	9
1	-								
2	0.73 **[11.06]**	-							
3	**-1.84** **[3.65]**	**-2.56** **[3.03]**	-						
4	0.15 **[6.99]**	-0.58 [1.58]	**1.98** [1.91]	-					
5	0.19 **[4.36]**	-0.53 [2.54]	**2.03** [1.19]	0.05 [1.60]	-				
6	**1.64** **[6.00]**	0.91 **[66.36]**	**3.47** **[21.92]**	**1.49** **[41.95]**	**1.44** **[26.18]**	-			
7	**-1.73** [1.36]	**-2.45** **[8.10]**	0.11 **[2.68]**	**-1.87** **[5.12]**	**-1.92** [3.20]	**-3.36** **[8.19]**	-		
8	-0.79 **[5.01]**	-1.52 [2.21]	1.04 [1.37]	-0.94 [1.40]	-0.98 [1.15]	**-2.43** **[30.07]**	0.93 [3.67]	-	
9	**-1.41** **[5.69]**	**-2.13** **[62.96]**	0.43 **[20.79]**	**-1.55** **[39.79]**	**-1.60** **[24.83]**	**-3.04** [1.05]	0.32 **[7.77]**	-0.62 **[28.53]**	-
10	**-1.17** [1.69]	**-1.90** **[6.55]**	0.67 **[2.16]**	-1.32 **[4.14]**	**-1.36** **[2.58]**	**-2.81** **[10.14]**	0.56 [1.24]	-0.38 **[2.97]**	0.24 **[9.62]**

Note. Mean differences (player on left column subtracted from player on top row) are represented by Dunnett's C post-hoc comparisons. Significant values at a .05 level are represented in bold. Variance values are represented by the F-Ratio of each player's variance. Significant values at a .01 level are represented in bold.

Table 11

Interindividual Comparisons of Mean Difference [and Variance] for Negative-Functional Feeling Intensities during Poor Performances

	1	2	3	4	5	6	7	8	9
1	-								
2	**1.70** **[8.00]**	-							
3	**-4.30** **[7.99]**	**-6.00** [1.00]	-						
4	**-3.70** **[9.55]**	**-5.40** [1.19]	0.59 [1.20]	-					
5	**-3.02** [1.49]	**-4.72** **[5.36]**	1.28 **[5.36]**	0.69 **[6.40]**	-				
6	**-3.89** **[4.57]**	**-5.60** [1.75]	0.40 [1.75]	-0.19 [2.09]	-0.88 [3.06]	-			
7	0.79 [2.01]	-0.91 **[3.98]**	**5.09** **[3.97]**	**4.49** **[4.75]**	**3.81** [1.35]	**4.68** **[2.27]**	-		
8	**-4.26** [1.34]	**-5.96** **[10.74]**	0.04 **[10.72]**	-0.55 **[12.82]**	-1.24 [2.00]	-0.36 **[6.14]**	**-5.05** **[2.70]**	-	
9	**-2.92** **[10.56]**	**-4.62** [1.32]	1.38 [1.32]	0.79 [1.11]	-0.10 **[7.08]**	0.98 [2.31]	**-3.71** **[5.25]**	1.34 **[14.17]**	-
10	-0.89 [2.15]	**-2.60** **[3.73]**	**3.40** **[3.72]**	**2.81** **[4.45]**	2.12 [1.44]	**3.00** [2.13]	**-1.68** [1.07]	**3.36** [2.88]	**2.02** **[4.92]**

Note. Mean differences (player on left column subtracted from player on top row) are represented by Dunnett's C post-hoc comparisons. Significant values at a .05 level are represented in bold. Variance values are represented by the F-Ratio of each player's variance. Significant values at a .01 level are represented in bold.

Table 12

Interindividual Comparisons of Mean Difference [and Variance] for Negative-Functional Feeling Intensities during Average Performances

	1	2	3	4	5	6	7	8	9
1	-								
2	-1.51 [1.18]	-							
3	**-4.39** [1.94]	**-2.88** [1.65]	-						
4	**-3.83** **[6.71]**	**-2.32** **[5.70]**	0.56 **[3.46]**	-					
5	-1.18 **[3.50]**	0.33 **[2.98]**	**3.20** [1.80]	**2.64** **[1.92]**	-				
6	**-2.23** **[3.26]**	-0.71 **[2.77]**	**2.16** [1.68]	**1.60** [2.06]	-1.04 [1.07]	-			
7	**-3.35** **[3.39]**	**-1.84** **[2.88]**	1.04 [1.75]	0.48 [1.98]	**-2.17** [1.03]	-1.12 [1.04]	-		
8	-0.33 [1.01]	1.18 [1.19]	**4.06** **[1.95]**	**3.50** **[6.76]**	0.86 **[3.53]**	**1.90** **[3.29]**	**3.02** **[3.41]**	-	
9	**-3.43** **[7.47]**	**-1.91** **[6.35]**	0.96 **[3.85]**	0.40 [1.11]	**-2.24** **[2.14]**	-1.20 [2.29]	-0.08 **[2.21]**	**-3.10** **[7.53]**	-
10	**-3.60** **[5.22]**	**-2.09** **[4.44]**	0.79 **[2.69]**	0.23 [1.29]	**-2.42** [1.49]	-1.38 [1.60]	-0.25 [1.54]	**-3.27** **[5.26]**	-0.17 [1.43]

Note. Mean differences (player on left column subtracted from player on top row) are represented by Dunnett's C post-hoc comparisons. Significant values at a .05 level are represented in bold. Variance values are represented by the F-Ratio of each player's variance. Significant values at a .01 level are represented in bold.

Table 13

Interindividual Comparisons of Mean Difference [and Variance] for Negative-Functional Feeling Intensities during Good Performances

	1	2	3	4	5	6	7	8	9
1	-								
2	**-4.01** **[9.57]**	-							
3	**-5.99** **[2.61]**	-1.98 **[3.66]**	-						
4	**-5.04** [1.26]	-1.03 **[12.01]**	**0.95** **[3.28]**	-					
5	**-1.65** **[2.71]**	2.36 **[25.96]**	**4.34** **[7.09]**	**3.38** [2.16]	-				
6	**-2.70** [1.44]	1.31 **[13.80]**	**3.29** **[3.77]**	**2.34** [1.15]	-1.04 [1.88]	-			
7	**-7.25** [1.17]	**-3.24** **[8.18]**	**-1.26** [2.23]	**-2.21** [1.47]	**-5.59** [3.17]	**-4.55** [1.69]	-		
8	-1.20 **[17.08]**	2.81 [1.79]	**4.79** **[6.54]**	3.83 **[21.45]**	0.45 **[46.36]**	1.49 **[24.65]**	**6.04** **[14.61]**	-	
9	**-6.48** **[5.44]**	-2.47 **[52.07]**	-0.48 **[14.22]**	**-1.44** **[4.34]**	**-4.82** [2.01]	**-3.78** [3.77]	0.77 **[6.37]**	**-5.27** **[92.99]**	-
10	**-6.20** **[2.39]**	-2.19 **[22.88]**	-0.21 **[6.25]**	**-1.16** [1.91]	**-4.55** [1.13]	**-3.50** [1.66]	1.04 [2.80]	**-5.00** **[40.87]**	0.27 [2.28]

Note. Mean differences (player on left column subtracted from player on top row) are represented by Dunnett's C post-hoc comparisons. Significant values at a .05 level are represented in bold. Variance values are represented by the F-Ratio of each player's variance. Significant values at a .01 level are represented in bold.

Table 14

Interindividual Comparisons of Mean Difference [and Variance] for Negative-Dysfunctional Feeling Intensities during Poor Performances

	1	2	3	4	5	6	7	8	9
1	-								
2	**-2.80** [1.70]	-							
3	-2.97 [2.09]	-0.18 [1.23]	-						
4	**-1.16** **[26.74]**	**1.63** **[45.37]**	1.81 **[55.81]**	-					
5	**-4.24** [1.21]	-1.45 [1.40]	-1.27 [1.72]	**-3.08** **[32.42]**	-				
6	**-5.06** [2.33]	**-2.27** **[3.95]**	-2.09 **[4.85]**	**-3.90** **[11.50]**	-0.82 [2.82]	-			
7	1.05 [1.68]	**3.85** **[2.85]**	4.02 **[3.51]**	**2.21** **[15.89]**	**5.30** [2.04]	**6.12** [1.38]	-		
8	-0.72 [1.21]	2.08 [1.40]	2.25 [1.72]	0.44 **[32.36]**	**3.53** [1.00]	**4.35** [2.82]	-1.77 [2.04]	-	
9	**-2.35** [1.55]	0.44 [1.10]	0.62 [1.35]	-1.19 **[41.36]**	1.89 [1.28]	**2.71** **[3.60]**	**-3.41** **[2.60]**	-1.63 [1.28]	-
10	**-3.84** [1.94]	-1.04 [1.14]	-0.87 [1.07]	**-2.68** **[51.93]**	0.40 [1.60]	1.22 **[4.52]**	**-4.90** **[3.27]**	**-3.12** [1.60]	-1.49 [1.26]

Note. Mean differences (player on left column subtracted from player on top row) are represented by Dunnett's C post-hoc comparisons. Significant values at a .05 level are represented in bold. Variance values are represented by the F-Ratio of each player's variance. Significant values at a .01 level are represented in bold.

Table 15

Interindividual Comparisons of Mean Difference [and Variance] for Negative-Dysfunctional Feeling Intensities during Average Performances

	1	2	3	4	5	6	7	8	9
1	-								
2	0.16 [1.16]	-							
3	0.45 [1.47]	0.29 [1.27]	-						
4	0.49 **[8.82]**	0.33 **[10.22]**	0.04 **[12.96]**	-					
5	-0.95 [2.18]	**-1.11** **[2.52]**	**-1.40** **[3.20]**	**-1.44** **[4.05]**	-				
6	**-1.72** [2.17]	**-1.88** **[2.51]**	**-2.16** **[3.19]**	**-2.20** **[4.06]**	-0.76 [1.00]	-			
7	**2.39** **[6.27]**	**2.23** **[7.26]**	**1.94** **[9.21]**	**1.90** [1.41]	**3.33** **[2.88]**	**4.10** [2.89]	-		
8	**2.14** **[2.83]**	**1.98** **[3.27]**	**1.69** **[4.15]**	**1.65** **[3.12]**	**3.09** [1.30]	**3.85** [1.30]	-0.25 [2.22]	-	
9	0.28 [1.59]	0.13 [1.84]	-0.16 **[2.33]**	-0.20 **[5.56]**	**1.24** [1.37]	**2.00** [1.37]	**-2.10** **[3.95]**	**-1.85** [1.78]	-
10	0.47 **[1.98]**	0.31 **[2.29]**	0.02 **[2.90]**	-0.02 **[4.46]**	**1.42** [1.10]	**2.18** [1.10]	**-1.92** **[3.17]**	**-1.67** [1.43]	0.18 [1.25]

Note. Mean differences (player on left column subtracted from player on top row) are represented by Dunnett's C post-hoc comparisons. Significant values at a .05 level are represented in bold. Variance values are represented by the F-Ratio of each player's variance. Significant values at a .01 level are represented in bold.

Table 16

Interindividual Comparisons of Mean Difference [and Variance] for Negative-Dysfunctional Feeling Intensities during Good Performances

	1	2	3	4	5	6	7	8	9
1	-								
2	0.38 [1.98]	-							
3	**1.36** [1.87]	0.98 **[3.70]**	-						
4	0.02 **[6.47]**	-0.35 **[12.82]**	**-1.33** **[3.47]**	-					
5	**-1.23** [1.59]	-1.60 **[3.14]**	**-2.58** [1.18]	**-1.25** **[4.08]**	-				
6	**-2.94** [1.05]	**-3.31** [1.88]	**-4.29** [1.97]	**-2.96** **[6.82]**	**-1.71** [1.67]	-			
7	**1.76** **[50.65]**	1.38 **[100.32]**	0.40 **[27.12]**	**1.73** **[7.82]**	**2.98** **[31.91]**	**4.69** **[53.35]**	-		
8	**1.89** **[4.21]**	1.51 **[8.34]**	0.53 [2.25]	**1.87** [1.54]	**3.12** [2.65]	**4.83** **[4.44]**	0.13 **[10.29]**	-	
9	-0.94 [1.66]	-1.31 [3.29]	**-2.29** [1.12]	-0.96 [3.89]	0.29 [1.05]	2.00 [1.75]	**-2.69** **[30.47]**	**-2.83** [2.53]	-
10	0.42 **[4.92]**	0.04 **[9.75]**	-0.93 **[2.63]**	0.40 [1.32]	**1.64** **[3.10]**	**3.36** **[5.18]**	**1.34** **[10.29]**	**-1.47** [1.17]	1.36 [2.96]

Note. Mean differences (player on left column subtracted from player on top row) are represented by Dunnett's C post-hoc comparisons. Significant values at a .05 level are represented in bold. Variance values are represented by the F-Ratio of each player's variance. Significant values at a .01 level are represented in bold.

Table 17

Interindividual Comparisons of Mean Difference [and Variance] for Positive-Functional Feeling Intensities during Poor Performances

	1	2	3	4	5	6	7	8	9
1	-								
2	**-1.75** [1.79]	-							
3	-0.53 **[5.51]**	1.22 [3.07]	-						
4	**1.98** 1.22]	**3.73** [2.18]	2.51 **[6.70]**	-					
5	**2.81** [1.13]	**4.55** [1.58]	3.34 **[4.86]**	0.83 [1.38]	-				
6	**-1.20** [1.41]	0.54 [1.27]	-0.67 **[3.90]**	**-3.18** [1.72]	**-4.01** [1.25]	-			
7	**4.33** **[245.8]**	**6.08** **[441.2]**	**4.86** **[1353.6]**	**2.35** **[202.0]**	**1.52** **[278.8]**	**5.53** **[347.2]**	-		
8	**3.33** **[2.99]**	**5.07** [1.66]	3.86 [1.84]	1.35 [3.63]	0.52 [2.63]	**4.53** [2.11]	-1.00 **[734.2]**	-	
9	**3.77** **[3.11]**	**5.52** **[5.58]**	**4.30** **[17.13]**	**1.79** [2.56]	0.96 [3.53]	**4.97** **[4.39]**	**-0.56** **[79.00]**	0.44 **[9.29]**	-
10	-0.99 **[5.31]**	0.76 [2.96]	-0.46 [1.04]	**-2.97** **[6.46]**	**-3.79** **[4.68]**	0.211 [3.76]	**-5.32** **[1304]**	**-4.32** [1.78]	**-4.76** **[16.51]**

Note. Mean differences (player on left column subtracted from player on top row) are represented by Dunnett's C post-hoc comparisons. Significant values at a .05 level are represented in bold. Variance values are represented by the F-Ratio of each player's variance. Significant values at a .01 level are represented in bold.

Table 18

Interindividual Comparisons of Mean Difference [and Variance] for Positive-Functional Feeling Intensities during Average Performances

	1	2	3	4	5	6	7	8	9
1	-								
2	0.63 [1.96]	-							
3	1.19 **[3.02]**	0.56 [1.54]	-						
4	**2.55** [1.19]	**1.92** **[2.33]**	**1.37** **[3.59]**	-					
5	0.27 **[2.24]**	-0.36 [1.14]	-0.92 [1.35]	**-2.29** **[2.67]**	-				
6	-0.86 [1.61]	**-1.50** **[3.16]**	**-2.05** **[4.86]**	**-3.42** [1.35]	**-1.13** **[3.61]**	-			
7	**4.81** **[12.76]**	**4.18** **[25.04]**	**3.62** **[38.52]**	**2.25** **[10.73]**	**4.54** **[28.60]**	**5.67** **[7.93]**	-		
8	**2.15** **[4.88]**	**1.52** **[2.49]**	0.97 [1.62]	-0.40 **[5.80]**	**1.88** **[2.18]**	**3.02** **[7.85]**	**-2.65** **[62.26]**	-	
9	**4.21** **[2.45]**	**3.58** **[4.82]**	**3.02** **[7.41]**	**1.66** **[2.06]**	**3.94** **[5.50]**	**5.07** [1.53]	**-0.60** **[5.20]**	**2.06** **[11.97]**	-
10	**2.42** [1.57]	**1.79** [1.25]	**1.23** **[1.93]**	-0.14 **[1.86]**	**2.15** [1.43]	**3.28** **[2.52]**	**-2.39** **[20.00]**	0.26 **[3.11]**	**-1.79** **[3.85]**

Note. Mean differences (player on left column subtracted from player on top row) are represented by Dunnett's C post-hoc comparisons. Significant values at a .05 level are represented in bold. Variance values are represented by the F-Ratio of each player's variance. Significant values at a .01 level are represented in bold.

Table 19

Interindividual Comparisons of Mean Difference [and Variance] for Positive-Functional Feeling Intensities during Good Performances

	1	2	3	4	5	6	7	8	9
1	-								
2	0.49 [1.44]	-							
3	0.27 [1.01]	-0.21 [1.43]	-						
4	**1.27** **[3.58]**	0.79 [2.49]	1.00 **[3.55]**	-					
5	**-2.50** [1.75]	**-2.99** [1.22]	**-2.77** [1.74]	**-3.77** [2.04]	-				
6	**-1.63** **[7.47]**	**-2.12** **[5.19]**	**-1.90** **[7.42]**	**-2.90** [2.09]	0.87 **[4.26]**	-			
7	**3.97** **[0.00]**	**3.48** **[0.00]**	**3.70** **[0.00]**	**2.70** **[0.00]**	**6.47** **[0.00]**	**5.60** **[0.00]**	-		
8	0.36 [2.80]	-0.13 **[4.03]**	0.08 **[2.82]**	-0.92 **[10.02]**	2.86 **[4.92]**	1.99 **[20.92]**	**-3.61** **[0.00]**	-	
9	**2.97** [2.99]	2.48 [2.08]	**2.70** [2.97]	1.70 [1.20]	**5.47** [1.70]	**4.60** [2.50]	-1.00 **[0.00]**	2.61 **[8.37]**	-
10	**2.12** **[2.59]**	**1.63** [1.80]	**1.85** **[2.57]**	0.84 [1.38]	**4.62** [1.48]	**3.75** [2.88]	**-1.85** **[0.00]**	1.76 **[7.26]**	-0.85 [1.15]

Note. Mean differences (player on left column subtracted from player on top row) are represented by Dunnett's C post-hoc comparisons. Significant values at a .05 level are represented in bold. Variance values are represented by the F-Ratio of each player's variance. Significant values at a .01 level are represented in bold.

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