Exploring the Feasibility of a Novel Experimental Method to Study Talent Selection and Decision Making in High Performance Sport

by

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The above committee determined that the thesis is acceptable in form and content and that a satisfactory knowledge of the field covered by the thesis was demonstrated by the candidate during an oral examination. A signed copy of the Certificate of Approval is available from the School of Graduate and Postdoctoral Studies.

ABSTRACT

Talent selection in sport takes place from early stages of development through professional ranks. Athletes are regularly selected for youth teams, high school teams, as well as collegiate and professional teams (Jones, Johnston & Baker, 2020). Even with so much selection occurring, identifying talent is difficult and inaccurate. This is made evident by the poor ability of professional sports teams with ample resources to be able to accurately draft and select players for their teams (Koz, Fraser-Thomas, & Baker, 2012). This study aimed to pilot test a method for understanding what Canadian basketball coaches look for when deciding between athletes available for selection. Specifically, using blinded data, coaches and decision makers were asked to make talent predictions. Participants from various levels of coaching across Canada were able to complete the task. Results suggest that this method and task was challenging, and has the potential to inform talent identification decision making.

Keywords: Talent; Basketball; Selection; Identification; Coaching.

AUTHOR'S DECLARATION

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STATEMENT OF CONTRIBUTIONS

I hereby certify that I am the sole author of this thesis and that no part of this thesis has been published or submitted for publication. I have used standard referencing practices to acknowledge ideas, research techniques, or other materials that belong to others. Furthermore, I hereby certify that I am the sole source of the creative works and/or inventive knowledge described in this thesis.

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TABLE OF CONTENTS

LIST OF TABLES

CHAPTER 3

LIST OF FIGURES

CHAPTER 3

LIST OF ABBREVIATIONS AND SYMBOLS

TID	Talent Identification

Chapter 1. Introduction

One of the longest standing debates in sport is what role "talent" actually plays in performance and expertise development. A lot of this argument stems from the age old "nature vs. nurture" debate. Those arguing firmly for nature state that genes play a primary role in becoming an elite performer (Baker & Wattie, 2018; Dean & Lombardo, 2014; Ericsson, 2013; Kaufman, 2013; Tucker et al., 2015). Those who side with nurture typically take the stance that practice and training make the difference in who achieves success (Ericsson et al., 1993; Howe et al., 1998). Despite polarized arguments for either nature and nurture, in order to better understand talent, we must consider both sides of the argument and attempt to understand the two together (Baker & Wattie, 2018; Ericsson, 2013; Kaufman, 2013; Tucker et al., 2015).

Fans and decision makers (coaches, general managers, scouts, etc.) often use the word "talent" to describe and categorize athletes based on ability, performance, and potential (Herling, 2020; Howe et al., 1998). The term is used frequently by both practitioners in sport as well as researchers (Baker & Wattie, 2018; Baker et al., 2019; Howe et al., 1998). Given its widespread usage, one might assume it is a rather well understood concept. However, this is far from true (Baker & Wattie, 2018; Baker et al., 2019; Herling, 2020; Howe et al., 1998). Nevertheless, one characteristic of talent that underpins many processes and initiatives in sport is the notion that talent is something an individual possesses, which can be identified and used to predict future potential.

Talent identification is the process of identifying athletes who have the potential to compete in senior level athletics (Vaeyens et al., 2009), while selection refers to picking athletes for a team or development pathway. Since these decisions are made at a variety of levels throughout development, the importance of accurate talent identification (TID) and selection is critical (Baker et al., 2019; Baker et al., 2017; Durand-Bush & Salmela, 2001; Howe et al., 1998). When identifying athletes early and selecting or deselecting for various teams, coaches and decision makers are often tasked with making predictions for years into an athlete's future. By correctly identifying the best talent early, and selecting these athletes for development teams, organizations can focus their resources more efficiently (Durand-Bush & Salmela, 2001; Johnston & Baker, 2020).

Currently, tasks involving selection contain much variability, and there seems to be a lack of a "gold standard" (Johnston & Baker, 2020). Decision makers can incorporate a variety of processes and techniques including, but certainly not limited to, simple heuristics, advanced machine learning models and standardized testing batteries, to intuition and personal preference (Johnston & Baker, 2020). Decision making processes are further complicated by the existence of personal biases. Understanding these processes and their efficacy is important, as accurate and efficient talent identification and selection, at least in principle, allows athletes who are best suited for success to continue on their path in athletics with superior coaching, more resources available, and higher levels of competition (Baker et al., 2017).

Not only is identification and selection a large factor for developing athletes, but these decisions cost organizations millions of dollars. For example, Great Britain spent 355 million pounds for the 2016 Olympic games cycle (Rees et al., 2016). This number

was more than 100 million pounds more than 8 years prior. These decisions are also costly within the world of professional sports. Decisions about talent made by coaches and managers affect salaries and player compensation, ticket sales, and organizational dynamics. Despite the significant expenditure spent yearly on talent identification and selection, doing this process accurately remains incredibly difficult. This has been observed across the four major sports leagues in North America (Koz et al., 2012). Each year, teams from these leagues (i.e., the National Hockey League, National Basketball Association, Major League Baseball, and National Football League) select new talent through draft processes, as well as from international pools, and players not currently under contract. These decisions also occur at youth levels, where the decisions involve more time between investment and fruition (latency), less resources available, and realization of potential is more challenging (Abbott et al., 2005; Jones et al., 2020; Vaeyens, 2008). In summary, talent identification and selection, in all forms, is limited by poor accuracy, with considerable room for growth and improvement (Johnston et al., 2021; Koz et al., 2012). Arguably, it is also even more difficult to identify talent at younger ages due to fewer resources at this level and a longer latency period for athlete development.

Selection decisions are often made by decision makers (e.g., coaches, general managers, support staff) within a given organization who try to select players who show potential in their sport or fit with that team (Baker et al., 2018). This process involves making predictions about the athletes, based on current and prior performance data, anthropometric and medical data, performance tests (speed, agility, power etc.), among other measures (Baker et al., 2018; Farah & Baker, 2020; Johnston et al., 2021; Koz et

al., 2012). Given the range of possible variables and the difficulties in accurately measuring them, selectors frequently rely on the ‘coach’s eye’, which is simply the subjective judgement used by coaches to select for or against a player based on what has been observed by the coach (Lath et al., 2021). Despite the financial resources and interest in the notion of talent at all levels of sport, it is important to acknowledge the difficulty of this task (i.e., talent identification and selection), as there is no exact formula to determine talent or fit for a given team (Farah & Baker, 2020; Johnston et al., 2021; Koz et al., 2012). Furthermore, there is a wide variety of differences in both physical and physiological characteristics within and between different sports and positions. This diversity, or variation, further adds to the complexity of making predictions on talent (Johnston et al., 2021; Plotkin et al., 2021).

Over the last 25-30 years there have been approximately 1700 research papers published on talent and its identification, including a considerable rise in publications over the last ten years (Baker et al., 2020; Johnston et al., 2017). Despite a large number of published papers, very few have explored accuracy rates of those attempting to identify talent and the factors contributing to it. While some studies have been able to identify various predictors of talent, none could identify a variable that could uniformly predict talent. This is likely due to researchers focusing on a single variable and the different demands between sports. Moreover, most of the research in this area has focused on physical or physiological variables. This type of research is limited and does not give a full, accurate picture of TID and selection. More research needs to be done using a multivariable approach, looking at many aspects of talent, and how coaches use this information to make selection decisions (Baker et al., 2020; Johnston et al., 2017).

In addition to the multidimensional nature of talent, the latency between selections and the (non)fulfilment of potential can be significant, spanning years or even decades. As such, there have been calls for more prospective longitudinal designs in this area (Johnston et al., 2017). Longitudinal studies allow researchers to track progress over longer periods of time, but are costly, and time consuming (Johnston et al., 2017). As a result, there is a need for more creative research methods and designs, as well as longitudinal studies (Johnston et al., 2017). For instance, researchers could utilize retrospective data and/or creative study designs to explore prediction-based tasks over shorter periods of time (e.g., using historical player data with all names and identifiers coded, we can have decision makers predict outcome metrics for these players while already knowing the outcomes, thus allowing us to score in real time. This would allow researchers to bridge the gap between early identification in the development pathway and the eventual (non)materialization of potential.Overall, more research is needed to better understand TID and how coaches and decision makers make selections (Baker et al., 2020). Very little is known about how these decisions are made, and practitioners continue to make decisions on talent with incomplete knowledge of the quality of their decisions (Baker et al., 2020). This need has led to our research project, where we attempt to better understand coaches' decision making when identifying talent. Specifically, the goal of this project was to create and pilot test a novel methodological approach to researching talent selection decision-making in basketball.

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Chapter 2. Literature Review

2.1 **Introduction**

In the world of sport, athletes are the force that drives competition. In order to push sports forwards, these athletes, young and old, are constantly training with coaches and specialists so that they can one day reach the peaks of their chosen sport. This process, known widely as *athlete development* and *expertise development*, is affected by a range of primary and secondary factors (Baker & Horton, 2004). Primary factors (genetic factors, training factors, and psychological elements) as well as well as secondary factors (socio-cultural factors, cultural importance, instructional resources, familial support, contextual factors, sport maturity, and depth of competition) have a direct impact on development (Baker & Horton, 2004). This process of athlete development is quite complex and the influence of things such as practice hours and types of participation on expertise development remains widely debated (Howe et al., 1998; Ericsson et al., 1993; Collins & Macnamera, 2017). One important complication is the fact that talent identification and athlete selection punctuate the athlete development process multiple times throughout athletes' development pathways. As such, an increasing area of interest, and the focus of this research, is to develop means of better understanding the factors that affect decision-making and selection on talent (Baker & Wattie, 2018; Kaufman, 2014; Ericsson, 2013).

2.2 **Talent in Sport**

In coaching circles, the words "talent" and "expertise" are often used synonymously, even though the two words possess clearly different meanings. Herling provides a working definition of expertise across disciplines: "displayed behaviour within

a domain and/or related domain in the form of consistent actions of this individuals that are both efficient in execution and effective in results" (p. 8) (Herling, 2000). Talent on the other hand is generally viewed as a component or predictor of expertise (i.e., one of the factors that can contribute to becoming/being an expert). Compared to conceptualizations of expertise, there are many different definitions of talent.

One of the problems underpinning the nebulous nature of "Talent" is undoubtedly the fact that this term has been viewed differently by both researchers and practitioners. For instance, it can be used to describe a promising young athlete who is continuing to hone their craft (e.g., as 'talents' within an athlete development system), or to comment on the best athletes from a given a sport (i.e., those with 'talent'). In some instances, the term "talent" is not defined at all (Howe et al., 1998). In an effort to provide conceptual clarity, Howe et al. (1998) proposed a working definition of talent. Their definition included 5 properties of talent. In their view, talent 1) originates in genetically transmitted structures, and therefore is partly innate; 2) is not always evident in early stages, but signs exist that allow trained individuals to identify it early; 3) early indications provide a basis for predicting who is likely to succeed; 4) is found in a minority of individuals and 5) is relatively domain specific (Howe, Davidson, & Sloboda, 1998).

More recently, Baker and Wattie (2018) revised the Howe et al (1998) definition for sport, arguing that some factors of this definition are still accurate, while others need to be revisited. The authors agree that talent is at least partially genetically transmitted and feel that components 2 and 3 are also relevant to consider. Baker and Wattie added that talent will have some advanced indications, and that those individuals

with training can predict those with greater likelihood of success. The authors also agreed with component 4, that a minority of individuals are talented. However, they noted that talent is structured in an exclusionary hierarchy, where only the best athletes are selected for teams, and then the best of the athletes from those teams are eligible for awards and All-Star teams. With regards to component 5, Baker and Wattie argued the idea that talent is relatively domain specific was unreasonable. They state that expertise is domain specific, however, to say that talent is domain specific defies biological parsimony. Talent is more likely to start as a capacity that can then lead to a specific group of domains. Over time and practice, talent can then result in a domain specificity at later stages (Baker & Wattie, 2018).

Researchers have also conceptualized talent as 'giftedness'. Gagne (2004), for instance, proposed the Differentiated Model of Giftedness and Talent (DMGT) as a developmental theory. In Gagne's DMGT theory, 'giftedness' designates the possession and use of untrained and spontaneously expressed natural abilities (outstanding aptitudes or gifts) in at least one ability domain, to a degree that places an individual in the top 10 percent of age grouped peers. In this theory, 'talent' reflects the outstanding mastery of systematically developed abilities or skills and knowledge in at least one field of human activity to a degree that places an individual in at least the top 10 percent of age grouped peers.

Other researchers have also attempted to give a working definition of talent. For example, Cobley et al. (2012) suggested "talent refers to the quality (or qualities) identified at an earlier time that promotes (or predicts) exceptionality at a future time" (p. 5) while Nijs and colleagues (2014) referred to talent as "systematically developed innate

abilities" (p. 182). The authors go on to state that this "innate ability" can lead to excellent performance in one or more domains of human functioning, to better performance than other individuals of the same age or experience, and/or as performing consistently at their personal best (Nijs et al., 2014). In reviewing the literature on talent in sport, Baker, Wattie, and Schorer (2019) proposed a more comprehensive definition, arguing that sporting talent had several features. The first feature is that talent is innate. The authors propose that talent is "that component of development that is present at birth" (p. 29) which differentiates it from skill (Baker et al., 2019). The second factor is that talent is multi-dimensional and involves factors across a multitude of areas including the physical, psychological, technical and tactical domains. The third factor is that talent is emergenic. The term emergenic refers to talent "arising as a novel or emergent property resulting from the interaction of more elementary and partly genetic properties" (p. 1569) (Lykken et al., 1992). Essentially, this reflects that talent emerges as a result of genetic properties interacting with environmental factors over the course of development. The fourth factor is that talent is dynamic. This dynamic approach to talent can be demonstrated by the non-linear pattern that development takes. Talent itself is unpredictable due to the fact that genes are expressed across development time (Baker et al., 2019). The final factor is that talent is symbiotic. Since skill development does not operate in a vacuum, the value of a characteristic is determined by other contextual factors like relevance and cultural importance (Baker et al., 2019). Such variety of definitions and properties for talent, and some research papers lacking a definition altogether, highlight the conceptual and evidentiary issues needing resolution within this field.

In an online poll conducted by Tucker via Facebook in 2013, he set out to answer the question *"what is talent?"* by polling coaches, athletes, fans of the sport, as well as researchers. Many answers fit across a wide range of responses, leaving no clear definition for the term. This highlights the need for further research to investigate how talent is seen by both practitioners, parents, and researchers alike. To further complicate the talent identification and selection processes, coaches and researchers often struggle to articulate and define what talent is and how they identify it, and rely on intuition (Lath et al., 2021). Roberts et al. stated that this intuition, or coach's eye, is the primary contributor to the process of talent selection (Roberts et al., 2019). This makes conducting research studies on the matter difficult, since coaches and researchers both have preconceived bias and different definitions of the term "talent", or no definition at all (Smith & McGannon, 2018).

Since coaches and researchers can struggle to agree on what exactly talent is, some researchers are attempting to provide suitable definitions. It has been suggested that for most people working in sport, the term "talent" is used in a broad sense to describe someone who currently has, or is predicted to have, some level of success in sport (Baker et al., 2019). This is another basic definition for the term that can provide the building blocks for future definitions, as researchers continue to study those who are deemed "talented".

It is clear that the definitions used in scientific literature are not precise enough for determining what "talent" is. Some examples mentioned simply describe the general characteristics and properties of talent. Some definitions stipulate a genetic factor. Others do not mention genetics at all. This leaves practitioners without clear guidance for what

“talent” actually is and how to identify it. These vague descriptions of talent make it difficult for practitioners to implement current evidence from talent research.

2.3 **Arguments for and Against Talent**

One of the most enduring debates in sport science is whether not talent is an important component of expertise development and performance. For example, the theory of deliberate practice states that height is the only genetically constrained factor that can limit expertise development in sports, and that it is only through extensive deliberate practice that one can achieve expertise (Ericsson et al., 1993). However, within the context of sport, this theory is often criticized as overly simplistic (Baker et al., 2009).

A number of examples have been put forward in support of the existence of talent. When looking at the world’s fastest men and women, Lombardo and Deaner (2014) found that to be a world class sprinter, you must already be faster than your peers. This study found that the fastest athletes in sprinting across the planet began their careers beating runners who had been training for years, without any technical or formal training. This training became useful to improve their innate talent, but this rule of ten thousand hours would not make just anyone an Olympic calibre sprinter (Lombardo & Deaner, 2014). Similarly, Kenyan runners, specifically Kalenjin runners, produce forty percent of the world’s best marathon times each year (Tucker et al., 2015). This strong representation of success is not solely because Kenyan runners participate in extensive deliberate practice, but arguably due to the innate abilities they possess that cannot be found in other parts of the world (Tucker et al., 2015). These runners’ practice to hone their craft and some become experts, however when they begin to run, they can run longer and faster than their counterparts who may have been training for years. This is

due to advanced differences and interactions between genotype, phenotype, and socioeconomic factors (Tucker et al., 2015). A potential example of this genetic predisposition is found through the ACTN3 gene, which encodes the protein alpha-actinin-3 and is found in fast glycolytic type 2 fibers. There are 2 variants in the gene: R and X, with the R variant strongly correlated with sprint running performance (Eynon et al., 2013). Scientists have found that the XX variant of the gene, which is not favourable for distance running, is almost non-existent in Kenyans (Yang et all, 2007). This hypothesis attempts to explain the dominance maintained by the Kenyan people (specifically the Kalenjin people), which is believed to be due to sexual selection and a history of evolution that made distance running a favourable trait, that people of this descent are naturally more gifted in this sport.

In their seminal paper, Howe et al (1998) attempted to further investigate the existence of talent. Examples included reports of extraordinary children performing impressive feats at an early age, rare capacities which occur in a select few children (for example, perfect pitch), biological correlates of certain skills and abilities, as well as autistic individuals who have impressive skills with less learning opportunities (Howe et al., 1998). This evidence for the existence of talent does not come unopposed. Howe et al. further outlined direct correlations between the amount of practice a person performs and their overall performance. With increased practice, comes increased performance (Ericsson et al., 1993; Sloboda & Howe, 1991). That said, researchers have strongly indicated the capacity to practice over extended periods of time is influenced by factors such as parental support, self-belief, and access to resources (Howe et al., 1998; Collins et al., 2016; Baker et al., 2009).

More recently, Baker and Wattie (2018) argued that due to evolutionary principles, certain individual characteristics align more favourably with certain sports (Baker & Wattie 2018). For example, height in sports where height is more advantageous (Baker & Wattie, 2018). Overall, in order to better understand the two, we must look at nature and nurture together. One cannot exist in a vacuum without considering or understanding the other. Consider athletes with a high amount of "innate talent". Even these athletes need to practice and develop their skills over time to show high degree of proficiency in their discipline (Baker & Wattie, 2018; Kaufman, 2014; Ericsson, 2013). However, the variance in expertise development cannot solely be explained by deliberate practice, as other traits are also critical for development (Ericsson, 2013; Hambrick et al., 2014). In the field of music for example, this variance can be explained by a number of factors, including starting age, intelligence, personality, as well as genetics (Hambrick et al., 2014). While it is clear that deliberate practice is important for athlete development, there are many other factors that affect success as well the identification of talent, including physiology, anthropometric factors, psychological factors, and emotional factors (Baker & Wattie, 2018; Kaufman, 2014; Ericsson, 2013). To gather a clearer picture of talent, we must consider that both "nature" and "nurture" need to be understood together. Ultimately, Baker & Wattie (2018) conclude their review with the assertion that in order to have utility in the real-world applications of talent, then talent itself must be measurable. As currently constituted, it is not (aside from a few anthropometric and body size measurements that would relate to innate talent) (Baker & Wattie, 2018). This, paired with the low efficacy of talent identification programs across various levels in

sport (Collins, 2004; Koz et al., 2012; Johnston et al., 2018), creates a number of problems in sport programs who make early athlete selection decisions.

2.4 **Talent Identification and Selection**

The concepts of talent identification (TID) and talent selection (TS) exist across many disciplines and have proven integral within the world of sport. Talent identification (TID) is the identification of athletes who have the potential to compete in senior level athletics and may or may not involve explicitly interacting with the athlete to make them aware of this process (Vaeyens et al., 2009). Talent selection on the other hand refers to explicitly choosing athletes for a team or development pathway. These can occur simultaneously, like when coaches need to select athletes for a development team after observing a tryout. They can also be done separately. For example, professional sports teams employ scouts to identify talent and observe the progress of these identified players over time. Talent decisions are made on an ongoing basis at a variety of levels, including youth development pathways all the way through to the professional ranks. These decisions carry significant weight, as they can determine which children will have access to the highest level of sport development programs but can also mean millions of dollars to professional organizations who are always looking for the best talent at the best price.

The concept of TID and TS has a long history, originating in ancient Greece, when youth were identified and trained for various sports at a young age (Ghristopoulos, 2003). Currently, the ability to identify young talent, and then develop it, plays a crucial role in the pursuit of success on both the international and professional sporting stages (Vaeyens, 2008). The practice of TID can be seen across many sports and at a variety of levels, which has led to an increase in the amount of research being done in the field

(Baker et al., 2020). Over the last 25 years there have been approximately 1700 articles published in the field, with many of those publications being published within the past ten years (Johnston et al., 2017). Baker et al. noted that, while there has been a rise in publications, the literature review done by Johnston et al. highlighted a lack of high-quality evidence presented in many of these papers (Baker et al., 2020). Baker and colleagues noted the lack of longitudinal studies, as well as a lack of understanding of the term "talent" as main limiting factors in the quality of the research being done (Baker et al., 2020). The growing prevalence and importance of TIDS reinforces the need for research that informs effective and efficient information to improve their ability to select talent (Johnston et al., 2018).

2.5 **Importance of TID**

In many organizations, the process of identifying talent begins early during athletes' developmental trajectory. By identifying this talent early on in development, athletes can then be placed in more ideal environments to allow them to continue the path to for expertise development (Baker et al., 2017). High quality TID programs may have the ability to predict future success and thus allow for organizations to focus their resources on these "targeted" individuals (Durand-Bush & Salmela, 2001). Based on these presumptions, countries and sporting organizations have been using TID programs for years and invest millions of dollars towards successful performance the Olympics and other international world games (Hogan & Norton, 2000). To provide context, Great Britain (at least between 2008 and 2016) continually increased their spending year after year in an attempt to win more medals (Rees et al., 2016). For the 2008 Olympics, spending was at 235 million pounds (Rees et al., 2016). This number climbed to 261

million pounds for 2012, and then reached an astonishing 355 million pounds for the 2016 games (Rees et al., 2016).

TID programs are not just heavily funded at the international amateur competition level. In major professional sports leagues across North America millions of dollars are spent annually on scouting and development. For example, each year the National Basketball Association (NBA) holds its annual draft to allow its member teams to select new talent to bolster their rosters. Each pick taken in the first-round signs a rookie contract for a minimum of ten million US dollars. This number can be much higher in sports like baseball, where MLB draft signing bonuses can be in the tens of millions for each player, on top of million-dollar contracts. With so much money on the line for these young players, it is clear how important TID is for the athletes and the professional teams investing in them.

2.6 **Accuracy of TID**

Despite the popularity and investment in this process, accurate TID remains difficult. For instance, even with significant time and money invested by professional sport organizations, teams continue to struggle to accurately identify and select the top talent. Across the four major sports leagues in North America (National Hockey League (NHL), National Basketball Association (NBA), National Football League (NFL), and Major League Baseball (MLB), an annual draft occurs where teams from across the league select eligible players in rotating order (Farah & Baker, 2020). This order is usually determined by the previous years' standings, where teams who performed poorly get to select ahead of teams who performed better (Farah & Baker, 2020). The idea behind these drafts is that players with higher potential will be taken in earlier rounds,

and those with less would be selected in later rounds (Johnston et al., 2021). Koz, Fraser-Thomas, and Baker found that teams struggle with accuracy in these drafts, suggesting that there is a lot of room for improvement. When comparing the round a player was selected in to the number of games they played in their given league, they discovered a consistent negative relationship between the draft round and the number of games played. However, the effect was small across every sport. Even the strongest relationship found (in the NBA) explained less than 17 percent of the variance in games played. This means a high amount of variability is found in other factors like injury, late blooming, and type I/II errors (Koz et al., 2012). The researchers noted that the MLB draft was particularly poor, while the NBA draft was difficult to draw conclusions from since there are only two rounds to select talent. In summary, these findings suggest the draft systems in place currently are limited in accuracy and have room for growth (Koz et al., 2012).

Selection decisions are often made by coaches and other decision makers (general managers, scouts, assistants, etc.). Their job is to prepare for selection by identifying players they see as having high potential in their sport, or who they see as a fit for their team (Baker et al., 2018). In order to accomplish this task, they make predictions about these athlete's future potential, which are used to predict who has the best opportunity for future success in their given sport (Baker et al., 2018). This can involve the use of anthropometric data, performance tests (speed tests, agility tests, power tests etc), and performance data from previous seasons, and perhaps video analysis (Baker et al., 2018; Johnston et al., 2021; Koz et al., 2012; Farah & Baker, 2020). Despite having all of this data at their disposal, making predictions of future performance has proven a highly challenging task (Farah & Baker, 2020; Johnston et al., 2021; Koz et al., 2012).

Johnston et al. (2017) found that although there are a large number of research papers (approximately 1700 over the last 25 years), very few of these papers were able to accurately identify talent. In fact, the authors found that no variables in the studies they examined were uniformly able to predict future skill level. Some of the variables that were examined by the papers appeared in multiple studies, such as height, weight, sprint tests, and strength tests; however, there was no consistent relationship found between these common variables and greater skill level. Very few of the studies found success in identifying talent, however there were a few that could correctly predict or identify talent early on. For example, di Cagno et al. (2014) found that coordination and precision capabilities can in fact be used as long-term predictors of success in gymnastics. This study was able to correctly find predictors of future success to help practitioners identify talent better earlier in development. It is also worth noting that certain sports, such as sprinting, swimming, distance running, or rowing have similarity in physical and physiological profiles within the sport (for example, sprinters uniformly have a higher ratio of type IIa and type IIx muscle fibers to type I) (Johnston et al., 2021; Plotkin et al., 2021). However, within many sports there exists a greater amount of diversity amongst performers (Johnston et al., 2021). This can be seen across the genetic makeup, development experiences, as well as other physiological and psychological factors (Johnston et al., 2021).

Many of the studies examined by Johnston et al. looked at variables that helped differentiate between levels of competition. For example, Gonaus and Muller (2012) found that players who were drafted into an elite soccer league had higher levels of upper extremity power and other physiological advantages over their undrafted counterparts.

This study was able to differentiate between selected and deselected groups; however, these findings may not help practitioners at better identifying young talent. There are no pre-determined formulas that dictate who is “talented” and who fits best within a given team (Johnston et al., 2021). This further highlights the need for more research in the field, so that decision makers have greater evidence to inform decisions.

2.7 **Factors Influencing the Efficacy of Talent ID**

The process of TID can be extremely difficult. The ability of coaches and decision makers to accurately identify talent remains low, as evidenced by the sub-optimal success rates of predictions (Collins, 2004; Koz et al., 2012; Johnston et al., 2018). There is some recent evidence of improvement in the area, as outlined by Tetlock and Gardner (2016), however research also suggests continued difficulty of accurate TID (Schorer et al., 2017). Schorer et al. suggest that it (TID) be revisited frequently over the course of development to attempt to improve the efficacy of the process. Such evaluations would be able to further enhance the quality of coaching and the amount of resources that can be focused on top players throughout the pathway (Collins, 2004; Baker et al., 2017). Despite the great importance placed on being able to identify talent correctly and revisit it frequently, there are still many biases influencing this decision-making process, which affects athlete selection and development (Johnston & Baker, 2020; Christenson, 2009).

Bias in Selection and Issues with Decision Making:

One of the largest issues that affects accurate and effective TID is the confidence and many biases of those responsible for selection. Wherever there is the need for a “human decision”, there is the possibility for error based on human factors, including bias

(Johnston & Baker, 2020). This error can also be due to factors such as hunger (depleted glucose) and fatigue (Danziger et al., 2011). In sport, one of the greatest factors influencing decision making is often the beliefs, preferences, and goals outlined by the coach or the team itself (Christenson, 2009). An example of this was found by Bucci et al. (2012), where the authors noted that hockey coaches selected their best players based on how their performance and skills aligned with the coaching staff's ideologies and tactics.

Another example of bias in decision making can be found when examining how professional sports teams prepare for their yearly drafts. As previously mentioned, coaches and decision makers are forced into making predictions on "potential" of athletes. Before a team makes their selection, decision makers often have to go through film of the various players, scour their statistics, examine physical make up, conduct mental tests, and host pre-draft workouts (if allowed under the league rules) (Johnston et al., 2021; Farah & Baker, 2020; Koz et al., 2012). Since there are so many steps involved in the pre-draft process, there is an increased chance of an error occurring in the overall analysis of a player or in the decision makers judgement (Johnston et al., 2021). Humans are prone to making errors and cognitive bias when they are forced into making decisions where the outcome is not yet known (Johnston & Baker, 2020). Since we cannot possibly know with any certainty how a player will perform for the next 10-20 years of their career, these errors and biases are common. For example, consider the halo effect, a common cognitive bias where the observer's perception of a trait is influenced by information about a different trait, which is often irrelevant to the first trait (Forgas, 2011). If a scout observes a trait they deem positive (for example, height and long

wingspan), they may overlook negative characteristics such as poor shooting percentage. This style of observation is similar to the iCodes search effects (Lath et al., 2021). This iCodes search effect is simply when the observer notices a positive, attractive option, so they are directed to this player over others (Lath et al., 2021). For example, when considering the sport of basketball, if a coach observes a player with great height, they will be drawn to that player more due to this positive characteristic. They may begin to fight harder for this player, regardless of the negatives that would indicate that player may not be the best to select.

Another great example of this is found in "confirmation bias", which describes the tendency to look for evidence that corroborates or adds evidence to an existing theory or belief (Nickerson, 1998). In a sport context, this would translate to a coach or decision maker searching for evidence that would confirm a pre-determined bias or assumption about specific players or their traits. For example, if a soccer coach believes that larger sized players are inherently slower than skinnier, smaller players, that coach may look harder for evidence that large players are moving slower on the pitch than smaller ones. With bias and beliefs of coaches being such a large factor in TID, very few studies have been conducted on how these biases affect coaches' decision making (Johnston & Baker, 2020). There are many cognitive biases and beliefs that can influence how coaches select and deselect players from their teams (Johnston & Baker, 2020). More research is needed to better understand how coaches are making their decisions as well as how to reduce or eliminate bias.

Decision Making Processes:

It has been hypothesized that coaches and decision makers tend to take one of two approaches: clinical judgement or actuarial judgement (Baker et al., 2020). Actuarial judgement refers to the strategy of an organization developing a series of rules for making decision on talent (Dawes et al., 1989). These rules vary from team to team and organization to organization, and are also subject to change when new members are introduced or when new information becomes available. Information is combined and analyzed based on these rules, and decisions follow what the rules suggest (Dawes et al., 1989). The other approach, the clinical judgement approach, factors in the coaches' eye (what the coaches see in the talent), and their intuition and overall "sense" of the sport (Dawes et al., 1989). Since coaches in high level organizations are generally considered to be experts, their opinions in the decisions on talent come into play with this approach. However, these professional coaches are not the only ones who need to make talent decisions. As previously states, TID occurs along a continuum for athletes, at youth stages through to senior competition. This means younger, less experienced coaches are making decisions on talent that could exclude potentially promising individuals from youth and development teams based on uninformed ideologies of talent and development. Through the research, there remains a lack of understanding for how coaches of various levels identify talent, and more research must be conducted to better understand it.

The decision-making process contains another element for consideration: heuristics. These heuristics are, simply put, easy decision rules or "rules of thumb" (Lath et al., 2021). Humans often use and develop a number of heuristics to facilitate decision making (Gigerenzer & Selton, 2001). Heuristics ignore part of the information, which increases the speed at which decisions are made, the frugality and/or accuracy, when

compared to other, more complex methods (Gigerenzer & Gaissmaier, 2011). Lath et al. propose that heuristics could help provide simple, easy to apply decision rules, however the issue of validity and simplicity of these heuristics remains challenging (Lath et al., 2021).

In 2012, Rabb applied the 5 principles Marewski et al. developed for investigating heuristics to the world of sport. These principles aim to provide further insight on how coaches and decision makers can develop and test their heuristics in real world scenarios (Rabb, 2012). The first of five steps he identified is to build a precise model of heuristics. This involves identifying what to look for, when to stop and look at more information, and when/how to make a choice based on the information available. The second step is to test these heuristics, and compare them before the third step, which is to conduct comparative model tests, which are guided by selection strategy and theory. The fourth step examines the accuracy of the decision, and the fifth step is to implement the heuristic in real world applications (for example, talent decisions) (Rabb, 2012). While this heuristic model has many advantages, it is a rule, meaning they are fixed and defined, leaving no room for fluidity and variation, which is often involved when making judgements on athletic potential (Lath et al., 2021). Thus, heuristics can assist decision makers by providing clear predictions of the decision outcome, however more work needs to be done to investigate how new information or prior knowledge may impact these rules.

Limitations and Issues with Current Research:

Of the current research that exists on TID in sport, there are many gaps and limitations. As previously mentioned, there has been a considerable increase in the

number of papers published related to TID in the past 10 years (Baker et al., 2020). However, Baker, Cobley, and Schorer also note that with this increase in published research comes an increase in unidimensional research (Baker et al., 2020). This unidimensional focus reflects a high number of studies that focus on one single variable, which in most cases is a physical or physiological attribute (Baker et al., 2020). This type of research does not give a full picture of the multidimensional nature of talent (Baker et al., 2020). Instead, more research is needed using multiple variables (Johnston, Wattie, Schorer, & Baker, 2018).

Johnston et al. also highlighted the need for more longitudinal and creative research designs, as their review only found 16 longitudinal studies over an 11-year period (2004-2015) investigating an elite athlete sample (Johnston et al., 2017). This is because these longitudinal study designs help to prevent bias when working with a talented sample (Johnston et al., 2017). For example, current literature indicates that many TID decisions are made on youth athletes around the age of 15, when these athletes will likely not reach their peak age of performance until around 25-30 years of age (Abbott et al., 2005). This means that prognosis for these decisions must be made for at least 10 years into the future (Abbott et al., 2005). This long timeframe for predicting potential is less effective than when looking at shorter time spans (Baker et al., 2017). Longitudinal designs can help bridge the gap between when decisions on talent are made to when the athlete is finally ready to be selected or deselected for different teams. This is when we truly know how accurate these decisions were. While challenging and costly, these types of research methodologies are crucial to furthering our research in the field.

To improve our understanding of TID and how athletes are selected, more work needs to be done to understand how decisions are made by coaches, scouts, and other decision makers on talent (Baker et al., 2020). Baker et al. note that we still know very little about how these decisions are made, and we also come up short in our knowledge of whether or not these decisions are of good quality (Baker et al., 2020). In professional sport environments the budget exists to spend significant money on talent scouts, coaches, and managers to make decisions on drafting the correct players to enter their organization (Koz et al., 2012). This is a very different situation when looking at some amateur national sport organizations. In Canada, national teams only have a small number of coaches, in some cases just one, to make decisions on incoming talent for TID and development programs (Baker et al., 2020). These national coaches must also make these decisions in a much shorter window of time, further increasing the difficulty of making these decisions (Baker et al., 2020). In order to better understand the success rate of coaches and scouts, more research should be done to understand the differences between statistical decision-making processes and intuitive based decision-making processes (Koz et al., 2012). Finally, more research needs to be done to better understand how decisions on talent are made by coaches of all levels who use their intuition and knowledge of the sport to make decisions (Baker et al., 2020)

2.8 **Current TID Practice and Future Directions**

The current practices of TID are varied based on sport and organization. Many sporting organizations use development teams or junior clubs and programs to further develop the talent that they find through their TID programs. Examples of this would include professional soccer clubs' junior academies, Major League Baseball Minor

League affiliates, and the G-League within the NBA umbrella. For these organizations to select talent for these clubs, organizations rely on the development of their own TID protocols. Much of the current research suggests using a multi faceted approach, focused on factors such as physical, physiological, technical ability, tactical skill, and psychological attributes of the athlete (Burgess et al., 2012). According to a recent study by Larkin et al., recruiters of talent within Australian football are using this multi dimensional approach, however from organization to organization the focus on various factors is quite different (Larkin et al., 2020). Some clubs have a higher emphasis on tactical skill, while others favour the physical attributes of an individual player (Larkin et al., 2020). This suggests that TID may be incredibly heterogeneous even within sports.

As previously stated, we must also consider time frames in talent-based decision making. These time frames are crucial since talent can be seen as "emergenic" and may not present itself immediately. It can take time for talent to present itself and manifest in specific athletes due to the nature of genetics and childhood development. This makes the process of identifying talent that much more complex, since there is no specific age for practitioners to pinpoint when they should be looking for talent. Some athletes may find success early, while it may take others a longer period of time to develop. These slow developers can even overtake those who present signs of promise from a young age if given the necessary resources (coaching, facilities, support etc).

2.9 **Talent in Basketball**

Within the sport of basketball, there are a number of individual factors that could reflect talent. An important individual constraint to consider, and perhaps the most important to consider within the sport of basketball, is anthropometric and physiological

characteristics. Jones et al. (2020) conducted a study of how collegiate coaches identify talent, and their findings indicate that coach's value anthropometric and physiological attributes more than other contributing factors to talent. According to a study by Zaric et al. (2020), height was a contributing factor to success across all positions at the FIBA world cup. The authors also found that when skill and basketball IQ were the same, taller players performed better. Since these anthropometric measures are related to the individual, they act as a constraint on development. Since coaches in basketball have placed a high value on anthropometrics, youth athletes who develop slower than others can be left behind due to the lack of selection for TID programs and development opportunities (Vaeyens, 2008).

While anthropometric variables are important for evaluating player potential in basketball, there are also other sources of information that can be available to decision makers. For example, information on prior performance (e.g., points per game, rebounds, assists etc.) may be used to evaluate players' potential, as well as video to supplement these statistics. Similarly, performance on draft combine tests can also be a source of information that decision makers use when selecting between top prospects (Baker et al., 2018; Johnston et al., 2021; Koz et al., 2012; Farah & Baker, 2020). There are other factors that coaches often use as well, such as motivation or confidence, which can be harder to quantify, as there is no true formula for how to use these variables in tandem when making selections (Farah & Baker, 2020; Johnston et al., 2021; Koz et al., 2012). Finally, since there is such a large disparity physiologically in the make up of various basketball athletes (some positions may be up to a foot taller than others), selection is made even more difficult (Johnston et al., 2021; Plotkin et al., 2021). With all of this

information available to coaches, but no formula for how to select talent, the job of making decisions on basketball talent is no easy task.

2.10 **Conclusion**

Talent identification plays a crucial role in National as well as professional sports organizations. In order to study how talent is identified within Canadian Basketball, we designed a novel experiment which allows us to have coaches and decision makers make predictions on athletes while blinded to the known outcome of their predictions. Put simply, coaches and decision makers made 3 predictions which, under normal circumstances, would take years to know how their predictions turned out. However, with our design, we can know immediately since we are using historical data and coding the data and players names to prevent identification by participants. This novel experimental approach may provide a means to examine the accuracy of predictions made by coaches, which will help us further our understanding of how coaches make decisions on talent in basketball in Canada.

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Chapter 3. Investigating Talent Decisions in Canadian Basketball

3.1 **Introduction**

What is Talent?

The term "talent" is often used in sport to define and categorize players based on ability, performance, and future potential in their chosen sport (Herling, 2020; Howe et al., 1998). Despite the widespread use of the term "talent", it is still relatively misunderstood (Baker & Wattie, 2018; Baker et al., 2019; Herling, 2020; Howe et al., 1998). The definitions of practitioners, researchers, and fans all differ depending on individual beliefs of what "talent" truly is (Baker & Wattie, 2018; Baker et al., 2019). Furthermore, there continues be a debate about whether or not talent even exists, and if it does, what role it plays in performance and expertise development.

Regardless of the conceptual and theoretical debates within talent research talent identification and selection are integral parts of the athlete development pathways. These decisions are made at a number of different levels, further increasing the importance of accurate TID and selection (Baker et al., 2019; Baker et al., 2017; Durand-Bush & Salmela, 2001; Howe et al., 1998). If these decisions are made accurately early in an athlete's development, resources can be better allocated to promising athletes, who can receive improved coaching, higher levels of competition, and have more resources at their disposal (Baker et al., 2017; Durand-Bush & Salmela, 2001). Ultimately, however, TID and selection remains a difficult and sometimes expensive task.

TID is a complex issue and can be extremely costly for organizations. In professional sport, teams spend millions of dollars each year on top talent in attempts to improve their roster in an ultimate quest for league supremacy (Koz et al., 2012). Even in Olympic sport it as an expensive endeavour. Great Britain spent 355 million pounds for their Olympic teams and athletes in 2016, and this number is expected to continue to rise with each games (Rees et al., 2016). These financial costs can be wasted and lost if TID and selection processes are not optimized, and due to the difficulty of accurate TID and selection, this is often the case.

Despite the fact that teams spend millions of dollars to accurately identify and select athletes, accuracy of these decisions remains poor and inconsistent (Koz et al., 2012). For instance, the four major sports leagues of North America (the NFL, NBA, MLB, and NHL) hold yearly drafts to select the top young talent coming into the league. They also select talent from unsigned players in the off season to improve their squads. These teams often struggle with selecting the best players from the draft, as well as from the available talent pool through free agency (Farah & Baker, 2020; Johnston et al., 2021; Koz et al., 2012). With all the money spent on rookie contracts and being able to identify the best players, teams are continually looking for ways to improve their process, and there is a lot of room for improvement, especially in the draft and draft process (Johnston et al., 2021; Koz et al., 2012).

Factors Affecting Selection and Identification:

Decisions on who teams choose to identify and select are often made by the highest decision makers in the organization and are based largely on players who show the most potential in their sport or fit with the specific teams style, ideology, and vision

(Baker et al., 2018). However, because these decisions are being made by humans, and many of the staff already have their own preconceived biases and ideologies on talent, this task is difficult and error prone (Christenson, 2009; Johnston & Baker, 2020; Smith & McGannon, 2018). These biases can lead to players being selected for or against based on what decision makers have pre-determined about them (Johnston & Baker, 2020). They can also lead to coaches ignoring positive traits and focusing solely on negative traits, or vice versa (a bias known as the "Halo Effect" (see chapter 2.7) (Forgas, 2011).

The process of decision making can involve multiple processes and sources of information. Decisions can be based on current and previous performance data, anthropometric and physiological input, combine-based performance tests, and video-based analysis, among other elements (Baker et al., 2018; Farah & Baker, 2020; Johnston et al., 2021; Koz et al., 2012). Coach's intuition about an athlete can also play a critical role, a phenomenon known as the "coach's eye", (Lath et al., 2021). With so many different factors being looked at by coaches and decision makers, it is no wonder it is such a challenging process. Moreover, the variability and diversity amongst a group of players up for selection further increases the complexity of the task (Johnston et al., 2021; Lath et al., 2021; Plotkin et al., 2021).

Current Practices and Research Background:

With such a high number of resources devoted to TID and selection, the research in the area has accelerated in recent decades (Baker et al., 2020; Johnston et al., 2017). However, despite the rise in published papers and research, few researchers have been able to correctly identify stable indicators of talent. No single study could find a variable with any uniformity in predicting success or talent (Johnston et al., 2017). It is likely that

this is due to a disproportionate focus on single variables, which are often exclusively physical or physiological in nature (Johnston et al., 2017). While this research can give some useful information to coaches and decision makers, it does not reflect the multidimensional nature of talent in sport (Baker et al., 2019). Using a multidimensional approach to study talent decisions, based on an understanding of both primary and secondary factors (Johnston et al., 2017), may help us to better understand how decision makers use and balance different sources of information.

To further the research on talent decision-making, there exists the challenge of navigating the latency between when selection occurs and the fulfilment (or lack thereof) of an athlete's potential. This latency could be as long as decades, which from a research perspective would be expensive and/or time consuming. Schorer and colleagues attempted to creatively circumvent this latency problem in a study of talent selections in handball (Schorer et al., 2017). This study involved three distinct phases and had to be tracked over a ten-year period. Phase 1 involved players performing a battery of skill and sport specific tasks in handball. Phase 2 saw National and regional coaches who attended the camps where these skills were performed identify the most talented players. The final phase, phase 3, involved current novice and advanced handball players select the most talented players from short clips of the camps. By the end of the ten-year period, the predictions could be marked by the authors and scored for accuracy. While this study design provided important insights into talent decisions, these longitudinal studies are still time consuming and can be difficult to track over time (Johnston et al., 2017).

The aim of this study was to pilot test a novel method for studying how coaches use information to make decisions, and the accuracy of those decisions. Specifically, we

aimed to test the use of a novel method that could circumvent the latency challenge of studying talent decisions.

3.2 **Methods**

Participants:

To answer our ultimate question, and further investigate talent decisions, our selection task was made available to basketball coaches across the country for completion. Coaches were recruited via email as well as through other members of the coaching community. After providing informed consent, coaches and decision makers were asked to complete a brief demographic questionnaire to describe their role (coach, assistant coach, talent scout, general manager, etc.), their level of coaching (Professional, NCAA/USPORT, Preparatory high school, high school, youth), how long they have been involved with the decision making process (in years), and if they had any previous playing experience; what level did they ultimately reach. They were then asked to complete a talent decision making task.

Experimental Task Creation:

To gain the sort of feedback necessary to study how coaches and decision makers select and identify talent, a novel selection activity was created. This selection activity was based on a method utilized in a mass scientific collaboration by Salganik et al. (2020) Their collaboration study had researchers make predictions using their respective machine learning methods that had been optimized for making long term (15 years) predictions about youth development. Participants were asked to make predictions based on an incomplete dataset. This allowed researchers to score the results immediately,

saving time and resources (Salganik et al., 2020). Our prediction task modelled this approach, so we could score participants' data immediately based on objective existing outcomes, saving the time and resources needed to conduct an otherwise longitudinal study.

The experimental task consisted of a dataset of athlete information for 20 NCAA Division 1 basketball players from the 2003 NBA draft class. Athletes were chosen from the same class rather than different classes because decision makers generally must choose and compare athletes as part of a group, and may prefer one over another, just as was done by decision makers in real time, at the time of the actual draft in 2001. In short, information on athletes is relative to other athletes. As such, restricting athletes to the same draft class allows decision makers to consider the group of athletes when making their choices, instead of considering them on an individual level.

The dataset included NBA Draft Combine data from the year athletes were tested, their final year of performance statistics before their draft year (professional or NCAA statistics) and the conference the athlete played in, as well as their anthropometric measurements taken at the combine. Table 1 contains a complete list of variables included in the dataset. These variables were selected because they are commonly available, and assumed to be used by decision makers (Baker et al., 2018; Farah & Baker, 2020; Johnston et al., 2021; Koz et al., 2012). Those responsible for making draft decisions often use this quantitative data to further their selection process, and in essence, assist them in making predictions for athletes in a given draft class (Baker et al., 2018; Johnston et al., 2021; Farah & Baker, 2020). Although it was possible to include qualitative descriptors of each athlete, the inclusion of this information could have led to

identification of the specific athletes from the task, thereby allowing participants to achieve better scores based on their familiarity with the athlete. The research team felt the best way to pilot test this novel study design was to simply include their quantitative information.

Table 1: Summary of statistics given to participants

Statistic Given to Participants:	Explanation:
G	Games played.
GS	Games Started.
FG	Total field goals made.
FGA	Total field goals attempted.
3P	Total 3-point field goals made.
3PA	Total 3-point field goals attempted.
FT	Total free throws made.
FTA	Total free throws attempted.
TOV	Total turnovers.
PF	Total personal fouls.
FG%	Field goal percentage.
3P%	3-point field goal percentage.
FT%	Free throw percentage.
MP/G	Minutes played per game.
PTS/G	Points scored per game.
ORB/G	Offensive rebounds per game.
DRB/G	Defensive rebounds per game.
TRB/G	Total rebounds per game.
AST/G	Assists per game.
Weight	Weight measured at combine (pounds).
Height NO SHOES	Height from combine without shoes (inches).
Wingspan	Wingspan from combine (inches).
Standing Reach	Standing reach from combine (inches)
Pro Lane Agility	Pro lane agility test (seconds) measuring speed/agility (from combine).
¾ Court Sprint	¾ court sprint (seconds) measuring speed on court (from combine).
No Step Vertical Jump	Vertical jump with feet set (inches) measuring lower body power (from combine).
Maximum Vertical Jump	Vertical jump with momentum (inches) measuring lower body power and maximal jump height (from combine).

Bench Press	185-pound bench press (repetitions) measuring upper body strength (from combine).
Combine Age	Age of the athlete at the time of the combine (years) (from combine).
Conference	Conference the athlete played in during their final year of collegiate basketball.
Body Fat	Body fat calculated at the combine (percentage).

Multiple sources of information were removed from the dataset to prevent identification by participants. Most notably, athlete names and the collegiate institutions they attended were omitted. Furthermore, all athletes selected for the task were from Division 1 NCAA schools. As is the case with the NBA draft, players can be selected from a number of different levels of basketball. At the time of the draft used for this task, the NBA and its member clubs could select players from high school, college, as well as professional leagues around the globe. With this variety comes a number of issues. Statistics from a player who was already playing professionally could be looked at as dramatically different from someone playing in high school. Without a true way to quantify the differences in style of play, we chose to pick athletes who shared the same path to the NBA draft, the NCAA division 1 route. This also helped prevent participants from being able to identify athletes from the dataset, as players drafted from high school or from international leagues are often easier to identify, as these pathways to the NBA are far less common.

To pilot test this task, participants were asked to make predictions based on where the athlete would be taken in the draft. For example, when predicting where an athlete would be taken in the draft, the participants placed them into either “Lottery”, “late 1st round pick”, “second round pick”, and “undrafted player”. These categories were chosen

to simplify the task for participants. The NBA draft is broken up into 2 rounds, however the leagues clubs who miss the playoffs each year (14) are entered into a draft lottery with varying odds depending on how the teams finished in the standings. This lottery is very important, and players picked in the draft lottery are often standouts and receive better financial compensation for being selected in these first 14 picks. Each category is assigned a numerical value for the purpose of analyses.

Secondly, participants were also asked to predict how many years the athlete would play in the NBA. This task was also broken into numerical categories based on a time frame in years played. These time frames included 0-1 years, 1-3 years, 4-7 years, 8-11 years, 12-15 years, and 16+ years. This task was designed to better understand the selection decisions of participants and determine whether there was a relationship between a player's position in the draft and preconceptions of them having a longer NBA career. It is also used to explore whether coaches associated certain variables or positions with having longer careers in the league. Finally, participants were asked whether they feel the athlete would be an All-Star or All-NBA selection[1] at some point in their career. This task was designed to have participants outline who they felt were the standouts from the group, or which players they felt could end up with the best careers. Again, this task

[1] An All-Star selection is when a player is nominated by the general public and through approved NBA media personnel to make a team of the best players from the first half of a season in their given conference. 12 players are selected from each conference to play in this mid-season basketball showcase. An All-NBA selection is determined by a vote of approved media personnel, coaches, and peers, and determines the best players from each position. 3 teams are made, a 1st team (the best at each position), a 2nd team, and a 3rd team.

was designed in an attempt to identify any variables that decision makers feel are most important when identifying exceptional talent for their teams.

This project was approved by institutional Research Ethics Board through Ontario Tech University (REB #16462). All participants will provide informed consent prior to the commencement of the activity.

Data and Measures:

In order to accurately assess and compare how coaches of various levels faired in the activity, prediction results were scored on an individual level, noting the level and age range of players they currently coach. Twenty players from a single draft class were selected at random for this activity (n=20).

Draft position. Coaches placed players into a group based on draft position. If a coach predicted the player will be taken in the lottery (picks 1-14), then the player is a "Rank 1". If the coach believes he is a late first round pick (15-30), the player is a "Rank 2". A second-round pick was a "Rank 3" and an undrafted player was a "Rank 4". Each 'Rank' was numerically dummy coded as 1, 2, 3, and 4 for the purpose of analyses.

The base rates for each selection made gave an indication of the likelihood a participant gave a correct answer by chance. For "Rank 1" (lottery picks), there were 5 players with this designation. Therefore, 5/20, or a 25% proportion. This was the same for "Rank 3" (second round pick). "Rank 2" (first round non-lottery) contained 4 correct answers, or 4/20. This means there was a 20% frequency. Finally, "Rank 4" (undrafted players) had 6 players in the data set, meaning 6/20 or 33%.

Career Longevity. Coaches were also asked to predict the number of years (longevity) a player will have played in the NBA. Response options fell into 6 categories: "Rank 1" included players who played 0-1 years, "Rank 2" were players who played between 1 and 3 years, "Rank 3" between 4 and 7 years, "Rank 4" between 8 and 11 years, "Rank 5" between 12 and 15 years, and "Rank 6" included players who played 16 or more years. Coaches were not told ahead of time how many players there are from each group. Each 'Rank' was numerically dummy coded as 1, 2, 3, 4, 5, and 6 for the purpose of analyses.

The base rate of years spent in the league, between 0-1 years occurred 7 times, or 7/20 (35%). 1-3 years occurred 3 times in the dataset, or 3/20 (15%). Players who ended up with careers of between 4 and 7 years also occurred 3 times (i.e., a 15% chance of correct random selection) and players with careers of 8 to 11 years occurred 2 times in the dataset (i.e., 2/20 or 10%). Players with careers between 12 and 15 years occurred 4 times (4/20 or 20%) and, finally, 1 player in the dataset had a career of 16+ years reflecting a 5% frequency.

Career Notoriety. Finally, coaches were asked to identify the players from the group they believe would make an "All Star" or "All-NBA" team at some point in their career. This was scored by assigning a "Yes" for those who participants predicted would make a team, and a "No" for those they believed would not. Yes and No responses were numerically dummy coded as 1 and 0, respectively, the purpose of analyses.

The base rate of whether or not a player has made an All-Star team or an All-NBA team, there were 18 "No" correct responses (i.e., 18/20 or a frequency of 90%). There were only 2 "Yes" correct answer i.e., 2/20 or 10% frequency).

Analyses.

Draft Position Prediction:

To begin data analysis, the players from the data set (n=20) were separated by position and ranked based on each individual metric that was given to participants (for example, centers (n=3) were ranked 1-3 on each of the 21 metrics given to participants). They were also assigned a z score for each of the metrics to provide further context to their ranking. Coaches were then scored for their accuracy to the actual results of the draft they made predictions on. The mark scores were either "correct" or "incorrect" and each participant received a grade based on how many correct (out of 20) they were able to identify.

Once all participants were scored, descriptions were written about each player. These descriptions note whether the player was over or under valued by participants, as well as some statistical data from the metrics given to participants that might have played a role in the overall evaluation of the player.

Next, for the draft position prediction, "incorrect" answers were identified as either an over evaluation or an under evaluation. These numbers were totaled for each participant, as well as each player from the data set. When they overvalued an athlete, it meant they placed a higher draft value on them than was the "correct" value, with an undervalue indicating the opposite.

The average of all 11 participants was scored for each player based on draft position. Then, the difference value was found between the average answer of participants and the "correct" or "true" value. The difference indicated whether or not the

player was over valued or under valued by the group as a hole. Next, the standard deviation was found for the answers given for each player.

All-Star or All-NBA Prediction:

As with the draft position prediction, the All-Star and All-NBA prediction sub task was also scored. The correct answers of either yes or no were assigned a correct score, while the incorrect were marked accordingly. Participants were assigned a score out of 20, due to the fact that there are 20 players in the data set.

Career Longevity Prediction:

The career longevity prediction sub task was scored similarly to the other two subtasks. A total score for each participant was assigned out of 20. Next, an average was calculated for each player from the task and compared to the true value. The difference was calculated to identify which players participants assigned a higher or lower average career length to. Finally, percentages were calculated based on the number of correct responses given for each player.

To calculate the overall accuracy, or challenge, or the experimental task, odds ratios (OR) and 95% confidence intervals (CI) were calculated for each of the three outcome variables. Proportions of participants' correct answers were compared to proportion of actual correct answers within the dataset. OR's were deemed meaningful if the corresponding 95% CI excluded the value 1.00 as a possible value.

Relationship Between Predictions:

To test if the experimental task could illustrate decision-making processes related to the interrelationships between outcome measures, some descriptive inferential statistics were run. First, a rank-order correlation (Kendall's tau: τ_b) between draft position and career length was performed. Value of τ_b less than 0.10, 0.10-0.19, 0.20-0.29, and greater than 0.30, are very weak, weak, moderate, and strong, respectively. Second, a chi-square test, with eta squared (η^2) effect size, between draft position (lottery, 1st round, 2nd round, and undrafted) and All-Star/All-NBA (yes, no) was run. η^2 values of 0.01, 0.06, and 0.14 indicate small, medium and large effect sizes, respectively. All analyses were carried out using SPSS, and the criterion for statistical significance was set at $p < .05$.

3.3 **Results**

Our study was sent out to 34 participants in total, all of whom completed the initial survey in full. Of those 34, 11 returned the decision-making task and met the inclusion criteria, and thus were fully analyzed. All participants were involved in the decision-making process of basketball rosters in Canada. The majority of responses came from coaches that identified themselves as University or College level coaches (n=4). We also had responses from preparatory school coaches (n=1), high school non-preparatory (n=1), youth level (n=1), and the National team level (n=3). We also had 1 coach or decision maker from the professional level (n=1).

The majority of respondents were male decision makers (coaches, general managers or data analysts) (n=10). However, there was a more even split in terms of male vs. female teams that these decision makers are involved with. The majority of teams were still male (n=8); however, we saw more representation from those who work

directly with women's teams (n=3). The participants' data is displayed in Table 2 and is sorted by player position. The three centres from the pool of players given to participants are color coded in yellow, the point guards in orange, power forwards in green, shooting guards in blue, and small forwards in red. Participants performance is graded as a group in Table 2. Overall percentages are displayed based on whether or not the group over valued, under valued, or were able to correctly identify the draft round of the player. The totals of first place ranking metrics and last place ranking metrics are included as well, for the context of how they faired when compared to their positional counterparts. There are also some noteworthy statistics and ranking included in the Metrics of Importance column to provide further insight into what the participants may have seen if they chose to rank the players (these rankings were not provided explicitly).

Table 2: Task Player Breakdown

Player Name:	Position	TDP	AEDP	Diff	OVAL	UNVAL	TVAL	NOF	NOL	Metrics of Importance:
Jason Collins	C	2	2.36	0.36	27%	55%	18%	9	1	- Highest FG% - Highest PPG - Highest RPG - Highest FT% - Highest 3pt% - Highest MPG - Last in ¾ Sprint - Poor combine (no 1st place results across the 5 tests)
Brendan Haywood	C	2	2.73	0.73	18%	55%	27%	8	4	- Tallest - Longest wingspan - Highest blocks - Youngest player - Highest PF's - Most turnovers - Lowest FT%
Mike Mardesich	C	4	3.91	-0.09	9%	0%	91%	5	12	- Fastest from his position - Highest jumper at position - Last in MPG - Last in FG% - Last in PPG - Last in RPG - Last in APG - Last in steals - Last in blocks
Jeryl Sasser	PG	2	3.18	1.18	0%	73%	27%	8	6	- Tallest player at position - Longest wingspan at position - Most RPG - Most blocks - Fewest turnovers - Second in FT%

										- Second in 3pt% - Second in FG%
Jamison Brewer	PG	3	2.55	-0.45	45%	27%	27%	7	8	- Highest FG% - Highest assists - Most steals - Fastest lane agility - Last in PPG - Last in FT% - Last in MPG - Most turnovers
SirValiant Brown	PG	4	3.64	-0.36	27%	N/A	73%	9	7	- Shortest at position - Shortest wingspan - Last in FG% - Last in RPG - Fastest ¾ court sprint - Best vertical jump - Best max vertical jump - Highest MPG - Highest PPG - Highest 3pt% - Highest FT% - Youngest of group
Michael Wright	PF	3	2.55	-0.45	45%	18%	36%	5	4	- Fastest lane agility - Fastest ¾ court sprint - Highest FG% - Highest bench press reps - Best max vertical - Fewest blocks - Fewest assists - Did not make a 3pt shot
Eddie Griffin	PF	1	1.27	0.27	N/A	27%	73%	12	3	- Tallest at position - Longest wingspan - Fastest ¾ court sprint - Highest MPG - Highest 3pt% - Highest PPG

										- Highest RPG - Most blocks - Low fouls - Low body fat - Youngest of position - Lowest FT% - Lowest FG% - Lowest bench press reps - Low vertical jump number
Brian Scalabrine	PF	3	3.45	0.45	9%	55%	36%	3	7	- Second tallest of group - Lowest wingspan - Last in ¾ court sprint - Last in lane agility - Lowest vertical jump numbers - Low rebound numbers - High turnovers - High personal fouls - Second in FT% - High steals - High assists - Second in 3pt%
Anthony Evans	PF	4	3.55	-0.45	36%	N/A	64%	3	7	- Longest wingspan to height ratio - Best vertical jump - Most bench press reps - Second FG% - Lowest turnovers - Second in blocks - Fewest MPG - Second in FG% - Lowest steals - Lowest PPG - Lowest RPG - Shortest of group - Did not make a 3pt shot - Slowest in pro lane agility
Gilbert Arenas	SG	3	1.73	-1.27	82%	18%	0%	9	3	- Longest wingspan

										- Highest vertical jump - Most bench press reps - Highest FG% - Highest 3pt% - Most steals - Youngest at position - Lowest body fat % - Second in PPG, RPG, APG - Most turnovers - Lowest FT%
Brandon Armstrong	SG	2	1.82	-0.18	45%	18%	36%	8	6	- Longest wingspan - Tallest player - Fastest ¾ court sprint - Best max vertical jump - Highest MPG - Highest FT% - Highest PPG - Lowest turnovers - Highest body fat % - Highest foul number - Lowest blocks - Lowest assists - Lowest in RPG
Darren Kelly	SG	4	3.73	-0.27	18%	N/A	82%	6	11	- Highest RPG - Highest APG - Most blocks - Lowest foul count - Least steals - Fewest PPG - Lowest FG% - Lowest 3pt% - Lowest MPG - Fewest bench press reps - Lowest max vertical jump - Lowest height - Lowest wingspan

Shane Battier	SF	1	2.00	1.00	N/A	64%	36%	9	0	- Tallest at position - Longest reach - Fastest pro lane agility - Highest MPG - Best FT% - Highest PPG - Highest RPG - Most steals - Most blocks - Second in 3pt% - Low FG% for position - Poor vertical jump numbers - Low APG - High foul numbers -
Joe Johnson	SF	1	1.82	0.82	N/A	55%	45%	3	3	- Highest 3pt% at position - Youngest at position - High steals - High assists - Low foul count - High FT% - Sixth in wingspan - Poor pro lane agility - Poor vertical jump metrics - Low MPG - Low FG% - Last in PPG at position - Low RPG - Low blocks - High turnover number
Sean Lampley	SF	3	2.45	-0.55	64%	27%	9%	1	4	- High FG% - High FG% - Low 3pt% - Second highest PPG - Highest APG - Lowest steals

										- Low blocks
Ryan Carroll	SF	4	2.00	-2.00	91%	N/A	9%	2	2	- Smallest wingspan - Second smallest in height - Fastest in ¾ court sprint - Second highest FT% - Worst FG% - Fourth in PPG - Last in RPG - Second in APG - Second in steals - Second in blocks - Fourth in MPG
Jason Richardson	SF	1	2.09	1.09	N/A	82%	18%	2	3	- Longest wingspan of group - Fifth in height - Poor MPG - Second in FG% - Third in 3pt% - Poor FT% - Low PPG - Low RPG - Low turnovers - Second in blocks - Second youngest at position
Kenny Gregory	SF	4	2.55	-1.45	64%	N/A	36%	6	3	- Lowest height - Third in wingspan - Fastest ¾ court sprint - Best in jump measures - Highest FG% - Lowest FT% - Highest RPG - Sixth in steals - Lowest in blocks - Third youngest
Rodney White	SF	1	2.55	1.55	N/A	82%	18%	2	4	- Second in height - Longest wingspan - Lowest jump metrics

										- Third in MPG - Most bench press reps - Fourth in FG% - Poor 3pt% - Poor FT% - Third in PPG - Second most turnovers

TDP = True draft position; AEDP = Average estimated draft position; Diff = Difference between TDP and AEDP; OVAL = Percentage of responses over valuing a player; UNVAL = Percentage of participants undervaluing a player; TVAL = Percentage of true evaluations of players (correct responses); NOF = Total number of 1st place rankings in the metrics given to participants; NOL = Total number of last place rankings in metrics given to participants; FG = Field Goal; FT = Free Throw; 3pt% = Three Point Shooting Percentage; PPG = Points Per Game; RPG = Rebounds Per Game; MPG = Minutes Per Game; APG = Assists Per Game.

Draft Position Prediction:

Overall, participants struggled to accurately identify which players would be selected, or not selected throughout the draft (see Table 3). Overall, the average correct predictions by participants were 7.6 (SD=1.55) answers out of 20 predictions. There was an even split between the number of times a player was over valued and under valued. The average of participants over valuing a player was 6.4 (SD=2.6) and the average for participants under valuing a player was 6 (SD=2.37). The highest score of all participants was 10 out of 20 when making a prediction on draft position. This was achieved by 2 participants.

Odds ratios were calculated for each of the 4 draft positions available for participants. The OR for lottery pick, was 0.38 (95% CI: 0.22-0.65). The OR for a non-lottery first round pick was 0.27 (95% CI: 0.14-0.53). For second round pick, there was a 78% lower likelihood of correct identification (OR: 0.22, 95% CI: 0.11-0.42). Finally, there was a 41% lower likelihood of correctly identifying undrafted players (OR: 0.59, 95% CI: 0.38-0.92).

These odds ratios, indicate that participants were more accurate when the players draft value was either Lottery pick (Rank 1) or Undrafted player (Rank 4). The six most accurately identified players from the task were all from one of those two groups. In fact, the three most correctly identified players (Mike Mardesich, Darren Kelly, and SirValiant Brown) were all undrafted players. All three were accurately identified by over 70% of participants (91%, 82%, and 73% respectively). Of those two groups (1's and 4's) there were only 11 in the pool of players from the task, meaning over half of the lottery players and undrafted players (6 of 11) fell at the top of the rankings for being most accurately

identified. A similar pattern was recognized in the difference between the participants average and the true value of the player. Of the 8 averages closest to 0 (the most accurately identified players based on the average answer of participants, and not just who got it right), 5 of those 8 players were from the 1 and 4 categories, further highlighting that participant's performed better when identifying the players from those groups.

Table 3: Draft Position Predictions Results

Athlete:	Position	Draft Position:	Part. 1	Part. 2	Part. 3	Part. 4	Part. 5	Part. 6	Part. 7	Part. 8	Part. 9	Part. 10	Part. 11
Jason Collins	Center	2	3	1	1	4	3	1	2	3	3	2	3
Brendan Haywood	Center	2	4	2	2	4	4	3	1	2	3	1	4
Mike Mardesich	Center	4	4	4	4	4	4	4	4	3	4	4	4
Jeryl Sasser	Point Guard	2	4	3	4	4	4	2	2	3	3	2	4
Jamison Brewer	Point Guard	3	4	2	3	4	4	1	2	1	3	1	3
SirValiant Brown	Point Guard	4	4	4	4	4	4	3	3	4	2	4	4
Michael Wright	Power Forward	3	2	1	3	4	4	2	2	3	3	3	1
Eddie Griffin	Power Forward	1	1	1	1	2	1	1	1	2	2	1	1
Brian Scalabrine	Power Forward	3	4	3	3	4	4	4	4	3	4	2	3
Anthony Evans	Power Forward	4	4	2	4	3	4	3	3	4	4	4	4
Gilbert Arenas	Shooting Guard	3	1	4	1	1	4	1	1	1	2	2	1
Brandon Armstrong	Shooting Guard	2	1	4	1	1	2	2	1	2	2	3	1
Darren Kelly	Shooting Guard	4	4	4	4	4	4	4	4	2	4	3	4
Shane Battier	Small Forward	1	2	2	3	2	1	1	1	2	4	3	1
Joe Johnson	Small Forward	1	1	1	1	3	1	1	3	2	2	2	3
Sean Lampley	Small Forward	3	4	4	4	3	2	1	1	2	2	2	2
Ryan Carroll	Small Forward	4	4	2	3	2	1	1	2	1	2	2	2
Jason Richardson	Small Forward	1	4	2	2	2	3	1	2	2	2	2	1
Kenny Gregory	Small Forward	4	4	4	1	4	4	1	1	3	2	1	3
Rodney White	Small Forward	1	3	3	4	3	1	3	3	1	3	2	2

Table 3 Cont'd:

Athlete:	Position	Draft Position:	AVERAGE ANSWER	DIFF (Ave-corr)	St. Dev	Over V.	Under V.	True V.
Jason Collins	Center	2	2.36	0.36	0.979121	27%	55%	18%
Brendan Haywood	Center	2	2.73	0.73	1.135454	18%	55%	27%
Mike Mardesich	Center	4	3.91	-0.09	0.28748	9%	0%	91%
Jeryl Sasser	Point Guard	2	3.18	1.18	0.833196	0%	73%	27%
Jamison Brewer	Point Guard	3	2.55	-0.45	1.157084	45%	27%	27%
SirValiant Brown	Point Guard	4	3.64	-0.36	0.642824	27%	N/A	73%
Michael Wright	Power Forward	3	2.55	-0.45	0.987525	45%	18%	36%
Eddie Griffin	Power Forward	1	1.27	0.27	0.445362	N/A	27%	73%
Brian Scalabrine	Power Forward	3	3.45	0.45	0.655555	9%	55%	36%
Anthony Evans	Power Forward	4	3.55	-0.45	0.655555	36%	N/A	64%
Gilbert Arenas	Shooting Guard	3	1.73	-1.27	1.135454	82%	18%	0%
Brandon Armstrong	Shooting Guard	2	1.82	-0.18	0.935966	45%	18%	36%
Darren Kelly	Shooting Guard	4	3.73	-0.27	0.616575	18%	N/A	82%
Shane Battier	Small Forward	1	2	1	0.953463	N/A	64%	36%
Joe Johnson	Small Forward	1	1.82	0.82	0.833196	N/A	55%	45%
Sean Lampley	Small Forward	3	2.45	-0.55	1.075651	64%	27%	9%
Ryan Carroll	Small Forward	4	2	-2	0.852803	91%	N/A	9%
Jason Richardson	Small Forward	1	2.09	1.09	0.792527	N/A	82%	18%
Kenny Gregory	Small Forward	4	2.55	-1.45	1.304791	64%	N/A	36%
Rodney White	Small Forward	1	2.55	1.55	0.890724	N/A	82%	18%

*Table 3 indicates the scores of participants for each player from the task. A green number indicates a "true" or "correct" prediction. The red numbers indicate an "over-value" or a prediction that is higher than the true value for that player. An orange number indicates an "under-value" or a value that is below the true value. The average answer given by participants for each player in the task is in the "AVERAGE ANSWER" column, and the difference between the average and the true or correct value is in the "DIFF (ave-corr)" column.

All-Star or All-NBA Prediction:

Participants faired better in the task related to prediction of whether or not the players would go on to become All Stars or make an All-NBA roster (see Table 4). As outlined in Table 3, it is clear that the participants performed far better with their accuracy in this task, both individually and as a group. Six of the 20 players from the task were unanimously correctly identified, however it is worth noting that all of these players were NO answers, meaning they did not go on to become All Star players or make an All NBA roster. This task was the easiest of the three tasks assigned to participants, as it had the highest base rate, specifically for the NO responses (18/20 or 90%). The base rate for the YES responses was 2/20 (10%), however they were each identified by 45% of participants. The lowest score observed was 12/20 (60% accuracy) players correctly identified, while the highest score observed was as high as 19/20 (95% accuracy).

Participants were 55% less likely to identify players that would go on to make an All Star or All-NBA team in their career (OR: 0.45, 95% CI: 0.21-0.98). For the No answer on the other hand, the OR was 0.82 (95% CI: 0.62-1.08). Based on these ORs, it is evident that participants faired better when selecting the No answer, as opposed to the Yes answer. However, only 10% of all answers were Yes values, and participants were able to identify them correctly 45% of the time, indicating participants performed better than what would have been mathematically expected in this task.

As for specific players, in this prediction task, there were 2 players who received more yes votes than the 2 players in the data set who truly were the All-Star/All-NBA

caliber players. These 2 players (Eddie Griffin and Kenny Gregory) both had very different profiles, as one was a lottery pick (Eddie Griffin) and the other went undrafted (Kenny Gregory). Eddie Griffin was one of the most correctly identified players based on draft position (8 of 11 participants correctly placing him in the 1 category). Kenny Gregory on the other hand was one of the most over valued in the task, with 4 participants assigning a 1 value, and a difference between his true value (4) and his average participant assigned value (2.55) of -1.45. In fact, of the 46 yes predictions by participants, 39 of them had that player ranked as a 1 or lottery pick player, while the remaining 7 had the player ranked as a 2, or a player who would be taken between picks 15 and 30 in the draft (late 1st round pick).

The players who received the most yes votes (Joe Johnson, Gilbert Arenas, Eddie Griffin, and Kenny Gregory) had very little in common (see Table 2). When examining their key metrics, some had some of the highest statistics, while others were last at their position in different categories. For example, Eddie Griffin had the tallest numbers in height and wingspan of his group, while Kenny Gregory was the shortest and had a small wingspan compared to his group. Joe Johnson also had very unimpressive physical numbers, however he shot the highest percentage from 3-point range, and Gilbert Arenas had great shooting ability and physical metrics, but turned the ball over a lot. There was one metric that was fairly high amongst all of the four players, regardless of their position group: age. 3 of the 4 players were the youngest of the position group, while the other was third in age for his group (out of 7 players). This highlights decision makers could have favoured a young age when looking at who would find themselves on an All-NBA or All-Star team at some point in their career.

Table 4: All-Star or All-NBA Prediction Results

Athlete:	All Star or All NBA?	Part. 1	Part. 2	Part. 3	Part. 4	Part. 5	Part. 6	Part. 7	Part. 8	Part. 9	Part. 10	Part. 11	Correct	Percentage
Shane Battier	NO	NO	NO	NO	NO	YES	YES	YES	NO	NO	NO	NO	NO	73%
Jeryl Sasser	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	100%
Jamison Brewer	NO	NO	YES	NO	NO	NO	NO	NO	YES	NO	YES	NO	NO	73%
Joe Johnson	YES	YES	NO	YES	NO	YES	YES	NO	YES	NO	NO	NO	YES	45%
Michael Wright	NO	NO	YES	NO	NO	NO	NO	NO	NO	NO	NO	YES	NO	82%
Gilbert Arenas	YES	YES	NO	YES	YES	NO	YES	NO	YES	NO	NO	NO	YES	45%
Eddie Griffin	NO	YES	NO	YES	NO	YES	YES	YES	NO	NO	YES	YES	NO	36%
Sean Lampley	NO	NO	NO	NO	NO	NO	NO	YES	NO	NO	YES	NO	NO	82%
Ryan Carroll	NO	NO	NO	NO	NO	YES	NO	NO	YES	NO	NO	NO	NO	82%
Jason Richardson	NO	NO	NO	NO	NO	NO	NO	NO	YES	NO	NO	NO	NO	91%
Kenny Gregory	NO	NO	NO	YES	NO	NO	YES	YES	NO	YES	YES	NO	NO	55%
Jason Collins	NO	NO	YES	YES	NO	NO	NO	NO	NO	NO	NO	NO	NO	82%
Brandon Armstrong	NO	NO	NO	YES	YES	NO	NO	YES	NO	NO	NO	YES	NO	64%
SirValiant Brown	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	100%
Brian Scalabrine	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	100%
Darren Kelly	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	100%
Rodney White	NO	NO	NO	NO	NO	YES	NO	NO	NO	NO	YES	YES	NO	73%
Anthony Evans	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	100%
Brendan Haywood	NO	NO	NO	NO	NO	NO	NO	YES	NO	NO	YES	NO	NO	82%
Mike Mardesich	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	NO	100%

Career Longevity Prediction:

The third and final piece to the task, the prediction on career longevity, is where participants averaged the lowest scores (see table 5). There was even one player from the group of 20 who no participant could correctly identify. This task did have the most options available to participants (1-6 compared to 1-4 and 1-2), leading to the most challenging base rates overall. Only 2 players were correctly identified by more than 50% of participants, and only 7 players were correctly identified by more than 25% of participants. Interestingly, of the 7 players to have been correctly identified by more than 25% of participants, 4 of them share the same draft position: 4 or undrafted. Similarly, the Draft Position prediction, participants seemed to fair better when making predictions for these undrafted players. This highlights that participants faired better when making predictions and selections for those athletes who were undrafted. The highest score achieved on this portion of the task was only 7/20 identified correctly, while the lowest score was 1/20 correctly identified.

Odds ratios were calculated for this task as well, for all 6 different groups. Participants were most likely to identify players in the 0-1 years group (OR: 0.32, 95% CI: 0.20-0.53), compared to the other career length groups. For the remaining career length groups, participants were 77% to 85% less likely to correctly identify career lengths (i.e., 1-3 years = OR: 0.21, 95% CI: 0.09-0.49; 4-7 years = OR: 0.15, 95% CI: 0.06-0.40; 8-11 years = OR: 0.23, 95% CI: 0.08-0.61; 12-15 years = OR: 0.16, 95% CI: 0.07-0.36). Finally, group 6, or the 16+ years group, failed to have a correct answer reported by participants, so no OR was calculated. These ratios indicate that participants

faired slightly better when estimating career length to be short or non-existent in the NBA (0-1 years), compared to having the player compete in multiple seasons.

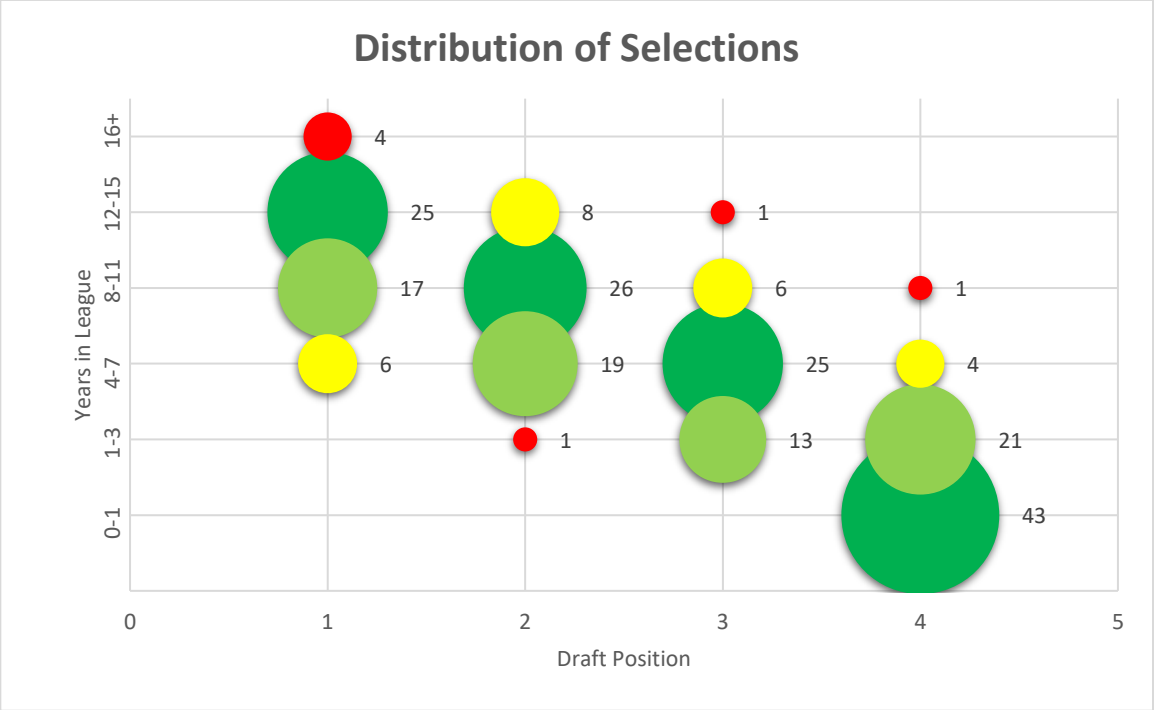
Table 5: Career Length Prediction Results

Athlete:	Years in League:	Part. 1	Part. 2	Part. 3	Part. 4	Part. 5	Part. 6	Part. 7	Part. 8	Part. 9	Part. 10	Part. 11	Average	DIFF	Total Correct:
Shane Battier	5	4	3	3	4	4	5	5	4	2	3	4	3.70	-1.30	18%
Jeryl Sasser	2	1	3	1	2	1	3	4	4	3	3	1	2.50	0.50	9%
Jamison Brewer	3	2	4	3	1	1	4	4	5	3	4	2	3.10	0.10	18%
Joe Johnson	6	5	5	5	2	4	5	3	4	4	3	2	3.70	-2.30	0%
Michael Wright	1	3	3	4	1	1	4	4	2	3	3	4	2.90	1.90	18%
Gilbert Arenas	4	4	1	5	4	1	5	5	5	4	3	5	3.80	-0.20	27%
Eddie Griffin	3	5	3	6	5	6	5	5	3	4	4	5	4.60	1.60	18%
Sean Lampley	2	2	1	2	4	3	4	5	3	5	4	2	3.30	1.30	27%
Ryan Carroll	1	1	4	3	3	4	3	4	5	5	3	4	3.80	2.80	9%
Jason Richardson	5	1	4	5	3	3	4	4	4	5	4	3	3.90	-1.10	9%
Kenny Gregory	1	1	2	5	1	1	6	5	2	5	4	5	3.60	2.60	27%
Jason Collins	5	2	5	6	1	2	3	4	3	4	3	3	3.40	-1.60	9%
Brandon Armstrong	2	4	2	5	4	3	3	5	4	5	3	5	3.90	1.90	9%
SirValiant Brown	1	2	1	2	1	1	2	3	3	4	2	1	2.00	1.00	36%
Brian Scalabrine	4	1	2	4	1	1	1	1	4	3	3	3	2.30	-1.70	18%
Darren Kelly	1	1	1	3	1	1	2	2	3	2	3	1	1.90	0.90	45%
Rodney White	3	3	3	2	2	4	3	3	3	3	3	4	3.00	0.00	64%
Anthony Evans	1	2	3	3	2	1	2	3	4	2	2	1	2.30	1.30	18%
Brendan Haywood	5	2	5	4	2	1	2	5	4	3	4	1	3.10	-1.90	18%
Mike Mardesich	1	1	2	1	1	1	1	1	3	1	2	1	1.40	0.40	73%
Sum of Correct Answers:		7.00	7.00	5.00	7.00	6.00	3.00	4.00	3.00	5.00	1.00	5.00	4.82		
Values for Years in League: 1 = 0-1; 2 = 1-3; 3 = 4-7; 4 = 8-11; 5 = 12-15; 6 = 16+															

Relationship Between Decisions:

For many participants, there existed relationships between their answers for each of the 3 different tasks. One area where we see this specifically, is between the draft position prediction and the years in league predictions (see Figure 1). As demonstrated on the bubble chart, there exists a large correlation size between where a participant predicted an athlete would be drafted (or undrafted), and how many years they would spend in the league ($\tau_b = -0.66$, $p < .001$). For example, the majority of participants who predicted a player would go undrafted, or a Rank 4, also indicated they would be a Rank 1 or spend 0-1 years in the league. The inverse could be seen for those players who were predicted by participants to be a lottery pick, or a Rank 1. These players had the majority of their corresponding years in league predictions as being a Rank 5, or spending 12-15 years in the league. The lowest answer for any player indicated as a lottery pick was a Rank 3, or 4-7 years spent in the league.

Figure 1: Distribution of Selections (Draft Position vs. Career Length)



*Dark green indicates the most populous response of participants, light green the second most populous, yellow the third most populous, and red the least populous.

There was also a statistically significant relationship between All-Star or All-NBA prediction compared to their estimated draft position prediction [χ^2 (3) = 98.8, $p < .001$, $\eta^2 = .30$]. Of the 46 All-NBA predictions made by the participants, 39 of them corresponded with a lottery pick prediction. The remaining 7 All-NBA answers corresponded with a non-lottery first round pick. This means that no second round or undrafted predictions made by all participants corresponded with a Yes prediction in the All-Star or All-NBA task.

Finally, a statistically significant relationship (i.e., asymmetry) also existed data between the All-Star or All-NBA task and the career length prediction [χ^2 (5) = 95.5, $p < .001$, $\eta^2 = 0.35$]. Of the 46 Yes answers in the All-Star or All-NBA task, 23 of the

answers corresponded with a Rank 5 value, or a 12–15-year career. 17 of those Yes answers correspond to a Rank 4, meaning an 8–11-year career, and the only 4 values in the entire career length prediction which predicted a 16+ year career, corresponded with a Yes answer for the All-Star or All-NBA task.

3.4 **Discussion**

This aim of this study was to pilot test a method to examine the accuracy of decision makers in Canadian basketball when making predictions using quantitative player data. By making having participants make predictions on draft position, making an All-Star or All-NBA team, and career longevity, we aimed to further the test the utility of this method's capacity to inform what quantitative data coaches and decision makers use to help them make their decisions and how accurate are these coaches and decision makers when making these predictions on future outcomes. This study will further contribute to the growing body of literature on talent identification and selection that exists, specifically in the basketball context.

Draft Position Prediction:

Coaches and decision makers, even at the professional level, struggle to identify and select top talent for their teams each year when their team is up for selection at their league's annual entry draft (Koz et al., 2012; Johnston et al., 2021; Farah & Baker, 2020). The issue is, they may not know how well they have done with their selections until far after the draft has taken place. It is often years down the road before a team can truly examine their draft, as it requires seasons of progress and development, and in some cases, a lack there of before a team can determine the accuracy of their selection. This specific subtask was designed to examine this process, but without having to wait years to

be able to examine decisions of coaches and other decision makers involved. By using historical, coded data, we are able to have coaches make their predictions and decisions and then subsequently grade them immediately.

The findings from this subtask further highlight the limitations of the professional drafting process, as highlighted in previous research (Koz et al., 2012). The decision makers who took part in the task struggled with this particular prediction. The highest scoring participant was only able to correctly identify the area of the draft where 10 of the 20 players would be taken. That means the highest score was only 50%. The group as a whole however struggled, as the average from all participants was only 7.6 out of 20, or 38% accurate. It should also be noted that this performance was especially poor, considering the decision makers were not forced to select or rank one player before or below another. While the results were poor, they were still found to be better than Koz et al.'s findings from NBA draft accuracy when comparing NBA draft round to games played (they found less than 17% variation in their strongest relationship). It should be noted however that Koz et al. were investigating the true accuracy of selection decisions made in the NBA, while our study investigated *identification* predictions. Participants simply had to put players in categories based on where they thought the athlete would be taken in the draft (when compared with the other players available). In real draft scenarios, decision makers make often only 1 or 2 selections per round, while having to pick from the best remaining players. As such, the task as it was designed in this pilot study was perhaps more akin to a talent identification task than a talent *selection* task. Nevertheless, the task still demonstrated some potential to provide insights into the decision-making processes involved in comparing athletes' potential.

When examining trends that exist between athlete profiles and how they were selected, there is very little evidence that participants used the same information in their decision-making processes. Trends were examined between players in the same position group, as well as between players from different position groups, however outside of a small minority of players who were accurately identified, it seemed participants valued different metrics at different positions. For example, PPG was important at the center position, as the highest ranked center (based on average draft position) by participants scored the most points per game. However, this trend disappears at the point guard position, where the player with the most PPG was ranked last by participants.

Another commonly discussed variable from basketball is height, however there was no discernable relationship between how a player ranked in this category compared to where he was drafted on average by participants. Only one of the five position groups tallest players had the highest average draft position of the position group (Eddie Griffin, power forwards). No relationship could be observed among any of the combine test metrics, or any other anthropometrics, such as wingspan or standing reach. There was also no correlation between positions that 3-point percentage and free throw percentage led to higher average draft position by participants, further highlighting the variability of this process.

Among point guards, centers, and shooting guards, the highest ranked players possessed the highest field goal percentage. However, this trend was not observed at the other two positions. At the power forward and small forward position, the players with the highest field goal percentages were drafted on average near the middle of their positional group. This indicates that field goal percentage may have some added

importance to decision makers for these three positions, however a larger sample size is needed to truly test this theory.

Overall, the trends from the athlete profiles highlight the significant variability in talent-based decision making. There exists a high amount of inter individual and intra individual variability, especially considering the high number of variables that must be considered. This task only contained 32 specific variables for decision makers, however in real world decisions there exists many more, which further highlight's the difficulty of selection. While challenging, with a larger sample size it may be possible to use this task to identify *types*, or subgroups, of decision makers based on the variables that relate to their responses.

All-Star or All-NBA Prediction:

The subtask where participants found the most success was in the All-Star or All-NBA predictions task. This task was designed to identify the players that participants felt most strongly stood out from the group as high performers. This subtask aimed to help identify which players participants felt stood out among the rest, as well as if the participants had any uniformity in their responses. This piece of the method can inform the researchers whether or not decision makers find it easier to spot top talents using quantitative data, or whether they struggled without being able to observe the players and discover some of the intangible's coach's value.

We asked participants to identify with a simple yes or no response as to whether or not they felt each of the 20 players from the dataset could one day go on and make an All-Star team or be named to one of the NBA's All-NBA teams in a season. The

participants faired far better in this task with an average of 15.6 out of 20 correct answers, or 78%. This number is very similar to the results of Schorer and colleagues' longitudinal prediction study on European handball players (Schorer et al., 2017). In their study, the findings indicated that participants most similar to those from our study, National and regional coaches, scored 79.3% and 75.8% respectively (Schorer et al., 2017). This similarity could be due to the degrees of freedom of each task. In each case, there were only two options for participants. In the Schorer et al. study, participants chose whether they felt the player had the potential to continue to high level handball or not. In our study, participants were asked whether or not they felt the players could go on and make an All-Star or All-NBA roster during their career. In both cases, responses were either yes or no. With only two possibilities, and a background in the area of TID and selection across participants from both tasks, it is clear that this could be the reason the percentages of correct responses were so similar.

As mentioned previously, the base rate for the no answer (90%) is quite high, meaning the likelihood of a participant identifying a player as not being able to make an All-Star or All-NBA team was quite high. The base rate for a yes answer was much lower (10%), and yet participants did far better than this base rate at identifying those 2 players from the data set (45%). Two players received a higher percentage of yes votes, and it is likely tied to their draft prediction from the participants. Participants tended to select their All-Star or All-NBA players from the pool of players they had ranked as a lottery pick. This finding indicates that participants correlated or equated success in the draft (being a higher draft pick) to being more likely to make an All-NBA or All-Star team in the league. As with many of the findings, there was apparent inter-individual variation in the

number of players that participants selected. Going forward this experimental method may be able to allow us to explore participants *perceived* probabilities of outcomes. In this case, how common do they think All-star/All-NBA nominations are within a cohort of athletes? Essentially what cognitive prior probabilities are decision makers operating with? It may be useful to manipulate such variables within this task to gain clearer insights into decision makers intuitive estimates of probability.

Career Longevity Prediction:

The final prediction-based task participants were asked to complete was based on career longevity for each of the 20 players from the dataset. This task was designed to identify if participants would simply assign a number of years based on the draft position prediction, or if they were looking for certain variables that they may believe indicates a longer career longevity. The findings from this task are consistent with previous work, indicating decision makers prediction skills are low, given the high complexity of the task at hand (Johnston et al., 2021; Plotkin et al., 2021). Since, in most cases, these predictions are made well into the future (in our task, up to 16 or more years into the future), these findings further highlight how difficult the task is when decision makers have to select talent for their teams (Farah & Baker, 2020; Johnston et al., 2021; Koz et al., 2012). The results of this outcome variable highlight this task's potential to test a potentially interesting feature of talent decision making. That is, when the degrees of freedom (i.e., number of potential outcomes to select from) increases, so too do the number of ways a decision maker can be wrong.

Relationship Between Decisions:

The findings of the various relationships identified between the three tasks indicate that the coaches and decision makers who took part in this study considered their previous predictions when considering the others. In other words, coaches who valued a certain player as being drafted fairly high (early in the draft), meant they saw them as having the potential to play longer in the league. Participants did not just consider this for length of career, but the higher draft predictions also meant they were more likely to select them as being an All-Star or All-NBA caliber player as well. Although it was not clear if this was done implicitly or explicitly by participants, by including multiple outcome variables in the task, this experimental method demonstrated the importance of being able to look for inter-relationships between decision making outcomes going forward. While it was not possible to distinguish correlation from causation in the current design, manipulating the order of predictions could yield insights into the underlying decision-making architecture.

Future Research:

The results of this pilot study suggest that this method has potential for future research. While this study outlined some of the key metrics involved and where each athlete ranked in them, future research could be able to better understand which variables contribute the most to selection, and which one's coaches tend to shy away from, or disregard entirely. This could be expanded to include other metrics not used in this study, such as intangibles like work ethic, drive, attitude, family history, and others. This will be especially important, since we know these factors are also used by decision makers when deciding on talent, on top of the physical, physiological, performance data, and the coach's eye (Baker et al., 2018; Johnston et al., 2021; Koz et al., 2012; Farah & Baker,

2020; Lath et al., 2021). In this specific data set, Gilbert Arenas was a player who was dramatically over valued by participants (82% of participants ranked him in a higher draft position than his true value). If participants had access to some of the intangibles, they would have been made aware of the red flags surrounding this player, which then led to his lower draft position in his actual draft year. Future studies in this area could also attempt to better understand if certain subgroups of decision makers fair better than others when identifying and selecting talent. This would require more participants, and enough participants from each pool of decision makers (professional, collegiate, youth etc. as well as General Manager, Head Coach, Assistant, Scout etc.) to draw better conclusions on who may fair better or worse.

Other investigations into the NBA draft specifically could explore how coaches and decision makers compare performance statistics between conferences or other leagues where talent is selected from. In this study, only collegiate level players eligible for the draft in the chosen year were used in the dataset of 20 athletes. The NBA draft often has players selected from various leagues and academies worldwide each year, along with these collegiate players, however there is no established conversion for statistics from other leagues and how they may compare with collegiate level players. Even within the collegiate ranks in the US (where most players selected are taken from), there exists a number of levels and conferences. While “Division 1” is considered the highest level, players can also be selected from “Division 2” and “Division 3”, or even junior colleges across the US depending on secondary factors like academics, family resources, and exposure to coaches (Baker & Horton, 2004). Even within division there is further breakdown of talent level in the name of “conferences”. Some are considered

“Major Conferences” such as the ACC, Big 12, Big 10, and SEC, while others would be considered “Mid Major” or “Low Major” conferences like the MEAC, the MAC, and the Sun Belt conference. With such a variety of levels that coaches, and decision makers must look at, this method could allow researchers to quantify how decision makers *weigh* information differently based on relevant contextual variables (e.g., between divisions and conferences). For example, is 20 points per game in a high major conference worth more than 20 points per game in a mid-major conference? Moreover, these variables could also be manipulated to see if they alter decision makers evaluation of an athlete. The addition and/or manipulation of such contextual variables could help to maximize the potential of this method.

While talent decisions are often discussed as accurate or inaccurate, the reality is that the accuracy of these decision exist on a continuum of ‘rightness’, rather than a dichotomy. The nature of the outcome variables in this task, particularly for draft position and career longevity, was such that it would be possible to study *degrees of rightness* (or wrongness). This would make it possible to examine decision making with a level of fidelity that could provide context to just *how* accurate participants were, instead of simply whether or not they were right or wrong. For example, a participating that identifies a lottery pick (rank 1) player as a first-round pick (rank 2) is more accurate than a participant that identifies that athlete as undrafted (rank 4). Future studies could investigate this relationship and provide more accurate feedback to decision makers on not simply the fact that they may have made an incorrect prediction, but how incorrect the prediction was. This could provide valuable feedback to participants and can provide insight into how to improve their accuracy of decisions.

Strengths and Limitations:

This study used a novel approach for looking at how coaches and decision makers identify talent. By using historical data, with coded player names and identifiers, we were able to score prediction tasks in real time, instead of having to wait for the predictions to come to fruition. This can save valuable time (in some cases up to 15 years, depending on career lengths) and resources, while still allowing us to investigate talent decisions of decision makers. Despite this there are a number of limitations to this study. The first being that only collegiate level players were used in the task. Each year's NBA draft has players that are eligible for selection from a number of different leagues, countries, and ages. Due to the fact that statistics vary depending on the league you are in, we decided it was best to only use NCAA draft eligible players in the task. Another limitation based on the athletes used for the task was that not all athletes choose to attend the NBA combine. In some cases, players may be battling injury, and in other cases they may choose to skip the event if they do not feel it would help them get drafted in a higher position. Our task also only looked into predictions on where players were drafted and did not look at how well or how poor the original draft results actually were. Essentially participants were only asked to predict the outcome of the draft, not which players should be taken where and then graded based on how well the player performed in their time in the league. The metrics used in our study also only focused on the quantitative and did not include intangibles or qualitative data such as a write up of the athletes' preferences, personality, or other traits.

Of the 34 participants who showed interest in our study, only 11 fully completed the task. This low percentage of completion could be due to the length of time it took

participants to complete the task. In many cases, the completed tasks were not returned for weeks or months. It could also have been linked to the COVID-19 pandemic. At the time of REB approval, many seasons were returning to action, leading to less time for coaches who showed interest to complete the task. Future iterations of this study should investigate reasons as to why or why not some participants were able or unable to complete the task.

Other limitations in our study were mostly related to time. We chose to use a single draft year for the task, since each year players are chosen before or after one another and mixing the years could have affected the task. However, since we chose to use just one single years' worth of draft data, we were limited in the number of players we could choose for the task. This also meant that the players from the task were all from the same playing era, which was not specified to participants. This is a limitation since certain eras allowed high school basketball players to be drafted, which could have affected how participants used "age" in their predictions. Furthermore, indicators of talent may be objectively, or subjectively, different for contemporary players. Finally, and perhaps the largest limitation of the study, is the number of participants. Only 11 participants filled in the full task answers sheet and were eligible for participation. With so few participants it is difficult to explore the full potential of this method increase our understanding of decision-making processes. Due to there being so few participants we were also unable to evaluate how well different demographic groups of participants did (based on years coached, level coached, and whether it was a men's or women's team), as there was often only one or two participants per group, or in some cases, zero. As mentioned in future research, this novel method can be applied across a number of sports

and age levels, however researchers should be aware of some of the limitations mentioned from our study and attempt to correct for them in future projects.

In summary, decision making in the world of sport is a complex and difficult problem. Coaches and decision makers struggle with this task daily in an attempt to better their teams or organizations. This task has the potential to provide valuable feedback and insight on how decision makers currently look at talent, which can help identify biases that exist, or other tendencies they may not know they have. By identifying these tendencies, coaches and decision makers can improve in the area of talent identification and selection, and better help their teams' moving forward

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Chapter 4. Overall Discussion

Talent is often seen as someone having greater ability or aptitude when compared with other members of society. In the context of sport and high performance, the term "talent" is usually used to refer to the best athletes; more specifically those who have achieved high levels of success within their domain or sport (Baker et al., 2019; Howe et al., 1998). The levels of success differ depending on the sport or level of sport that is being described. For example, success can be measured in terms of performance metrics (how many goals scored, points scored, assists etc.), accolades (all star appearances, championships, playoff success), and competition stage (minor professional rank vs. major professional rank, major college program vs mid major vs junior college system). With so many ways used to measure an athlete's success, it can be easy to look back on someone's career and define their level of talent. Unfortunately, coaches and others in charge of making talent decisions do not have the luxury of looking back in hindsight.

Professionals in the sport landscape often use the terms talent identification and talent selection synonymously, yet the terms have very different meanings. Talent ID is the process of identifying athletes who have the potential to one day compete in senior level athletics, while selection refers to the selection of athletes for a team (youth, development, even professional) (Vaeyens et al., 2009). The concepts, while very different from one another, do share some common traits. In both cases, decision makers are often making predictions on talent, and this is commonly done years into the future. There are also differences between the two. When making selection decisions, other variables come into play, like team fit, style of play, other players who may currently be

under contract at a given position, as well as financial constraints (Baker et al., 2020; Johnston et al., 2017). In identification, there are less team-based constraints, as decision makers and scouts often have to focus solely on prediction and whether or not they think that an athlete has the potential to compete at senior level athletics (Vaeyens et al., 2009). It is only when they reach the stage of selection that they will be considered based on those other, team-based factors. With such a high number of variables at play, both of these processes are difficult, lengthy, and unique propositions of one another (Baker et al., 2017; Johnston & Baker, 2020).

In our talent ID task, we were investigating how decision makers look at talent from an identification standpoint. As previously stated, selection is a bit more involved, and when the athletes from the 2001 draft class were being selected, teams had to consider things like need, fit, position, style of play, and other factors independent of simply identifying who is or is not talented or shows promise (e.g., if an athlete had been previously selected by another team). In this task, we asked our participants to make predictions on 20 athletes, while a true selection task would have to mimic the draft in which teams have only 2 allotted picks (before trading or acquiring other assets). We were attempting to look at how decision makers think about the process of talent ID, and what quantitative data is most important to them when making their predictions for the future.

Creating a study to investigate how coaches think about talent ID or selection decisions is made increasingly difficult by the ecological validity constraints. It can be very difficult to replicate a true decision-making situation that reflects the true demands of real-life scenarios. For example, when decision makers are forced to draft a player,

they are constrained by the round and pick of where they are drafting, and it is often a highly scrutinized process. The fans of the team, upper management, as well as ownership will all be watching closely and judgement on selection is often cast early. This is a very difficult scenario to replicate, as in the research context when the selection does not have any true impact, the pressure element is not in play. It goes far beyond the pressure element. Consider the fact that decision makers often have the ability to both watch and observe a player, while also having access to statistical data, anthropometric data, and in some cases go as far as having personal conversations and interviews with them (Baker & Wattie, 2018; Farah & Baker, 2020; Johnston et al., 2021; Koz et al., 2012). This is a difficult process to replicate in the research, as these tasks are often simulated with fake players or historical data (as we have done). When real athletes are used, the research process often involves much longer time frames for completion and is often expensive and difficult to manage.

Other factors that were not replicated in our study must also be considered when making talent decisions. Consider the intangibles and more qualitative pieces on athletes. For example, personality, work ethic, drive, attitude, injury history, and others. These are difficult pieces to quantify, yet coaches speak to their importance in the selection process (Johnston et al., 2020). Strictly looking at the quantitative data you may make certain judgements on a player, yet when intangibles are introduced, these ideas and judgements may change. Consider Gilbert Arenas from the 2001 NBA draft class. He was one of the most overvalued players by participants in our task, as his quantitative numbers were quite impressive, especially compared to his positional counterparts. Yet, in the actual draft, he fell to the second round. Decision makers at the time had questions about his

injury history, as well as his personality. These became red flags and prevented him from being taken in the lottery, or later in the first round. Our participants did not have access to this type of data, or perhaps their predictions for him may have been more reflective of what occurred during the actual draft. This further highlights the difficulty of creating an ecologically valid study for talent ID or selection decisions.

Despite the inherent difficulty developing these studies, gaining better insight into the decision-making process is extremely valuable for a number of reasons. One of the main reasons is that while we often look at sports as having "decision makers" on staff (consider a general manager or a head coach), the processes of identification and selection involve far more people, and it is often seen as more of a group task, with members of the organization providing various amounts of input, including qualitative and quantitative data on the athletes (Baker et al., 2018; Farah & Baker, 2020; Johnston et al., 2021; Koz et al., 2012; Wattie et al., 2022). With so much information available to decision makers and various teams and organizations, what information is truly being used the most? By gaining more insight into these decisions and the process in which they are made, we will be better able to provide feedback to those responsible for these decisions. With increased understanding of how decisions are made and what coaches are looking at when making their decisions, we can help identify promising athletes early on, thus saving organizations precious resources like time and money (Durand-Bush & Salmela, 2001; Johnston & Baker, 2020).

To manipulate and further enhance this method of investigation, additional steps can be taken to enhance our understanding of decision-making processes. Specifically, it would be useful to increase our understanding on whether or not coaches used actuarial

judgement or clinical judgement in their assessments, or what heuristic(s) decision makers relied upon. Did coaches tend to use the dataset and manipulate it in an actuarial manor? Or did they take more of a clinical approach, and go with instinct or gut feeling? Is it possible to quantify i-codes search effects using modified versions of this method? The first step to investigate these questions would be to conduct qualitative interviews with participants. This will allow the research team to ask specific questions about how the participants used the data, where they felt they focused their attention, what variables were most important to them in their process, as well as what other variables they may commonly use that were not included in the dataset when making decisions on talent. Another inclusion in future versions of this study should look at how participants manipulated the dataset. This could be gathered from a qualitative interview or could be collected after the task is completed by asking the participants to return the excel spreadsheet with their changes saved. This would provide the research team with further information on how participants chose to rank players from the dataset, as well as what variables they chose to alter and manipulate (for example, height to wingspan ratio was not given, but could have been calculated if participants thought it was important).

Additional insights in future variations of this study could also look to have participants record and save journals or notes from their experience completing the task. The aim of this addition would be to provide further insight into the thought process and evaluation methods used by each of the decision makers from the task. This could help us understand where the participants focused their attention and their time. For example, what variables were they considering or deciding between for certain players? Which factors were mentioned the most in their journaling? Were the factors consistent between

the 5 positions or was there some variation? These sorts of questions could be better answered by having participants journal and log their experience when completing the task.

This task, or a similar version of this task, is also transferable across other sports, particularly those with a selection or drafting process (NFL, MLB, NHL etc.). By simply coding for the names involved in a historical draft, we can have decision makers from these other sports make predictions for players while we already know the answers. This would provide further insight into the decision-making processes in those sports, as well as continue to grow the body of literature on talent ID and selection.

This project, and other research projects similar, aim to provide context and evidence to the complex and ever evolving world that is talent in sport. The process of TID and athlete selection is difficult to navigate, with a lot of questions yet to be answered (Johnston et al., 2017). By continuing to study these decisions, researchers can provide more and more context to those making these decisions, and hopefully help them save valuable resources. This research also aims to help athletes. By preventing young athletes who show promise from being alienated by the sports they love and enjoy, various sports and their governing bodies could have far more athletes engaged and competing at a high level. In order to move forward and better understand talent decisions, more work must be done to understand how these decisions are made and what can be done to improve them. Utilizing a diverse array of methods, evidence-based recommendations and feedback can further enhance our knowledge on TID and selection.

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Appendices

Appendix A.

A1. Talent ID Handout

Player:	Position:	Weight:	Height NO Shoes:	Wingspan:	Standing Reach:	Pro Lane Agility Drill:	3/4 Court Sprint:	No Step Vertical Jump:	Maximum Vertical Jump:	Bench Press (185 lbs.):
A	Small Forward	229	80.25	82.5	105	10.95	3.3	29.5	33	12
B	Point Guard	194	77.5	82.5	103.5	11.47	3.22	29	34	1
C	Point Guard	178	74.5	80.75	102.5	9.65	3.15	26	32.5	12
D	Small Forward	226	78.75	81	105	12.05	3.4	32.5	36.5	12
E	Power Forward	247	79	83.5	106.5	11.37	3.21	27.5	33.5	18
F	Shooting Guard	199	74.25	81.5	99.5	11.27	3.25	31.5	36	12
G	Power Forward	222	81.25	87	110	11.77	3.21	26.5	33	3
H	Small Forward	213	77.5	81.25	101	11.06	3.12	36	40	12
I	Small Forward	202	76	80.25	99	11	3.1	34.5	39	14
J	Small Forward	213	76.75	83.5	102.5	11.75	3.12	32.5	39.5	15
K	Small Forward	200	75.5	83.25	101	11.33	3.1	39.5	45.5	10
L	Center	251	82.25	88.5	110	12.1	3.54	25.5	28.5	8
M	Shooting Guard	188	75.5	81.5	99.5	10.91	3.2	30	37	6
N	Point Guard	176	71	76	92.5	11.23	3	31	39.5	10
O	Power Forward	241	80.75	81.75	105.5	11.75	3.47	27	30.5	14
P	Shooting Guard	178	74	78.75	100	11.38	3.21	30.5	34.5	1
Q	Small Forward	243	79.5	83.5	104.5	12.07	3.47	27.5	33	16
R	Power Forward	267	78	83.5	101.5	12.56	3.31	31.5	33	18
S	Center	266	83.75	90.5	113.5	12.87	3.5	27	28.5	17
T	Center	247	82.25	84.5	108.5	11.65	3.45	24	30	8

Combine Age:	Conference:	Body Fat:	G	GS	FG	FGA	3P	3PA	FT	FTA	TOV	PF	FG%	3P%
22.7	ACC	9.3	39	39	251	533	124	296	152	191	60	80	0.471	0.419
22.3	WAC	6.7	29	28	170	431	35	122	117	163	62	62	0.394	0.287
20.5	SEC	6.7	32	32	97	207	10	44	64	121	92	49	0.469	0.227
19.9	SEC	6.7	30	27	162	346	35	79	68	91	70	46	0.468	0.443
21.4	PAC-10	9.3	36	36	202	340	0	3	157	197	63	85	0.594	0
19.4	PAC-10	5.3	36	33	208	434	69	166	97	134	101	82	0.479	0.416
19	Big East	4	30	30	206	480	41	128	80	109	67	71	0.429	0.32
21.7	PAC-10	8	31	31	209	416	7	33	180	244	112	79	0.502	0.212
21.8	Big 12	8	31	31	182	393	76	209	101	129	41	84	0.463	0.364
20.3	Big 10	5.3	33	32	182	362	49	122	73	106	42	74	0.503	0.402
20.5	Big 12	6.7	30	30	204	360	22	57	39	92	51	45	0.567	0.386
22.5	PAC-10	12.9	34	34	168	271	12	26	145	185	53	79	0.62	0.462
20.9	WCC	9.3	31	30	240	537	76	198	128	155	65	85	0.447	0.384
20.4	Atlantic 10	6.7	31	26	174	471	50	170	138	192	74	106	0.348	0.275
23.2	PAC-10	13.6	34	33	173	362	20	66	133	166	104	89	0.478	0.303
22.7	Big 12	6.7	26	26	133	369	35	127	98	129	84	50	0.36	0.276
20.9	Conference USA	9.3	28	26	188	386	33	95	114	160	82	73	0.487	0.347
22.6	SEC	12.9	31	31	126	235	0	2	103	137	38	84	0.536	0
21.5	ACC	12.9	33	33	155	262	0	0	95	184	66	97	0.592	0
23.9	ACC	13.6	36	1	53	112	0	0	24	45	25	45	0.473	0

FT%	MP/G	PTS/G	ORB/G	DRB/G	TRB/G	AST/G
0.796	34.9	19.9	2.4	4.9	7.3	1.8
0.718	34.9	17	3.5	4.9	8.3	0.8
0.529	32.3	8.4	2.8	4.4	7.2	5.8
0.747	29.1	14.2	2.2	4.2	6.4	2.6
0.797	27.9	15.6	3.3	4.5	7.8	0.3
0.724	29	16.2	0.8	2.8	3.6	2.3
0.734	32.6	17.8	3.1	7.6	10.8	1.6
0.738	34.6	19.5	1.5	5.7	7.2	3.3
0.783	34.3	17.5	2.1	3.7	5.8	2.6
0.689	28.5	14.7	1.8	4.1	5.9	2.2
0.424	31.7	15.6	3.3	4	7.3	2.4
0.784	26.3	14.5	2.7	5.1	7.8	1.5
0.826	33.1	22.1	1.2	2.1	3.3	1.5
0.772	31.2	17.3	0.8	1.9	2.7	1.8
0.801	32.8	14.7	2.1	3.9	5.9	2.8
0.76	34.6	15.3	0.8	3.8	4.6	2.9
0.713	30.9	18.7	1.8	4.7	6.5	1.5
0.752	28.2	11.5	2.4	5.1	7.5	1.1
0.516	27.3	12.3	3.2	4.2	7.3	1.3
0.533	10.2	3.6	1.1	1.5	2.6	0.4

Legend:	ONLY FINAL COLLEGE SEASON STATISTIC IS USED
G	Games played
GS	Games started
FG	Total field goals made
FGA	Total field goals attempted
3P	Total 3-point shots made
3PA	Total 3-point shots attempted
FT	Total free throws made
FTA	Total free throws attempted
TOV	Total turnovers
PF	Total personal fouls
FG%	Field goal percentage
3P%	3-point field goal percentage
FT%	Free throw percentage
MP/G	Minutes played per game
PTS/G	Points scored per game
ORB/G	Offensive rebounds per game
DRB/G	Defensive rebounds per game
TRB/G	Rebounds per game
AST/G	Assists per game

A2. Task Answers Sheet

Athlete:	Draft Position:	Years in League:	All Star or All NBA?
A			
B			
C			
D			
E			
F			
G			
H			
I			
J			
K			
L			
M			
N			
O			
P			
Q			
R			
S			
T			
	1. Denote each in the given square with a "1" for lottery pick, a "2" for first round non lottery, a "3" for a second-round pick, a "4" for an undrafted player.	1. In the given square for each player, please note how many years you feel they would last playing in the NBA. The options are 0-1 years, 1-3 years, 4-7 years, 8-11 years, 12-15 years, and 16+ years.	The final piece is predicting which players would make an All-Star roster at some point in their career. This can be selected by simply putting a "YES" or "NO" in the appropriate box.