ANALYTICS IN PROFESSIONAL SPORTS:
APPLICATIONS OF ANALYTICS IN TENNIS

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THESIS

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ABSTRACT

Data analytics in professional sports has become a major part of competition in the last two decades, especially in major sports such as American football, basketball, baseball, and soccer. Professional tennis has not developed analytics to this level yet, but there is a litany of research on the different technology platforms that are currently available and being developed for the sport. However, little is being done to understand the applications and uses of these technologies by the professional tennis players and coaches that they are designed for. Thus, the purpose of this study was to investigate the role analytics play in professional and elite level tennis as perceived by its users.

Using a qualitative research approach, this study explored the attitudes of coaches towards tennis analytics, and how they would like to see technology develop to create a more effective product. Data collection was done through individual, semi-structured interviews with nine coaches of professional tennis players. These interviews were then transcribed verbatim and analyzed using pattern coding. Findings showed that video review and analytics from match statistics are common applications of analytics used currently by professional tennis coaches. These are viewed as very helpful in the preparation of their players for future matches, but other forms of analytics such as practice review are not widely used. Future developments should focus on reliability and accuracy improvements to further increase usefulness of tennis analytics.

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CHAPTER 1: INTRODUCTION

Analytics in sports have been popularized by movies such as *Moneyball*, where computer-driven data analysis was used to find undervalued baseball players (Miller, 2011). More recently, analytics to determine winning tactics, develop practice regimens, and scout opposing players have come to the forefront of major sports (Cokins & Schrader, 2017). Data collected by modern cameras allow for Major League Baseball (MLB) pitchers to better choose in what fashion they are going to throw the ball depending on the opposing player and the environment (Streib, Young, & Sokol, 2012). Film review and analysis is similar in concept to pitching analytics, in which players in various sport organizations such as the National Basketball Association (NBA), National Football League (NFL), and international soccer leagues all watch previous recordings of both their own games as well as their opponents to better understand themselves and who they are playing (Thomas et al., 2017).

These developments have been brought on as a result of competition and a need for performance advantages. In the tennis analytics space, there are a lot of data collected from a camera system called Hawkeye that is employed in almost all professional competitions. The Hawkeye system is comprised of 10 high-speed cameras that capture video at 2000 frames per second. The cameras are split into five on each side of the court, with one camera on each side capturing one axis of the ball to render a 3D image. The other two cameras on each are used to collect player location data. This means that the location of both the player and the ball are recorded at all times by Hawkeye (Baodong, 2014). There exist a multitude of other analytics platforms for tennis such as PlaySight, which is a similar camera-based system, as well as other wearable analytics (Renò et al., 2017). However, through my personal experience working with the United States Tennis Association (USTA) as well as a staff member of University of Illinois

Tennis, I have observed a distinct disconnect between the analytics technology that is available and the actual knowledge of these tools possessed by players and coaches out in the field. Too often I have heard questions and thoughts from coaches wishing for some form of technological aide that already exists. This has also been noted by Zaharia and Kaburakis (2016), who have highlighted inconsistencies between research and industry practice.

While there have been studies done primarily on the four major American sports of baseball, football, basketball, and hockey related to the importance of analytics to the different teams (e.g., the Oakland A's from *Moneyball*), there is a gap in the literature when the focus is put on tennis (ESPN, 2015; Streib et al., 2012, Thomas et al., 2017). A lot of research exists into the different technological platforms of tennis analytics, mostly done by the developers of the differing technologies. For sports such as basketball and baseball, there is some qualitative research and interviews of users into their perceptions of modern-day analytics. Reports such as Davenport's study interviews several high-profile individuals such as Darryl Morrey, who revolutionized the modern game of basketball by using analytics to highlight the 3-point shot, to provide a social science perspective on analytics in the four major sports (2014). However, there is little research as to how analytics technology is actually perceived and utilized by players and coaches in tennis. Thus, the purpose of this study is to investigate the role analytics play in professional and elite level tennis as perceived by its users.

Conceptual Framework

Innovation Diffusion Theory (IDT) and the Technology Acceptance Model (TAM) will provide a conceptual framework for this research to understand the process by which individuals and organizations embrace and incorporate new technology (Al-Rahmi et al., 2019). IDT contends that there are five pillars that affect innovation adoption – relative advantage,

compatibility, complexity, trialability, and observability. According to IDT, these five traits determine the ability of a given innovation to spread (Al-Rahmi et al., 2019). While similar to IDT, TAM looks more specifically at the adoption of human-machine interactions, and states that this relies on whether people perceive that new technology would benefit their work without adding a degree of difficulty (Davis et al., 1989). In other words, TAM focuses on the experience users have with a new technology itself and how well the product is designed to maximize this experience, while IDT also considers sociological factors in professional settings to see how innovation will spread. These two theories will inform interview questions and continue to provide a perspective to analyze the responses of participants.

TAM also has two main constructs in perceived usefulness (PU) and perceived ease of use (PEU) that help to understand how human-machine interactions develop. Perceived usefulness relates to whether or not people find the given new technology to be important. In other words, if a new innovation will be additional value. This is weighed against perceived ease of use, where the degree of difficulty of learning and adopting a new machine interface is defined. Perceived value is a similar measure that was used in this study and is similar to PU in that both seek to understand how valuable users view a certain technology. In this case, perceived value was only applied to individuals with personal experience with tennis analytics platforms.

Research Questions

This study will look to answer the following questions:

1. How, if at all, do coaches of elite tennis players use analytics in their work?

2. What is the perceived value of tennis analytics by these coaches?

3. What advances in tennis analytics would coaches like to see to help them better apply the technology?

Significance of the Study

While plenty of literature exists for the actual different technological means of collecting and creating tennis analytics, little has been done on the social science side of seeing how these means are actually being used (Baodong, 2014; Kovacs et al., 2007, Mlakar & Luštrek, 2017). Similarly, little research has explored players' and coaches' perspectives on them for actually playing tennis. This should be the most important knowledge as the end goal of these analytical platforms is to be of use for players and coaches and to help them perform better. Information obtained from this investigation can aid the development of future technologies that result in more useful analytics for tennis and inform development of more user-friendly interfaces or clearer user manuals. Further, the findings of this study can help organizations understand how to adopt new technologies more effectively and efficiently. This is important to tennis organizations specifically as knowledge from other major team sports may not be generalizable to tennis contexts.

CHAPTER 2: LITERATURE REVIEW

Theory Background

New technological advances have come at a much faster rate in recent years and has been well-documented in various studies across different industries (Karahanna et al., 1999, Al-Rahmi et al., 2019). Innovation Diffusion Theory (IDT) is used to understand how people choose to adapt to changes in technology and contends that "potential users make decisions to adopt or reject an innovation based on beliefs that they form about the innovation" (Agarwal, 2000). These "beliefs" can be classified into five different categories – relative advantage, compatibility, complexity, trialability, and observability. Relative advantage refers to the perception of the user that there is either a benefit or not to using the given new technology. Compatibility is how well the change fits into the existing workflow of the user, while complexity denotes the difficulty in learning the technology itself. Trialability can sometimes refer to the implementation system; however, IDT looks specifically at the product itself and the ease with which it can be quickly tested by customers to get a feel for the product. Finally, observability relates to the ability of users to see their peers use the product and help them with adopting new technology. Essentially, IDT proposes that if a given user finds a new innovation that provides adequate advantages for them without too much of a learning curve, then the innovation is much more likely to be adopted. However, if the change is believed to require more effort to adapt to than the conveniences it may provide then it is much less likely that the innovation will be well-received by its users. This theory has been previously applied to sport management research to understand how innovation is being accepted in this space (Seifried et al., 2017)

The Technology Acceptance Model (TAM) is an earlier model that looked at two main concepts to understand the adoption of new technology, perceived usefulness (PU) and perceived ease of use (PEU; Davis et al., 1989). This can be combined with the five categories of IDT to provide a comprehensive tool for understanding the results from this study. An example of using a combination of TAM and IDT to understand use of new technologies was done by Lee et al. (2020). This study investigated the use of e-learning systems in major Taiwanese businesses. Results indicated that compatibility, complexity, relative advantage, and trialability had a significant effect on the PU and PEU of e-learning systems (Lee et al., 2020). Just as IDT has been applied in the sport management industry, the same has been done with TAM to see how sport organizations have accepted new technologies (Mohammadi & Isanejad, 2018). A similar approach can be used to understand the perceived usefulness and perceived ease of use of tennis analytics by professional tennis coaches.

Overview of Sports Analytics

Analytics are simply the use of data to make informed decisions (Modello & Kamke, 2014). Anything from market research by real estate firms to targeted ads by internet giants such as Google can be considered analytics. Sports analytics refers more specifically to the sports industry, and can be classified as descriptive, predictive, or prescriptive (Davenport & Harris, 2007). Descriptive analytics organizes data to allow for comprehension but does not usually provide answers as to how to fix problems. Predictive analytics combines current data with previous data to forecast trends, but this method often is unreliable given any unforeseen circumstances. Prescriptive analytics are the most common form of analytics across all industries, with an example being optimization to fix existing problems (Davenport & Harris, 2007).

Current forms of sports analytics can be split into two types, front-office and back-office analytics (Fried & Mumcu, 2017). Front-office analytics is similar to customer relationship management (CRM) platforms that analyze fan experience, season ticket renewals, etc. Strategies such as ticket office optimization, concessions forecasting, and TV ratings are all examples of front-office analytics. This type of sports analytics focuses on consumers of the sport, while back-office analytics focuses more on the athletes, the playing of the sport, and how teams and individuals can improve. No matter the type of sports analytics, there is consensus among professionals that analytics will only become more important in the future. In a study by Davenport and Harris (2007) involving more than 100 senior managers in the sports industry, 96% of participants foresaw analytics as increasingly important in the next three years. This corresponds to Davenport's study in 2014 that found all 32 NBA teams to have some form of in-house analytics team. However, it is interesting to note that this trend does not apply to the use of analytics during play of live sports. This is because several professional leagues have existing regulations against these practices, where taping and analyzing opponents in-game may be classified as cheating. Another concern is that analytics may develop like an arms race, where larger market teams may have a financial advantage that equates to better technology and more analytics personnel. Leagues, such as MLB, have attempted to confront this issue by limiting data sets that teams may use (Davenport, 2014). Under these regulations all teams have access to the same data and cannot collect further data externally. Variations in analytics then comes down to personnel and how information is applied. This is meant to level the playing field for smaller-market teams that may not have as many resources to afford expensive data collection systems.

While league policies may help in regulating performance-based analytics, there are many other types of analytics. Many professional sports have been collecting and distributing statistics of matches and players for decades and serve as the baseline for performance evaluation by consumers and coaches alike. This is an example of performance-based and back-office analytics. In addition to performance evaluation, analytics in sports exist in a multitude of different areas including business management, injury prevention, and player management (Davenport, 2014). These all represent several areas for growth in analytics, and this development can be seen by the increasing popularity of a major conference for sports analytics hosted by the Massachusetts Institute of Technology (MIT). The inaugural conference in 2006 played host to 175 attendees while the 2013 edition featured over 2200 attendees and the most recent in-person event in 2019 recorded over 5000 attendees.

A study by Davenport (2014) interviewed several prominent figures in sports analytics and showed how they have impacted the industry. Participants included representatives from 25 different professional sports teams and leagues. Representatives ranged from analytics experts to general managers to team and league executives. Participants included Daryl Morey and Sandy Alderson who have been prominent individuals in popularizing analytics. Alderson was one of the main inspirations for the popular book *Moneyball* that was adapted into a movie of the same name. This story popularized the start of player management analytics in baseball, where the struggling Oakland A's turned their team around in dramatic fashion largely in part by using computer-based analytics to determine the best players that they could afford with the limited resources that they had. Morey entered the NBA (National Basketball Association) at a later date as the GM of the Houston Rockets when analytics were considerably more developed. While at this point all NBA teams were using analytics for management decisions as well as

injury prevention, Morey put a much heavier emphasis on the practice and even allowed it to dictate the team's style of play (Davenport, 2014). Analytics in tennis have not yet advanced to this level but is also developing in this direction and additional research is needed to better guide this development.

Analytics in Competitive Tennis

While equipment changes have often been highlighted for changing the way many sports are played, analytics have not had a similar impact on tennis as it has had on other major sports such as baseball and football (Cokins & Schrader, 2017). This is not due to a lack of data, as top-tier professional tennis tournaments all have similar camera systems installed that track both ball and player location at all times. However, further research and development is required for the efficient use of existing data to allow for an analytics impact on tennis. The following section will review common forms of existing tennis analytics technology to provide context for the current study.

Hawkeye

While only available at the highest echelons of the game in professional tour-level events, the use of the camera-based officiating technology called "Hawkeye" has been in place at major professional tennis tournaments since 2006 (Baodong, 2014). Since its advent until only a few years ago, the Hawkeye system has only been used to decide whether a ball is in or out and to allow players to challenge the decisions of line officials should they think they are mistaken. The system tracks and records the position of the ball at all times, and so has recently been used for analytical use for potential coaching applications. Similarly, recent updates to Hawkeye also allowed for tracking of player movement resulting in even greater amounts of data for statistical analysis. Currently, the large majority of tennis analytics used by top pros and coaches come

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from data collected by the Hawkeye system during live matches. A great deal of data is generated from the system, and research has focused on efficient use of these data as well as implementing machine learning to allow for more automated analysis of the existing information (Mora, 2016). According to Baodong (2014), the Hawkeye system is comprised of 10 high-speed cameras that capture video at 2000 frames per second. The cameras are split into five on each side of the court, with one camera on each side capturing one axis of the ball to render a 3D image. The other two cameras on each are used to collect player location data. This means that the location of both the player and the ball are recorded at all times by Hawkeye. With this amount of data, applications range far beyond the original use of line calling.

Modern TV coverage of professional tennis displays frequent graphics of different metrics such as serve placement, win percentages, and ball speeds among many other statistics. Similar data is given to players for scouting purposes; however, as described by Mora (2016), the process is unrefined. In regard to usage of Hawkeye data, external analysis is done primarily through a bug-prone proprietary software called TennisVR developed by Hawkeye Innovations. Mora (2016) stated that the process of creating individualized statistics and creating scripts is unnecessarily complicated, and there are efforts to modernize the secondary data analysis procedure. Work has been attempted on this front by major organizations including IBM and the United States Tennis Association (USTA), who are trying to use the raw data to develop their own coaching portal for USTA players and coaches complete with video and trends in a more user-friendly package. The final goal is to allow for artificial intelligence (AI) systems such as IBM's own "Watson" supercomputer to process and present useful match statistics and patterns automatically (Mora, 2016).

Another avenue for Hawkeye data applications is with investigating player movement (Thomas et al., 2017). Relative to ball location data, little is currently being done with player location information. Research is being done into different movement metrics that show how much energy a player is consuming due to movement and how those metrics may correlate to performance (Thomas et al., 2017). Besides simply recording player and ball location data, Hawkeye also combines this with point data, thus allowing for potentially easy comparisons between the various data points that can be generated and the play occurring within the match. This was also mentioned in the study done by Mora (2016), wherein IBM is experimenting with including movement data into a coaching portal and ultimately using Watson to process this information.

Several NBA teams also contracted Thomas et al. (2017) to develop similar movement metrics. This information processing technique has now spread throughout the league with the large majority of teams purchasing information from private analysts relating the movement of players to rates of winning. Per Cokins and Schrader (2017), this has led to fundamental changes in how NBA teams practice by placing a greater emphasis on on-court practices and less on weightlifting in an attempt to maximize player speed and endurance. The USTA and IBM hope to accomplish a similar task and have already made similar changes to practice as the NBA by limiting off-court cardio exercises and maximizing on-court training. That being said, current applications of Hawkeye in tennis are still for line calls. Studies like those done by the USTA and IBM can aid in making better use of the wealth of data this system provides.

Other video analysis platforms

While Hawkeye is the most prevalent system for camera-based tracking, there are other competitors in recent years. PlaySight is currently the main competitor and has been researched

by several teams for possible analysis purposes. Mlakar and Luštrek (2017) investigated the use

of PlaySight for video analysis in conjunction with another popular sports film analysis software

called Dartfish. In this application, PlaySight records video of matches and practice and also

employs shot recognition software to give metrics such as specific shot consistency and serve

placement. The Dartfish software was then used to separate gameplay video according to the

different shots and events that was recognized by PlaySight. The goal of their study was to find

a novel method of analyzing practice by leveraging the PlaySight system that now exists within

many tennis facilities. However, results from Mlakar and Luštrek's work showed that while it is

indeed possible to combine Dartfish and PlaySight footage to produce segmented film for

analysis, the actual shot characterization of PlaySight is unfortunately inaccurate. They

theorized that these inaccuracies are due in part to the lower number of cameras that PlaySight

employs when compared to Hawkeye. Compared to the eight or ten that Hawkeye uses, most

applications of PlaySight only feature four cameras. More advanced versions of the system are

said to be forthcoming with more cameras, albeit at a higher cost (Mlakar & Luštrek, 2017).

Demaj (2013) used a similar alternative called ArcScene 3D GIS in his investigation for

visualizing spatio-temporal patterns in tennis. ArcScene is another software-based AI solution

for shot characterization of sports footage. In his study, Demaj applied the GIS software to a

streaming replay of the 2012 Olympic Gold Medal match between Roger Federer and Andy

Murray. The ArcScene software allowed for ball trajectory and contact point to be captured and

recorded in real-time as the video was playing. However, other information such as shot type

and point within the match had to be collected manually by Demaj. He argued that at the time of

the publication of the study in 2013, it was still a technologically difficult task to track a

relatively small yellow tennis ball given the various distractions that exist in a professional tennis

match. Once all of this data were either manually inputted or tracked by GIS, the software also included several data analysis and regression tools to present interesting findings such as who served better on important points, amount of variation in serve placement, and effectiveness of serving to each position. When compared to Hawkeye data for the match, ArcScene was also found to have a much higher margin of error in shot placement with up to +/-20cm in variations. Demaj concluded that software such as ArcScene 3D GIS could be a viable option for secondary data processing for professional tennis matches given the usability and efficiency of the software but would be better combined with more accurate raw data such as that made by Hawkeye for more accurate findings.

Finally, TenniVis represents a visualization software that is more designed for immediate legitimization of coaching hypotheses (Polk, Yang, Hu, & Zhao, 2014). The inputs required are similarly straightforward, as all that is required is simple game footage and for a spectator to "tag" the match. In this situation, tagging describes a spectator that uses an accompanying application to take note of the start and end time of a point and notate some key events such as serve and return placement. The novel use for TenniVis is showing patterns and trends attached to video of gameplay. Polk et al. (2014) saw this as an easy and intuitive way for coaches to see and show gameplay trends as they are happening and being able to coach players with this information as proof. Unfortunately, TennisVis never became a commercial product. However, similar products designed with the same goals in mind have been developed and are available for consumer use. Currently, tagging matches is a common cost-efficient method of providing additional statistical information for matches that do not have Hawkeye available; college matches are a common example of this (Coleman, 2012). While this may be a simple process, extant research is focusing more on automatic methods based on AI technologies.

Wearables

On-body sensors such as heart rate monitors, insulin monitors, and even pacemakers have been commercially available for decades, but the current challenge is creating wearable devices that can detect not just that a sport is being played but can also obtain finer, sport-specific information. According to Mora and Knottenbelt (2017), action recognition software has made in roads recently and is quite stable and accurate. This is the technology that allows for common commercial systems such as the Apple Watch and Fitbit sensors to know when a user starts a specific activity. The issues lie within what occurs when the action and sport is detected; as of now, little information can be provided accurately especially for swing-based sports such as golf and tennis. Tennis specific-data from wrist-based sensors are currently very inaccurate and incapable of differentiating between different types of strokes such as a topspin backhand and a slice.

Researchers at the Samsung R&D Institute India developed a few different algorithms to rectify this (Srivastava et al., 2015). The challenge was to develop a machine-learning approach for shot classification and characterization using only a wrist-based sensor. First looking at existing work, most commercial products and research for wrist wearables employ the use of the inertial sensors, accelerometers, and gyroscopes that are commonplace in many electronics. Peaks in movement that are picked up by the sensors are then classified as actions. These actions are usually further refined into different shots such as forehands and backhands using machine-learning algorithms. A common challenge for this approach is to separate noisy data from actual actions; this is the main reason for the inconsistencies in tracking data such as step count. Even if quality noise reduction can be done and actions can be accurately separated from irrelevant

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movement, the simple input of action graphs is not enough data to accurately characterize what kind of action is being performed (Nieto & Sanchez, 2013).

Srivastava and his team (2015) made several adjustments to existing machine-learning algorithms in order to further refine data. In this setup, a wrist-based wearable is still employed, and the key sensors are still the accelerometers and gyroscopes in inertial meters. One of the improvements made was to separate sensor data into the three different special dimensions. The *x*-coordinate lateral data was then magnified for better action recognition as tennis shots are primarily executed in this dimension. Furthermore, another dimension of data was added to the traditional 3D dataset. The result are vectors known as quaternions; they are essentially generic three-dimensional coordinates with the addition of a vector that represents rotation and orientation. This additional number is what allows for more accurate shot classification, for example differentiating between a topspin and slice stroke on the same side.

In studying the efficacy of this technology, Srivastava and colleagues (2015) collected data from both professional and recreational players. Novice players introduce a separate challenge of wider variations in swing types that may make shot classification more difficult. Final accuracy results in primary shot characterization (forehand, backhand, serve, etc.) were found to be 99% for both professional and recreational players. Secondary classification – differentiating between slice, flat, and topspin – was accurately collected at a rate of 91% for professional players and 86% for recreational players. Data collection was done on a Samsung Gear S smartwatch, and analysis was also able to be completed on an accompanying smartphone (Srivastava et al., 2015). This degree of accuracy from such a portable setup is unprecedented and could mark an important step for improved statistics for tennis.

Future AI-based innovations

Modern technology is trending towards deep-learning and AI technologies, and similar applications are being researched for sports analytics. Mora and Knottenbelt (2017) showed one attempt to apply current machine-learning algorithms to generic video for shot characterization. The main challenge that they were trying to confront is allowing analysis of existing video footage that is unrefined. This would allow for a wealth of data of older film of non-HD video without any additional metadata that modern sports film is often accompanied with. To this end, Mora and Knottenbelt employed the use of an existing dataset called THETIS. These videos are low-definition shots of a collection of both novice and professional players performing tennis strokes in a multipurpose gym setting. This means that the background is dynamic as there are other parties performing different actions behind the subject, and that there is no tennis ball or traditional court setting involved. Videos include all major strokes such as forehand, backhand, and serve with the major variations such is topspin, slice, and volley.

Out of the 1980 strokes analyzed as part of the THETIS dataset, accuracy was found to be catastrophically lower compared with the earlier wearable innovation (Mora & Knottenbelt, 2017). Similar to the previous Srivastava et al.'s (2015) study, differentiation of THETIS testing was made between recreational players and professionals. Even when analyzing only professional players, Mora and Knottenbelt's (2017) method only showed 45% accuracy in stroke detection compared with 36% for the amateur players shot in the dataset. To understand these results, they grouped the secondary variations together and attempted to characterize just the primary stroke types of forehand, backhand, and serve. In this respect, the deep-learning approach performed much better and gave results of 77% accuracy for professionals and amateurs combined. This shows that much of the difficulties associated with this approach is

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differentiating between the subtle variations between similar tennis strokes. Mora and Knottenbelt concluded that their algorithm is proficient in determining the side of the body that the action is performed on, as the primary tennis strokes of forehand, backhand, and serve are each dominant on one side of the body.

Further, Mora and Knottenbelt's results were then compared to another existing dataset of professionally shot videos in a controlled tennis court environment, known as the KTH dataset. Using the same method, the KTH dataset gave accuracy results of 93% even when involving secondary shot characterization. One finding was that challenges are presented by dynamic background objects such as mobile fans and people surrounding the subject. The deep-learning algorithm was found to be primarily using the silhouette of the subject in the KTH dataset for characterization as it is a more regular object performing a broad motion. However, this is obviously impossible with a noisy video such as those presented in the THETIS collection that contains shifting background images with multiple silhouettes. It is unclear whether the definition and quality of the video plays any role in the accuracy of deep-learning characterization. Unfortunately, Mora and Knottenbelt's (2017) study shows that current AI technology is lacking when tasked with characterization from historic film.

Summary

The line calling system Hawkeye was necessary to aid line judges with officiating due to the increase in ball speed. The system has also brought along with it a wealth of data with ball and player location at all times for professional matches that could be better utilized by sport organizations. Various visualization software and programs are being developed to process and present this data such as TennisVR, Dartfish, and TenniVis. However, technological issues remain for tennis analytics products for consumers, as accurate data is currently difficult to

obtain with wearable technology and current consumer camera systems which may cause sport

professionals to be resistant to adopting similar technology. That being said, advances have been

made with deep-learning algorithms to improve the accuracy of shot characterization data. In

combination with improved camera technology, tennis analytics will be approaching widespread

application with education of coaching staff. As history has shown, the technology will continue

to develop and reach a point of maturation.

However, there is a clear gap in research of this area. While literature is rife with

research detailing the technical development of different platforms, there is little investigation as

to how the end users of players and coaches actually use and perceive these new technologies in

tennis settings. Managers and developers alike need to understand the attitudes and perceptions

of their coaches and players towards analytics. Keeping the coaches and players that these tools

are meant for up to date will be a key challenge in achieving sustainable development and

effective adoption. The current investigation focuses on the education aspect of consumers to

see what has been done and what future developments should be made.

CHAPTER 3: METHOD

A qualitative approach was taken to allow for greater depth of data collection while allowing for flexibility of response (Jennings, 2016). This is necessary due to the dearth of existing research on this topic. In addition, as participants are similar to each other and the purpose of the study is to understand the range of experiences rather than to generalize to a larger population, the large number of subjects that would be required for quantitative analysis are not needed to reach saturation.

Participants

Participants included 9 tennis coaches of elite players that are based in the United States. The study focused on coaches specifically because in the case of tennis analytics, coaches are the primary user of the data. Additionally, the analytics and technologies available differ from country to country and their respective tennis federations, so the study sample was limited to coaches of elite players that have access to analytics based in the U.S. Experience was a factor in purposively recruiting candidates to be interviewed. Professional coaches can range from young player-coaches that just finished competing themselves to veterans with decades of experience. This could result in potential subjects having different experiences, preconceptions, and familiarity with analytics. To account for this, the sample included individuals who just started coaching professionally to coaches that have been doing so for almost a lifetime. Finally, this study was limited to only coaches of elite players as analytics in any sport are much more common at the highest levels of the sport (Coleman, 2012). According to innovation diffusion theory (IDT), the progress that is made at the professional level of sport for analytics should trickle down to collegiate and club levels (Lee et al., 2020). See Table 1 for additional participant information.

Table 1

Participant pseudonyms and demographics

Pseudonym	Years of coaching experience	Age	Highest level of education	Gender
Steve	18	39	Undergraduate	Male
Sean	13	37	Graduate	Male
Lauren	23	47	Graduate	Female
Joe	25	49	Undergraduate	Male
Bob	20	53	High School	Male
Molly	15	46	Undergraduate	Female
John	9	35	Undergraduate	Male
Andrew	17	49	Graduate	Male
Bill	19	48	Undergraduate	Male

To collect pilot data from participants that fit these inclusion criteria, I first interviewed two coaches from the USTA and two coaches that practice privately. This reflected the public/private duality that exists in American professional tennis coaching. To recruit additional participants, I first emailed each potential participant an introduction as to who I am and why I contacted them (Appendix A). If they agreed to participate in this study, I sent a consent form as reflected in Appendix B.

I recruited participants from among tennis coaches with whom I have prior relationships and through snowball sampling (Jennings, 2016). Regarding these relationships, they can mainly be split into three different categories depending on the circumstances under which I first made the connection with the subject. One category of participants is from my background as a

competitive tennis player myself. I have competed and stayed in contact with several individuals that have continued to play or coach at the collegiate level, where tennis analytics are also prevalent, and professional level. For participants that I have known from this method, it was easy to ask for an interview as there was already an existing personal relationship. An example would be Steve, an individual that I have known for many years and have worked with repeatedly. Other than Steve, I know two other individuals that fit the requirements for my participants of this category. In contacting these potential participants, I first established their existing prior knowledge and use of tennis analytics before continuing with formal interviews. For this group of individuals that I have closer ties to, I ask them for suggestions of other coaches that they may know who have experience with using analytics in their work.

Data Collection

All participants completed one-on-one, semi-structured interviews using Zoom. Participants were first asked to introduce themselves and give their background as it pertains to tennis coaching and analytics. As these were semi-structured, focused interviews the questions followed a set of themes to be discussed but allowed for follow up questions that were conversation-driven (Jennings, 2016). Each lasted between 20 and 40 minutes. Once an interview was completed, analysis began with a personal reflection on the interview. In general, these memos contain my off-the-cuff thoughts about the interview and potential connections to research questions, past literature, and theory. Another use for these memos was to keep interviews centered on relevant topics and to make sure the pertinent research questions are being addressed (Jennings, 2016). Additionally, they also contained notes pertaining to the countenance of the participant. For example, how did the participant react to the question? Did the participant's response reveal that the question itself was well-constructed, and if not, how

could these questions be improved? As shown by this previous question, these memos were

critical in improving interview questions as the data collection process continued. Finally,

another important aspect of these reviews was to record any aspect of participant responses that

are unexpected and yield surprising results. Noting themes like these helped with the pattern

coding section of data analysis that will be further explained below. An example of these

interview notes as well as guiding questions can be seen in Appendix C.

After personal reflection memos, the next step was to transcribe each interview verbatim.

As interviews were conducted through Zoom video conferencing software, both audio and video

data were recorded. This was then transcribed using a combination of Zoom's built-in

transcription tool and Microsoft Word.

Data Analysis

Coding was the main form of analysis for the data collected in this study. The process

will start with preliminary coding, which are codes that are generated directly from the data.

Examples of this type of coding would be specific words and phrases taken directly from

transcripts (Saldaña, 2016). Preliminary coding resulted in many different codes that can later be

grouped together and further analyzed in a process that will be explained below. For this study,

these codes were generated by using a combination of Zoom transcriptions and Microsoft Word.

First, the Zoom transcriptions were opened in Microsoft Word and In Vivo codes were made by

highlighting important parts of the interview and codified using Word's comment function. An

example of this process can be seen below in Figure 1.

Figure 1

Example of transcript after preliminary coding

| Steve: Right so I do like to look through Dartfish and attach any data for any match video we have for players say if we're playing a match. Of course I also look through the reports that [they] and I'm guessing you have worked on before. So usually before a match I'll sort through Dartfish for head to head matches if we have them or just previous matches of the opponent and also go through [his] reports. After the match I'll get the tagged match and pick out some points I want to go through with my player. I'll have some notes from during the match of things I'll want to look for afterwards in the video to show to her. Might be either something she did well or needs to work on or an example of something we've been working on in practice that she did in the match. But that's usually the process I go through for analytics.
Kevin: Do you use or know of some of the other platforms out there like PlaySight or some of the wearables? | **Huang, Kevin** Process of applying analytics |
| Steve: We have PlaySight obviously throughout the Campus, but I don't really use it. I just haven't seen it to be really that reliable. Same thing for the wearables like the Sony sensor or whatever. The information just isn't accurate. Half the time you hit a kick serve and it says you hit a 130 flat serve that hit the back fence. Hawkeye data seems like the only really useful data out there right now. I think PlaySight could be really good for practice because it's cheaper and has some good practice tagging features. But it's just not reliable or accurate enough for me to use it yet. | **Huang, Kevin** PlaySight reliability and accuracy concerns

Huang, Kevin Wearables accuracy concerns

Huang, Kevin Positive view on Hawkeye

Huang, Kevin Potential advantages of PlaySight |

Once this was completed, the second stage of coding analysis is pattern coding. Here, the preliminary codes were analyzed and grouped together to create main ideas and major themes (Saldaña, 2016). These are the large thematic points that will be important for final results and discussion. For the data in this study, the commented sections seen in Figure 1 were replaced by color-coordinated highlights that correspond to different pattern codes. Figure 2 shows an example of the same section of transcript following pattern coding, and Figure 3 illustrates the accompanying codes.

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Figure 2

Example of transcript after pattern coding

Steve: Right so I do like to look through Dartfish and attach any data for any match video we have for players say if we're playing a match. Of course I also look through the reports that Dave and his guys and I'm guessing you have worked on before. So usually before a match I'll sort through Dartfish for head to head matches if we have them or just previous matches of the opponent and also go through Dave's reports. After the match I'll get the tagged match and pick out some points I want to go through with my player. I'll have some notes from during the match of things I'll want to look for afterwards in the video to show to her. Might be either something she did well or needs to work on or an example of something we've been working on in practice that she did in the match. But that's usually the process I go through for analytics.

Kevin: Do you use or know of some of the other platforms out there like PlaySight or some of the wearables?

Steve: We have PlaySight obviously throughout the Campus, but I don't really use it. I just haven't seen it to be really that reliable. Same thing for the wearables like the Sony sensor or whatever. The information just isn't accurate. Half the time you hit a kick serve and it says you hit a 130 flat serve that hit the back fence. Hawkeye data seems like the only really useful data out there right now. I think PlaySight could be really good for practice because it's cheaper and has some good practice tagging features. But it's just not reliable or accurate enough for me to use it yet.

Figure 2

Pattern Codes

1. Reliability
2. Current applications
3. Accuracy
4. Current positive uses
5. Future suggestions

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CHAPTER 4: FINDINGS

The semi-structured interviews were conducted to focus the conversation on the three

main research questions but allowed for a natural flow of conversation that resulted in other

findings. Connecting with the research questions, the findings focused on current uses of tennis

analytics, how valuable participants perceive analytics, and finally what developments

participants would like to see to improve in the future of tennis analytics.

Current Applications of Analytics

All but one participant reported that they utilize analytics to some degree. Other than the

one outlier, every coach used at least video analysis in their profession. Coach Andrew had the

following to say about using video analysis:

> I don't really do much with the Hawkeye data and things like that, but I definitely like to
>
> review match footage often times with the player. This is actually a pretty key
>
> component of my usual post-match routine, and something that I think the large majority
>
> of coaches and players do.

He continued by relating that he himself had relied on video review in his own post-match

analysis when he was both a collegiate as well as professional player. Results showed that video

analysis, where recordings of a match are reviewed, is regarded as a very simple form of

analytics that is widely used throughout the professional tour as well as on the collegiate level.

Other than video review, there are other uses of video analysis. Molly discussed the use

of video recordings for technical stroke analysis of a player. Equipment used on this front can

range from a simple smartphone video camera to professional-grade cameras that can record in

high-definition and super-slow-motion. "For stroke analysis, I record a lot of my younger

developing juniors and keep catalogs of their strokes as they grow. Sometimes I still do this with

my pros that might have a specific issue with a shot." Other than Molly, five coaches indicated that they used video analysis for technical stroke adjustments at least occasionally. Of these five coaches, all had similar perspectives to Molly suggesting that they used video for stroke analysis more often during the times that they worked with younger players.

  While not quite as universally endorsed, match analytics provided by commercial third-party companies were reported to be popular in the current tennis analytics market. These reports contain Hawkeye data-based match statistics such as serve percentage and placement, player position, and other related metrics. Coach John said:

> I buy reports from Tennis Analytics, which you might be familiar with, with almost all of my players. As you know, this shows a lot of the serve placement, shot placement, serve plus one data that you see a lot on TV. I would say that would probably be my most standard use of analytics, from a data perspective.

Out of the nine participants, six of the coaches stated that they regularly use Hawkeye data reports provided by Tennis Analytics or similar providers. However, a concern was noted by Lauren that while data provided in this form is helpful, not all players have access to this type of analytics regardless of whether they are willing/able to pay for it.

> I work with up-and-coming juniors as well as pros and I wish that I could get reports for my juniors too. I think Hawkeye is slowly being used at the top-level junior tournaments now, like the junior Grand Slams, but usually things like that aren't really available until you get on the professional tour.

  Despite the widespread use of some level of analytics, when asked if analytical tools were used during practice specifically, most coaches were not receptive to this notion. Out of all the participants, only one stated that they at least occasionally use some form of analytics in

practice. Sean went on to say that this was only done when recording practice matches and analyzing these recordings similar to what would be done for an actual match. While five of the participants have tried, none ended up applying the practice tools pushed by wearables and other analytics companies that promise shot characterization, ball speed, spin data, etc. When asked about the reason for this, Sean had this to say, "I did try using PlaySight before for drills, but I just got the sense that it classified a shot or called a ball in that was out way too many times to trust it." Bill had a few of his pro players try some of sensors and wearables available, but ultimately his reaction to that was equally negative with Bill saying, "Probably three out of every ten serves it would say my player hit a 140 mile per hour second serve which is obviously just ludicrous." While some participants described current uses of tennis analytics, most were used exclusively around an actual match. It was rare that coaches used any analytical tools during practice.

Another finding that may be a roadblock in widespread adoption of tennis analytics has to do with the players rather than the coaches. Participants noted that at times the challenge of adopting analytics was not related to coach buy-in, but rather the players that they are in charge of being resistant. For example, Andrew mentioned the tendency of not just tennis players, but of all athletes to often times resist change and fall back to what they are comfortable with. This was especially apparent in professional tennis, where coaches cannot intervene during the match itself and guide their players. Once a tennis match starts, individuals are on their own until the conclusion of the match. Without a coach to remind them of some key patterns of play that is introduced by analytics, players often times revert to their trusted strategies that have become muscle memory.

Molly expanded on the topic of muscle memory, and how it may be a natural barrier to the adoption of analytics. She explained that tennis training is based on repetition and ingraining skills and technique as muscle memory. The goal is for a player to be able to compete while making the correct decisions unconsciously as there is limited time during modern tennis points. This does make the incorporation of tactical changes suggested by analytics to be challenging if these tactics may be specific on the opponent and calls for a temporary but drastic tactical change. To this end, Molly stated that she most commonly employs analytics for the serve, as the decision for how and where to hit the serve is something that a player has complete control over.

Perceived Value of Tennis Analytics

One of the major themes that emerged from the interviews was that all participants have agreed that when presented properly, analytics in tennis matches are extremely useful. Talking specifically about match analytics, there was little disagreement on whether or not it is something useful within the industry. Steve said, "I don't think you will find anyone that has used analytics that would say it's not helpful. It's just that sometimes some analytics companies or platforms aren't very good at their job." These sentiments were echoed by Joe saying that the issue is not with the usefulness of the numbers, but rather with finding the best way to present them. Often times users reported unintuitive software making it difficult to access the analytics themselves. Other times data would simply not sync between devices and make information inaccessible. Six of the participants found match analytics to have a positive impact on their work. However, Bob was not as taken by the new wave of data, "All the cameras and sensors I don't really like. At least for me, it distracts me and my player from the actual tennis. I don't want to be thinking about numbers and data and I definitely don't want my player to be thinking

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about that." This was a point mentioned by two other coaches that otherwise found match

analytics to be helpful. Depending on the player, it is definitely a concern that the individual

may be given too much information and they are then over-thinking during a match. For match

analytics, it is an important job for a coach to pick out only the most useful information for their

players.

When asked about what type of data is usually deemed as important, the answers were

usually a bit more complex. Sean had this to say, "It definitely depends on the player. If I have

a guy that's 6'5" I'm obviously not going to be looking at the same things as another 5'7"

grinder." Despite some nuanced differences, there were similarities in the data types that were

usually highlighted. Of the eight participants who indicated they routinely read over match

statistics, six mentioned that serve and return location was something they looked at for every

player and matchup. Expanding on this point Sean continued by saying, "That being said, every

player should still have an idea what the best place to serve is on a given point. I think the

biggest thing that I usually look at first is the serve placement of their opponent. So for example,

if it's break point if the other player has a favorite serve that they like to hit so my player can be

ready for it." Other participants mentioned different data points such as rally hit point and net

win percentage, but all six agreed that serve placement – both for their player and the opponent –

was something they always looked at.

While the large majority of participants found this type of data to be increasingly

important, the same cannot be said of other data types. When asked if there was something

coaches have tried but found not to be useful, Andrew said, "So a lot of things like PlaySight or

the Sony Sensor and other wearables really highlight and ask you to look at the spin a guy hits or

the speed or something like that. Stuff like that isn't very helpful; I don't care if my player hit a

thousand forehands today with 3000 RPMs of spin." Other coaches had similar takes to these types of technology, with several labeling these objects as "gimmicky".

In summary, there seems to be two forms of analytics that were currently seen as most helpful by these coaches of professional tennis players at this moment. Video analysis was a common form of review done using recordings of matches. Match statistics provided by companies such as Tennis Analytics were another avenue that is currently used by many coaches regularly. Both of these tools apply to both the player themselves as well as their potential opponents. This means that coaches watch match recordings as well as read through analytics of their own players but also those of the player that they are about to compete against. Many of the other features that technology companies may provide, such as shot characterization, practice tagging, etc., were viewed as just additional features that are not typically used.

Future Direction

On the topic of challenges that participants may have experienced with tennis analytical tools and things they would like to see improved for the future, coaches had several main complaints with the technology. The most commonly reported problem was reliability, or the lack thereof. Speaking about her reliability concerns with PlaySight, Lauren summed it up well, "I feel like every other day I go out there and there's some kind of problem with it. Either I can't login, the camera won't turn on, I can't get the video afterwards, or something happens. Now, I get that it's probably hard on the electronics with all the storms that we can get around here, but it must be able to be improved. Otherwise I just find myself unwilling to even try it because it seems like it'll just be a crapshoot on whether or not it actually works." All but one of the participants had experience using the PlaySight system, and all of these individuals have had reliability concerns with the technology. This criticism extended to sensors and wearables,

although not to the same extent as only three coaches had used these types of devices. Of these three subjects, two reported reliability-related challenges with them.

For these devices, the larger problem was that of perceived data accuracy. "What really stopped me from using a lot of these things is that I just don't feel like they are very accurate. Hawkeye is obviously very accurate, but I think that costs a few thousand dollars just for a few days so you can't really use it in practice," is what Bob had to say about the accuracy of current tennis analytics. This reveals an important finding that almost all current technologies were not perceived by the coaches to be accurate, with the sole exception of Hawkeye. That is the system used for calling balls in or out during live professional match play and is thus held to extremely high standards of accuracy. However, as Bob noted, this requires constant maintenance to make this possible and results in a system that is too expensive for setups outside of professional tour events. In order to improve tennis analytics to be more widespread, participants agreed that either the premier Hawkeye system needs to be made cheaper without the need for in-person supervision, or lower-cost alternatives have to become more accurate.

While there are definitely problems with reliability, accuracy, and cost at the moment, all participants agreed that the future of professional tennis will most likely involve greater amounts of technological aide. As the only coach to not regularly use any form of analytics, including basic video review, Bob still agreed with this point, "While I don't think I will ever use much technology in how I coach – I'm probably just too old – I do understand how important technology is nowadays and that that will only continue to grow."

CHAPTER 5: DISCUSSION

Analysis of User Applications

Participants agreed that analytics are a generally accepted aspect of elite tennis and that technology will likely play an increasing role in the future. However, some participants were personally much more resistant to technological advances and changes than others. Looking at the collected demographic information, age and years spent coaching may affect how open an individual is to try new innovations. Bob was the only coach that stated he did not regularly use analytics in any form. He also happens to be the oldest subject as well as the only one that received only up to a high school education. It is possible that both of these factors may play a role in his decision to omit analytics from his work processes. However, further data collection would be needed to explore this possibility.

Just as some coaches were to be resistant towards changes, participants also noted an inability to adapt to analytics by many of their players. The repetition and muscle memory that modern tennis training and match play is based on presents a unique challenge (Kovacs et al., 2007). Participants noted that due to this issue, the most useful types of analytics usually centered on the serve and situational points such as pressure points. These are occasions where players have the time to think more tactically in between points and are simple enough to keep athletes relatively clear-minded. In general, this contradiction presents a potential limiting effect on the overall usefulness that analytics can have in tennis and is something to monitor as the industry develops. Realizing this reality may be an important point for developers. They could focus on enhancing data accuracy for these types of information and explore new data metrics within these confines.

Comparing to Literature on Sport Analytics

When compared to other studies done in the tennis analytics field, there were both

similarities and differences. Srivastava et al.'s (2015) study on a Samsung wearable showed shot

characterization that was 95% accurate, which is definitely at odds with what coaches had to say

about their experiences with similar devices. As Srivastava et al. were the developers of the

technology itself, it was most likely tested under optimal conditions for the technology to

maximize its potential. It is quite possible that these results would not hold up in real world use.

However, results from other studies such as Demaj's (2013) work with ArcScene 3D GIS and

TenniVis by Polk et al. (2014) that showed accuracy rates of 73% and 80% respectively are more

in line with coaches' perceptions in the current study. Regardless of which application it may be,

they all pale in comparison to the stated 2mm margin of error that is associated with Hawkeye

(Baodong, 2014). This is why other than video analysis, match analytics reports based on

Hawkeye data was one of the only forms of tennis analytics agreed upon by coaches to be

currently relevant and useful.

The other type of analytics that was used frequently by participants was video analysis.

Mora's (2016) study focused on developments to AI and machine learning to bring these two

types of analytics together. Separately, Hawkeye match reports and video analysis were already

frequently used by coaches in their trade. The combination of the two where AI would pick the

most important trends and combine these with applicable video could be an extremely enticing

tool. The result could be similar to what is currently being done manually by using a camera

platform such as PlaySight to capture video and then combining this with tagging information

using Dartfish (Mlakar & Luštrek, 2017). As this is already a popular method adopted by

professional coaches to infuse analytics, it should be a safe assumption that an auto-generated version of this would be equally well-received.

Integration of Theory

The five constructs of Innovation Diffusion Theory (IDT) can first be applied when trying to understand the data (Al-Rahmi et al., 2019; Davis et al., 1989). Participants agreed that there are relative advantages to incorporating analytics, dependent on the type of data that was discussed earlier. Compatibility and complexity can be challenging depending on the individual that is using the technology. For example, Bob mentioned an unwillingness to use analytics in his routine while others like Andrew were at least open to trying new forms of technology. This leads to the fourth construct of IDT which is trialability. Depending on the analytics platform, these technologies can range from being easily used on a trial basis to having a high initial cost that forms a large barrier of entry. Camera-based systems such as PlaySight and Hawkeye are onerous to setup and are thus difficult to demo unless users go to an existing location and trial the system there (Baodong, 2014). On the other hand, wearable sensors can be easily bought and returned; trialing these products is something that coaches already do. Finally, analytical systems in this situation are very observable.

Following this analysis according to the five constructs of IDT, some assumptions can be made according to the Technology Acceptance Model (TAM) constructs of perceived usefulness and perceived ease of use of these products. Relative advantage in IDT relates to perceived usefulness, and findings have shown that participants do mostly perceive tennis analytics as being useful. However, as with many new innovations, data has found analytics to be perceived as possibly complex and even incompatible in some instances. Another one of these incompatibilities was discussed regarding the nature of tennis players and tennis training.

During tennis matches, having too much information and over-thinking can be catastrophic. Analytics can go against this, thus decreasing the perceived ease of use of these platforms. Future developments should be made to simplify the user experience as much as possible to make integration a more seamless experience.

Limitations and Directions for Future Research

Further research could rectify some of the limitations of this study. As participants only included coaches, future research should explore the perceptions of players as well. Another limitation was the geographic location of participants. While recruitment was intentionally limited to coaches based in the U.S., investigations involving international participants could bring new findings. Finally, more participants with diverse demographics could be used to learn about connections between certain demographic factors and tennis analytics use. For example, this study only had two women out of the nine participants. While this ratio may reflect the broader gender breakdown within the professional tennis coaching landscape, more data would still be beneficial towards possible results having to do with gender. As this investigation was conducted due to a gap in literature, much more research is needed to continue to develop this line of inquiry.

CHAPTER 6: CONCLUSION

From this data, it can be seen that tennis analytics still has a lot of room for development to become more effective in practical settings. To answer the question of how valuable coaches think analytics are, it appears that all participants agreed that this type of information should be regarded with caution. While the numbers can present interesting trends that may otherwise be unseen, they can also cloud a player's thinking and result in an information overload. It is the coach's job to understand what the analytics show and what are the best patterns to pass on to the player. Another research question asked how participants currently use the technologies available to them. There was almost complete support for match analytics based on Hawkeye data as well as video review of both match recordings and stroke analysis. Wearables and related data are not as popular in the current market. Finally, there was consensus on certain areas that should be the focus of tennis analytical development. Perhaps most importantly is the reliability and accuracy of these platforms. For example, while Hawkeye may be extremely accurate, it is prone to weather-related failure and requires staff to maintain the equipment that results in high costs (Baodong, 2014). On the other hand, cheaper platforms like PlaySight have been cited by all participants to show disappointing levels of accuracy. These issues must be addressed to ensure successful, sustainable development and usage of tennis analytics platforms. A method of doing this would be to improve the communication and education between developers and users. Doing so would both ensure users are aware of all the tools at their disposal, and also allow developers to receive more feedback from their target audience. Hopefully tennis analytics may improve with this unique qualitative study on the perceptions of analytical technologies of professional tennis coaches.

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Appendix A: Participant Contact Email

Hello,

My name is Kevin Huang from the University of Illinois at Urbana-Champaign. *Fill with applicable personal meeting context.* I am currently interviewing candidates to conduct a study on the applications of analytics in professional tennis. If you would like to be a part of the study, the interview will last approximately 45 minutes.

Please feel free to email, call, or text me with any questions you may have. Hope to be able to speak with you!

Regards,

Kevin Huang

Social Behavioral Research Consent Form

Applications of Analytics in Tennis

You are being asked to participate in a voluntary research study. The purpose of this study is to ask about your thoughts on tennis analytics. Participating in this study will involve an individual interview and your participation will last approximately 30 minutes.

Principal Investigator Name and Title: Kevin Huang, Master's Student in the College of AHS
Department and Institution: College of Applied Health Sciences; Recreation, Sport, and Tourism
Contact Information: khuang47@illinois.edu

Why am I being asked?
You are being asked to be a participant in a research study about applications of tennis analytics. The purpose of this research is to ask about your thoughts on tennis analytics. You have been asked to participate in this research because you are a professional tennis coach with experience in analytics. Approximately 15 participants will be involved in this research at the University of Illinois at Urbana-Champaign.

Your participation in this research is voluntary. Your decision whether or not to participate will not affect your current or future dealings with the University of Illinois at Urbana-Champaign. If you decide to participate, you are free to withdraw at any time without affecting that relationship.

What procedures are involved?
The study procedures are an individual interview through Zoom.

This research will be performed at a time to be decided that works for the participant. The interview is expected to last approximately 30 minutes.

What other options are there?
You have the option to not participate in this study.

Will my study-related information be kept confidential?

When this research is discussed or published, your name may be included in the publication. Additionally, when required by law or university policy, identifying information (including your signed consent form) may be seen or copied by: a) The Institutional Review Board that approves research studies; b) The Office for Protection of Research Subjects and other university departments that oversee human subjects research; c) University and state auditors responsible for oversight of research

Will I be reimbursed for any expenses or paid for my participation in this research?
You will not be offered payment for being in this study.

Can I withdraw or be removed from the study?
If you decide to participate, you are free to withdraw your consent and discontinue participation at any time. The researchers also have the right to stop your participation in this study without your consent if they believe it is in your best interests, or you were to object to any future changes that may be made in the study plan.

Will data collected from me be used for any other research?
Your information will not be used or distributed for future use, even if identifiers are removed.

Who should I contact if I have questions?
Contact the researcher Kevin Huang at khuang47@illinois.edu if you have any questions about this study or your part in it, or if you have concerns or complaints about the research.

What are my rights as a research subject?
If you have any questions about your rights as a participant in this study, please contact the University of Illinois at Urbana-Champaign Office for the Protection of Research Subjects at 217-333-2670 or irb@illinois.edu.

I have read the above information. I have been given an opportunity to ask questions and my questions have been answered to my satisfaction. I agree to participate in this research. I will be given a copy of this signed and dated form.

_____   _____
Signature   Date

_____
Printed Name

_____   _____
Signature of Person Obtaining Consent   Date (must be same as subject's)

_____
Printed Name of Person Obtaining Consent

Appendix C: Interview Questions

Interview Questions

1. Background

    a. What have your experiences been up to this point?

    b. What is your current professional situation?

    c. Does your coaching philosophy commonly involve trying new concepts and

       technologies, or do you tend to stick to fundamentals?

2. Analytics

    a. What has your experience been with analytics?

    b. How much do you currently use analytics?

    c. What different methods of tennis analytics aware are you of and personally use?

    d. If you have used analytics, what have been some challenges that you have had?

    e. Would you say your overall experience with analytics has been positive or

       negative and why?

3. Future Development

    a. How do you see tennis analytics developing in the future?

    b. What changes would you like to see to analytics that would make you more

       accepting of routine use?

Thank you for your time and participation!