Generational Differences in Career Transitions Among Top 100 Ranked Golfers

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Abstract

Golf National Sport Organizations (NSOs) invest significant resources to help athletes achieve a top ranking. However, little objective data exists to inform this process. The Official World Golf Ranking (OWGR) may be a useful resource for benchmarking athlete progression. However, ranking data is retrospective, meaning that past data may not be relevant to inform current/future athletes. It is therefore necessary to appraise the OWGR data to determine whether such data is valid to inform future decision-making. Golfers who first obtained a top 100 OWGR between 1990-2018 were divided into four age-based cohorts. An overall developmental pathway was defined consisting of; career ranking milestones (e.g. first top 1000 ranking) and the time taken to transition between such milestones. Overall, a trend towards younger generations of golfers reaching milestones at significantly earlier ages and in less time was observed. The findings in this thesis will allow NSOs to appropriately apply the OWGR to their decision-making processes.

Keywords: Athlete Identification, Athlete Development, Golf, Generational Differences

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List of Abbreviations

AD	Athlete Development
AI	Athlete Identification
AID	Athlete Identification and Development
ATP	Association of Tennis Professionals
DT	Development Time
FTEM	Foundations, Talent, Elite, Mastery
HP	High Performance
NSOs	National Sport Organizations
OWGR	Official World Golf Ranking
PGA	Professional Golfers' Association
TT	Transition Time
WTA	Women's Tennis Association

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1. General Introduction

Introduction to the OWGR, Role of the Golf NSO, and AID Programs

The Official World Golf Rankings (OWGR) provide a relative ranking of professional male golfers who compete in tournaments around the globe (Broadie & Rendleman Jr., 2013). These rankings are widely used to measure success in men's professional golf. Furthermore, many golfers, coaches, and national sport organizations (NSOs) have considered the attainment of a top 100 OWGR as a significant career milestone (Golf Australia, 2019). Not only is such a ranking a reflection of being a successful professional, it paves the way for direct entry into major championships, world golf championships, and Olympic games – the most prestigious and lucrative tournaments of the sport (Broadie & Rendleman Jr., 2013, Golf News Net, 2019; PGA Tour, 2017). Due to the exposure athletes who play in these prestigious tournaments tend to garner, those who succeed in reaching this ranking benchmark often experience increased publicity and endorsement opportunities (Broadie & Rendleman Jr., 2013). Thus, the achievement of a top 100 OWGR increases the likelihood of professional golfers having a sustainable career in the sport. For NSOs, producing as many top athletes as possible is a priority as funding for high performance (HP) development programs is often linked to athletes' success at the professional level (Brouwers, Sotiradou, & De Bosscher, 2015; Green & Houlihan, 2006; Sam, 2012).

With the mounting pressure to produce world-class athletes, NSOs attempt to utilize systematic and evidence-based strategies (commonly known as Athlete Identification and Development (AID) programs) to identify and develop athletes with the potential for success at elite levels of competition (Cobley, Schorer, & Baker, 2012; Johnston, Wattie, Schorer, & Baker, 2017;Vaeyens, Gullich, Warr, & Philippaerts, 2009; Vaeyens, Lenoir, Williams, & Philippaerts, 2008). These HP programs generally encompass the entire AID process from grassroots sport participation to the point where elite athletes no longer require the support of their NSO (Gulbin, Crosser, Morley, & Weissensteiner, 2013). However, there is a need to progress our understanding of the transition period that ensues from when an amateur athlete turns professional to when they establish themselves at the professional level.

This period of development has been defined by high rates of athlete drop out (Barreiros, Côté, & Fonseca, 2014). Opportunities to compete at the highest levels are scarce, and thus the demands on the athlete to reach a certain level of performance rapidly increase (Stambulova, Pehrson, & Ollson, 2017). The transition from amateur to professional sport marks a crucial point in an athletes' career, as what occurs during this timeframe will ultimately determine whether or not they succeed at the professional level. However, evidence-based information to support AID programs during this transition period in sports such as golf is scarce (Hayman, Polman, Taylor, Hemmings, & Borkoles, 2011; Hayman, Borkoles, Taylor, Hemmings, & Polman, 2014; Stambulova et al., 2017). If one of the goals of golf NSOs is to produce as many top 100 ranked athletes as possible, it seems logical that these organizations would want to be equipped with the evidence needed to give themselves the best likelihood to identify and develop these athletes (Golf Australia, 2019). Thus, in order to make stronger evidence-based decisions, the pathway that professional golfers take to the top 100 should be investigated. Gaining an understanding of how exceptional athletes continue to develop once they have entered their professional sporting systems could improve our knowledge of this unique stage of development and showcase potential factors that differentiate these athletes from the rest of the field. Unearthing the ranking pathways of top 100 professional golfers will be a first step in contributing evidence-based information to inform both sides of AID programs.

Athlete Development

Athlete Development (AD) programs focus on optimizing the development process by providing athletes with the appropriate resources (e.g. training, support, medical, psychological, nutrition, etc.) and learning environments based on their current developmental stage (Cobley et al.,2012; Vaeyens et al. 2008). However, numerous factors that are dynamic throughout the development process contribute to athletes' outcomes (Baker & Horton, 2004). Therefore, outlining what these resources and learning environments may look like throughout the development process is a difficult task. In order to assist in unpacking the complexity of the AD process, models/frameworks are utilized (Gulbin et al., 2013). AD models/frameworks are based on the previous experiences of successful athletes. They are used to provide guidelines of best practice in an organized manner, so that NSOs may use data to inform their own practices (Balyi & Hamilton, 2004; Côté , 1999; Gulbin et al., 2013).

One prominent AD framework is the Foundations, Talent, Elite, Mastery (FTEM) framework, which outlines a developmental pathway that includes 10 differentiated stages, spanning from youth sport to the retirement years (Gulbin et al., 2013). Relevant to the current project, the framework consists of stages that encompass athletes' transition from being an entry level professional (Stage T4) to having success at the professional level (Stage E2). At each stage various developmental drivers (i.e. psychological characteristics, training patterns, monetary resources, and family, peer, and coaching relationships) that may influence the AD process are discussed. However, the authors acknowledge that the FTEM is not a sport-specific framework, and the drivers presented are done so in a broad manner. The presentation of a broad framework is designed to allow NSOs and researchers alike, the flexibility to build upon the framework by incorporating their own sport-specific data and drivers (Gulbin, Croser, Morley, & Weissensteiner, 2014). However, sport-specific research on athlete transitions from high level amateur competition to successful professional careers is scarce.

One sport-specific AD model that captures this unique and complex stage of development is derived from Stambulova and colleagues (2017) qualitative exploration of seven Swedish ice hockey players. Their analysis investigated the sequence of stages and relevant psychological content occurring during the transition from the amateur to professional level of Swedish ice hockey. The model describes this career transition as comprising four phases spanning four to six years: Preparation (athletes begin to participate in professional/senior competition while still on a junior team); Orientation (first year on a professional/senior team); Adaptation (second and third year on a professional/senior team); and, Stabilization (fourth year of professional/senior hockey) (Stambulova et al., 2017). Within each phase, the resources, barriers, and coping strategies that allow athletes to navigate through each stage of the pathway are outlined. However, as previously mentioned different sports may require unique developmental pathways. Therefore, this model is likely not generalizable to other sports.

An example of using data to better understand a sports' unique developmental pathway that better aligns with the broad structure of golf, can be seen in tennis. Similar to golf, the success of tennis players is measured by a ranking scale that aggregates points from different professional events around the world to provide a relative ranking of professional tennis players (Reid & Morris, 2013). Furthermore, the top 100 ranking milestone has also been used in the tennis literature as the penultimate benchmark for athlete success (Reid & Morris, 2013; Kovacs et al., 2015). These similar benchmarks make comparing the sports less complex than attempting to make comparisons to team sports, for example, which do not rely on relative player ranking ladders as a primary means of assessing individual performance.

To provide evidence-based information regarding the pathway that amateurs take to reaching a top 100 world ranking, Reid and Morris (2013) described the ranking milestones and progression of the top 100 ranked Association of Tennis Professionals' (ATP) players at the end of the 2009 season. Top 100 players earned their first ATP point at 16.9 years of age before taking 4.5 years to transition to the Top 100 at 21.5. Further, those aspiring to crack the top 100 earned their first ATP ranking at the age of 16 or 17, and by the age of 19 were seen to be ranked inside the top 250. Athletes who earned ATP points younger ages were also more likely to achieve better ATP rankings. This type of data may be used to guide the expectations and decision-making of athletes, coaches, stakeholders, and policymakers in the sport (Reid & Morris, 2013).

The lack of evidence on the transitions between stages of development emphasizes the need to enhance understanding of the sport-specific developmental trajectories athletes take, particularly from the elite amateur to elite professional ranks. More specifically, while the attainment of a top 100 ranking is a key milestone for aspiring golfers, little is known about the typical paths taken to reach this milestone. The OWGR offers a rich data source, as it tracks the ranking progression of every professional golfer on a week-by-week basis from when they gain their first professional ranking to retirement. Therefore, it is a valuable resource that can be used to understand the overall pathway athletes take to reach top ranking positions. Understandably the rankings only outline the ranking trajectory and do not explain the cause of these rankings. Increased understanding of the trajectories that amateur golfers take to the top will allow stakeholders to better plan AD policies to give athletes the best chance to successfully reach their desired benchmarks.

Athlete Identification

As NSOs strive to gain an edge in the international sporting arms race, athlete identification (AI) programs have become a staple in the athlete selection process (Hogan & Norton, 2000; Vaeyens et al., 2009). Such programs seek to identify athletes who are seen as having the highest potential for future success in professional sport (Cobley et al., 2012; Vaeyens et al., 2008). The idea is that potentially exceptional athletes who are identified at earlier points in time can be allocated available resources that NSOs offer through their AD programs (Cobley et al., 2012; Gulbin & Weissenstiener, 2013). The adoption of evidence-based approaches to provide the 'correct' resources to the 'correct' athletes at earlier stages in their development, seems like a logical course of action for NSOs to achieve the best return on their investments.

However, the variables used in AI programs have been shown to have low predictive validity when attempting to discriminate between athletes of different skill levels (MacNamara & Collins, 2012; Johnston et al., 2017; Vaeyens et al., 2008). For example, a systematic review conducted by Johnston et al. (2017) observed that anthropometric measures were seen to discriminate between selected and non-selected soccer players yet did not discriminate between different levels of Australian Rules Football players. Such gaps in knowledge mean that selecting the 'correct' athletes is no easy task. If the selection variables employed by NSOs for decision making purposes are inaccurate, the wrong athletes may be selected or indeed deselected. Thus, potentially draining the already limited resources that NSOs have to offer (Kovacs et al., 2015).

Due to the pitfalls in the current AI literature, it has been suggested that NSOs turn their focus to keeping as many athletes in the development system for as long as possible, especially during junior (i.e., under 18) sport (Vaeyens et al., 2008). However, in a sporting climate where finite resources exist for AD activities, at some point - particularly as athletes approach the professional level - selection decisions inevitably have to be made (Kovacs et al., 2015). As athletes progress through their careers, available spots in competitions become increasingly scarce. In addition, the cost of supporting athletes as they begin to reach these higher levels may increase considerably. For example, the average cost of supporting a professional tennis player who travels to approximately 30 tournaments per year and employs a coach along with other support staff can cost anywhere from 121,000 to 197,000 USD per year (Reid, Morgan, Churchill, & Bane, 2014). Clearly at such costs there are only a limited number of amateur athletes attempting to transition to the professional level that can be supported by their respective NSO. Despite the potential limitations of AI programs (e.g., low predictive validity of selection variables), evidence-based variables are still warranted to aid in making selection decisions.

It has been proposed that the accuracy of selection variables increases when predictions are made closer to the time of peak performance (Vaeyens et al., 2008). A potential explanation for this phenomenon is that the variables used in AI programs may not be useful indicators for selection at younger ages, as factors such as the athletes' growth and environmental situations are likely to be in a continuous state of flux (Johnston et al., 2017; Vaeyens et al., 2008). Previous studies have supported the notion that prior youth and adolescent performance may not be a strong indicator of future athletic attainment. For example, in one multi-sport study, only one-third of international pre-junior athletes (i.e., under 16) transitioned to the senior international level (Barreiros et al., 2014). Similarly, in tennis Brouwers, Bosscher, and Sotiriadou (2012) found low but significant correlations between under 14 tournament performance and future professional rankings. Additionally, when using a bottom-up perspective, they found that 43.2% of male under 14 tournament winners and 60% of female under 14 tournament winners reached a top 200 professional ranking. When examining athletes who previously held under 18 rankings on the International Tennis Federation (ITF) junior circuit, 65.8% of male and 64.4% of female junior top 20 players reached the top 200. Conversely, when the authors used a top-down perspective to determine the junior attainment of current and past top ranked professionals, 23.5% of male and 18.4% of female top 20 professionals never reached a junior top 200 ranking. These results showcase the variability and subsequent issues with using junior performances for predicting later success. While the authors mentioned that junior success does not guarantee the same success at the professional level, they concluded under 18 ITF rankings were a better indicator of professional success than under 14 tournament results (Brouwers, Bosscher, & Sotiriadou 2012). Essentially, the closer predictions are made to adult peak performance, the more accurate they are at reflecting future success.

An example of using previous performance variables (i.e., rankings) to forecast success of amateur athletes as they transition to the professional game can be seen in an analysis conducted on ATP players by Reid et al. (2014). Athletes who competed between 1973 and 2011 and obtained a ranking of 250 or better were sampled. To determine whether ranking trajectories were different for players of varying skill levels, ranking bands were used to group players by their peak ATP ranking: 1-10,11-20, 21-50, 51-100, 101-175, and 176-250. Players in different peak ranking bands (i.e. 1-10 vs. 51-100) showed significant differences in their peak yearly rankings from first turning professional to reaching their peak ranking. When this approach was replicated for female tennis professionals competing for ranking positions on the Women's Tennis Association (WTA) tour the same trends were observed. While the ages athletes reached certain ranking benchmarks were different, the finding that players who attained different peak rankings were distinguishable at relatively early ages was supported (Kovalchik, Bane & Reid, 2017).

While based on limited research, these findings support the notion that as athletes get closer to peak performance, certain variables may be used to discriminate between athletes of different skill levels to assist with selection decisions. Fortunately, like tennis, golf has a system that records the week-by-week ranking histories (i.e., OWGR) of male professionals from when they first turn professional to exit from the sport. As a result, the OWGR could be used to predict athlete attainment in the same way that the ATP and WTA rankings have been previously used in tennis. In practice, AI programs should be multidimensional and encapsulate a number of different variables to provide the most comprehensive identification guidelines possible. However, to our knowledge no previous work has explored the selection variables that may discriminate between golfers of different skill levels as they transition from amateur to top 100 professional status. Using the OWGR will be a useful first step to understanding AI variables at this stage of development in golf.

Generational Differences/ Methodological Issues with Retrospective Data in Sport

The data used to inform AID programs is commonly obtained from the previous experiences of successful athletes (Gulbin et al., 2013). A methodological issue that may arise when attempting to use retrospective data to inform current practice, is that generational differences may exist between past, present, and future athletes (Bane, Reid, & Morgan, 2014). Changes over time in sporting systems (i.e. in game play and developmental trajectories) may occur due to shifts in culture, values, social norms, equipment, and policy-making (Reid et al., 2014; Kovalchik et al., 2017). These shifts may differently influence the trajectories of athletes developing across different generations, making it potentially inequitable to compare athletes who developed during different time periods. For example, Bruce, Farrow, and Raynor (2013) examined specific sporting milestones (e.g., age first participated in netball, started formal coaching, first competed against older athletes etc.) of female Australian netballers who competed for the senior and junior national teams. Notably, they found that the junior team athletes reached many of these milestones earlier than their senior team counterparts. The authors attributed these results to the possible generational shifts in the netball landscape. For example, they noted that compared to when the current senior national team athletes were developing, the junior athletes were being identified and selected at an earlier age. As well, the current junior athletes had been exposed to a more prominent, established, and televised professional netball league. These different experiences may have led to younger athletes having clearer goals and aspirations to participate in netball specific activities at younger ages than their older peers (Bruce et al., 2013).

In tennis, Bane, Reid, and Morgan (2014) realized the potential shortcomings that generational shifts (e.g. ranking structure, number of available tournaments for developing players, and equipment improvements) could have had on their previous sport-specific benchmarking methodology, and in turn its application to current and future athletes. They investigated whether the time to reach career milestones previously examined by Reid and Morris (2013) and Reid et al., (2014) changed over time. The findings were mixed; that is, the age athletes achieved their first ranking point remained consistent, yet the development time (i.e., time from first ATP point to first top 100 ranking) increased. The authors noted that these findings may encourage tennis associations to provide financial support to their athletes for longer periods of time, as the time taken to reach a financially sustainable position on the ATP tour is now longer than previously noted (Bane et al., 2014). In contrast, over the last 25 years for WTA tour athletes, the age that players earned their first ranking point and reached the top 100 has remained stable over time (Kovalchik et al., 2017). These gender-specific generational changes within the same sport, may be due to the fact that generational shifts may occur at different times and in different capacities for men's and women's sport. It is also likely that generational shifts may also be sport-specific. Therefore, each sporting domain may need to be viewed as its own entity, as generational shifts and their resulting changes that occur in one domain may not be generalizable to another.

From a generational shift perspective, several documented changes have occurred in golf. Since 1996 the sport has become extremely popular, much of that has been said to be attributed to Tiger Woods' emergence on the PGA Tour, dubbed the 'Tiger-effect' (Herrington, 2016). Since Woods' debut as a professional, prize purses at tournaments increased from between $2.8 to $6.8 million to upwards of $10 million, due to the heightened interest in television rights and sponsorships (Peters, 2008). As well, there have been increases in both male and female junior golf participation, as well as the number of collegiate golf programs available for developing athletes to attend (Herrington, 2016). Thus, like Bruce and colleagues (2013) netball sample, golfers from current generations may have been exposed to increasingly prominent role models, lucrative career opportunities, and growing resources that younger generations were not exposed to.

The policies and structures of professional golf tours worldwide have also changed. One of the more recent structural changes has occurred on the Professional Golfers' Association (PGA) Tour - one of the major tours that contributes points to the OWGR. Traditionally, there were two ways to obtain full-time playing privileges on the PGA Tour. The first was through a single six round event known as "Qualifying School" (i.e., Q-school) while the second was through the season long Web.com tour (i.e., The major developmental tour under the PGA Tour). While the top 125 players on the PGA Tour money/points list at the end of each season retain their playing privileges/tour card, 50 new tour cards become available for players outside this ranking. In 1998, 35 of the 50 tour cards were allocated via Q-school, while the remaining 15 were allocated to the top finishers on the Web.com tour year-end money list (Rhoads, 2012). Since 1998, the PGA Tour has started to transition away from Q-school, by giving out a higher proportion of tour cards via the Web.com tour. Currently all 50 available PGA Tour cards are given out through the Web.com tour, as Q-school was completely phased out after the 2012 season (PGATOUR, 2017).

While these golf-specific shifts are well-documented, their potential impact on player development trajectories over time are yet to be investigated. However, if the retrospective data of previously successful professional golfers is to be used to inform AID practices, the limitations of such data must be understood. Furthermore, the guidelines being suggested need to be based on the most relevant data available. Examining the ranking trajectories of golfers from different generations will provide insight into whether generational shifts have influenced golfers' development over time. Understanding the changes that define different generations of developing professional golfers will allow current and valid data to be applied to AID programs. The following manuscript seeks to identify a relevant sample cohort of top 100 ranked golfers, so that the data may be used to inform both sides of the AID equation regarding the amateur to professional transition of male golfers.

2. Manuscript

Examining Generational Differences in the Ranking Trajectories of Top Ranked Golfers

Examining Generational Differences in the
Official World Ranking Trajectories (OWGR) of Top 100
Ranked Golfers’

For simplicity, references cited in the manuscript have been included in Section 4.

Abstract

For male professional golfers, the attainment of a top 100 Official World Golf Ranking (OWGR) is a significant career milestone. Golf National Sport Organisations (NSOs) allocate considerable resources to assisting golfers in their ascent up the ranking ladder. However, scientific data that can be used by NSOs to benchmark developing athletes and make decisions on where to allocate their finite financial and human capital is scarce. The OWGR offers a rich data source that may be used for benchmarking purposes. However, golf has undergone many changes over the last few decades; thus, before the ranking pathways can be investigated, it is crucial to appraise the temporal stability of such data and determine whether it is valid for use with current/future athletes. This study aimed to determine whether the ranking pathways of top 100 golfers have changed over time. Data were collected on 470 golfers who first entered the OWGR top 100 between 1 January 1990 and 31 December 2018. Golfers were assigned to cohorts based on their birth-year: Cohort 1 (1989-1999) (n=79); Cohort 2 (1979-1988) (n=153); Cohort 3 (1969-1978) (n=174); and Cohort 4 (1959-1986) (n=64). Key career ranking milestones (e.g. first turned professional, first top 1000 ranking, etc.), the time taken to transition between milestones, and development time (i.e., time between declaring professional status and entry into the top 100) were examined. Descriptive statistics were reported for each cohort and one-way ANOVAs used to investigate temporal trends. A trend towards younger generations of golfers reaching milestones at significantly earlier ages and in less time was observed. For instance, significant decreases in golfers' development time were found over time at 3.22, 6.16, 8.22, and 10.72 years for cohort 1,2,3, and 4, respectively. These results highlight the temporal instability of rankings data and the need to appraise such data before use with developing athletes. Golf NSOs looking to benchmark athletes using OWGR data should delimit comparative data to athletes born after 1978.

Keywords: Athlete Development, Athlete Identification, Golf, Generational Differences

Introduction

Professional golfers compete on many organised tours worldwide, with each tour comprising a series of individual events. Golfers receive points for events based on their respective finishing position. The Official World Golf Rankings (OWGR) aggregate points from different tours to provide a relative ranking of male professional golfers (Broadie & Rendleman Jr., 2013). For many golfers, coaches, and national sport organisations (NSOs) the achievement of a top 100 ranking is a significant career milestone. Not only is it symbolic of success at the professional level, but it paves the way for direct entry into major championships, world golf championships, and Olympic games – the most prestigious and lucrative events of the sport (Golf News Net, 2019; PGA Tour, 2017). Additionally, it affects golfers' endorsement income and creates further opportunities to forge a sustainable career through the sport (Broadie & Rendleman Jr., 2013. Producing top 100 golfers is also a key objective of golf NSOs, which typically rely on government funding to support their high-performance (HP) programs. With funding availability linked to athletes' professional success, it is no surprise that a focus of golf NSOs is to produce as many top ranked athletes as possible (Brouwers, Sotiradou, & De Bosscher, 2015; Green & Houlihan, 2006; Sam, 2012; Golf Australia, 2019; Hayman, Borkoles, Taylor, Hemmings, & Polman, 2014).

To give their athletes the best chance of professional success, NSOs employ Athlete Identification and Development (AID) programs. Athlete Identification (AI) is the process of identifying athletes seen as having the greatest potential for success in elite sport (Vaeyens, Lenoir, Williams, & Philippaerts, 2008) whereas Athlete Development (AD) focuses on optimising the development process by providing athletes with the appropriate resources (e.g., specialist coaching, sports science/sports medicine services) and learning environments relative to their developmental stage (Cobley, Schorer, & Baker, 2012; Vaeyens et al. 2008). NSOs that advocate for best practice utilise systematic strategies based on the experiences of successful athletes to inform their AID programs and activities (Cobley et al., 2013; Johnston, Wattie, Schorer, & Baker, 2017; Vaeyens, Gullich, Warr, & Philippaerts, 2009; Vaeyens et al., 2008).

In individual sports, AID programs in the HP stream encompass the development process from grassroots participation until athletes' emergence as financially self-sufficient performers (Gulbin, Crosser, Morley, & Weissensteiner, 2013). If a goal of NSOs is to produce top ranked professional athletes, a logical step is to focus research efforts on the transition period from when golfers declare professional status to when they first reach the top 100. Golf NSOs allocate considerable resources to assisting athletes in their ascent up the ranking ladder. The costs associated with funding individual sport athletes are also extensive. For instance, golfers require an estimated $150,000 USD per year to play on the PGA Tour, $100,000 for the Champions Tour, and $55,000 for the Web.com (Bae, 2012), with similar values reported in tennis (Reid, Morgan, Churchill, & Bane, 2014). Due to financial limitations a limited number of athletes can be selected for targeted funding, thus NSOs attempt to maximise their return on investment by identifying the "correct" athletes for which to allocate their finite financial and human capital (Kovacs et al., 2015). While the attainment of a top 100 OWGR is a key milestone for aspiring golfers, there has been little research conducted to inform current AID programs regarding the pathway athletes take to reaching the top 100.

In recent years, there has been growing interest in the ranking milestones and progression of top 100 professional tennis players. In one study, Reid and Morris (2013) used year-end rankings to establish benchmarks for players who reached the top 100 in the Association of Tennis Professionals (ATP) rankings. They found that on average top 100 players earned their first ATP ranking point at 16.9 years of age and took 4.5 years to transition to the top 100 at 21.5 years old. Players who earned their first ATP point at younger ages were also more likely to achieve better rankings. Notably, many players followed the same initial pathway as the best players yet failed to reach the top 100. To explore these skill-based differences, Reid et al., (2014) compared the ranking pathways of players who did and did not reach the top 100 ATP at one point in their career. Players were grouped into “bands” of 1-10, 11-20, 21-50, 51-100, 101-175, and 176-250 according to their peak career ranking. Players assigned to different ranking bands showed significant differences in their peak yearly rankings and these were observable from early on in the player’s careers. More recently, Kovalchik, Bane, and Reid (2017) examined the ranking pathways of top female tennis professionals on the Women’s Tennis Association tour. While the age at which benchmarks occurred were different, like the Reid et al. (2014) study, players who reached different peak career rankings were distinguishable from an early age.

Knowledge of the ranking pathways of golfers who have successfully transitioned to a top 100 OWGR could inform both AI and AD. By benchmarking the ranking progression of current/future athletes against previous successful athletes, NSOs can identify those tracking towards professional success and allocate resources/funding accordingly (Allen, Vandenbogaerde, & Hopkins, 2014). From an AD perspective, the ranking profiles of top golfers could assist NSOs and coaches in the establishment of long- and short-term performance targets for their athletes. With limited resources available, improving the AID process by providing a more objective basis for athlete selection and investment decisions is a critical focus for NSOs (Gulbin et al., 2013; Abbott & Collins, 2004).

While rankings offer a rich source of data with which to inform AID programs, it is important to keep in mind that these data are retrospective in nature. A methodological issue when applying such data is that sporting systems may evolve over time due to shifts in the socio-cultural environment (Baker & Wattie, 2018; Twenge, 2009). These shifts can result in generational differences between past, present, and future athletes. For example, Bruce, Farrow, and Raynor (2013) examined the sporting milestones of 20 amateur and 19 professional Australian netballers and found that younger athletes reported reaching milestones – such as age at which they first specialised in netball or attended regular training – earlier than their older peers. The authors attributed this finding to possible temporal shifts in the netball landscape. In tennis, Bane, Reid, and Morgan (2014) analysed the weekly rankings of 273 male professional players between 1985-2010 to examine historical trends in the time taken to reach career milestones. Results of the study indicated that the time between players earning their first professional ranking point and entry into the top 100 significantly increased over time.

Over the past few decades the game of golf has changed considerably. From a participation standpoint, greater television and media coverage and the rise of golf superstars like Tiger Woods have contributed to increased popularity of the sport (Chatterjee, Wiseman & Perez, 2002). Further, heightened interest in television and broadcast rights has resulted in increased PGA Tour prize purses from $2.8 to 6.0 million in 2000 to as large as $10 million in 2005 (Peters, 2008). Golf has also benefited from advances in club and ball designs and increasing physicality, which has contributed to a ~one yard per year increase in average driving distances on the PGA Tour from 256.89 in 1980 to 295.93 yards in 2018 (Wilco, 2018; O'Connor & Hawkes, 2013). These (and other) shifts may differently influence the ranking progression of golfers who developed across different generations thus affecting the validity of rankings data for use with current and future athletes; that is, it may be inequitable to compare athletes such as Tiger Woods and Jordan Spieth who turned professional 16 years apart. With this in mind, before the typical pathway to the top 100 can be described, it is crucial to determine any differences in the key career milestones of top golfers' who developed across different time periods. The aim of this study was therefore to conduct an exploratory analysis to determine whether the ranking trajectories of top 100 golfers from different age cohorts have changed over time.

Methods

Data

Ranking lists from 1988-2018 were obtained from the OWGR and comprised players' names, country of origin, cumulative ranking points, and analogues weekly rankings. As the OWGR was established in 1986, only golfers who received a ranking after 1990 were included; this resulted in golfers who had played parts of their careers before 1986 being excluded from the sample to ensure that athletes' full careers through the rankings were recorded. Data were collected on 470 players who first entered the OWGR top 100 between 1 January 1990 and 31 December 2018. An overall developmental pathway was constructed which consisted of a series of career milestones that were identified based on benchmarks often used by NSOs to represent key points in players' progression to the top 100. These include the age players:

declare professional status; first receive an OWGR (along with the respective ranking position); and, first reach the OWGR top 1000, 750, 500, 400, 300, 200, and 100. In addition, the time taken to transition between milestones (i.e., transition time – TT) and the total time taken from declaring professional status to first reaching the OWGR top 100 (i.e., development time – DT) was also determined. As the specific date players turned professional was not available, all dates were normalised to November 1st of the given year as this is the time most players turn professional.

Statistical Analysis

Analyses were performed to determine whether career milestones changed over time. Players were assigned to one of four cohorts based on their birth-year: Cohort 1 (1989-1999) (n=79); Cohort 2 (1979-1988) (n=153); Cohort 3 (1969-1978) (n=174); and Cohort 4 (1959-1968) (n = 64). Using players' birthdates and normalised dates of declaring professional status, descriptive statistics (means, standard deviations) were calculated for overall DT, TTs and career milestones for each cohort. To determine whether differences in the overall developmental pathways existed between cohorts, multiple one-way Welch analysis of variance (ANOVA) tests were conducted (unequal variances confirmed by Levene's test). Post-hoc comparisons using Games-Howell tests were subsequently undertaken where a significant main effect was found. A Shapiro-Wilk Normality test confirmed non-normal distribution of data, and therefore Kruskal-Wallis (K-W) tests were also carried out to confirm all ANOVA results. All statistical procedures were conducted using SPSS v.25 for Macintosh (SPSS Inc., Chicago, IL., USA).

Results

Figure 1 shows the mean ages that golfers from different cohorts reached career milestones. Golfers from relatively younger cohorts entered the professional ranks at significantly earlier ages than their older peers, with the exception of cohort 2 and 3. Younger golfers also obtained their first ranking earlier, with golfers from the youngest cohort being ranked before they declared professional status – reflected by the lower age value for first ranking compared to first turned professional in Figure 1. While they were first ranked at younger ages, younger golfers' first absolute rankings were significantly higher (i.e., worse) than older golfers. A progressive and significant decrease in golfers' average age at first top 1000, 750, 500, 400, 300, 200, and 100 OWGR was observed across all cohorts. Significant decreases in golfers' overall DT were also found over time (Table 2.1) at 3.22, 6.16, 8.22, and 10.72 years for cohort 1, 2, 3, and 4, respectively.

TTs between milestones (most noticeably between top 1000 and top 300 career ranking milestones) were highly variable and signified largely non-significant portions of total DT. To look at the data in a different way, the percentage of time that athletes spent between career milestones throughout their careers were calculated. When time between first top 1000 and first top 300 rankings were collapsed, all cohorts were seen to spend similar amounts of time (within 2%) at this stage of their career. Considering this, to provide a more valuable representation of golfers' overall development, TTs were collapsed and organised into three separate phases: Phase 1 (first turned professional to first top 1000 ranking); Phase 2 (first top 1000 to first top 300 ranking; and Phase 3 (first top 300 to first top 100 ranking). A linear decline in TTs for all phases was observed across cohorts; yet, this was only significant for some cohorts.

Discussion

The aim of this study was to investigate whether the overall developmental pathways of top 100 world ranked golfers changed over time. Golfers from younger age cohorts reached career milestones at progressively earlier ages and in less time than their older peers. TTs between milestones were relatively small, so to better represent development the pathway was collapsed into three phases. Once collapsed, a linear decline in phase TTs was observed across all cohorts; that is, younger cohorts transitioned between phases in less time. While TTs were not significantly different between all cohorts, this trend contributed to all younger cohorts having significantly quicker DTs than their relatively older peers. Differences in DTs may be driven by generational shifts occurring during and preceding phases 1 of the pathway; that being, TT's were only significant between all groups during phase 1. As well, the magnitude of TT differences between cohorts were greatest during phase 1. Overall, the results indicate a potential shift towards current and future top 100 ranked golfers emerging at significantly younger ages than have been seen in previous generations.

Similar to our findings, a shift towards athletes reaching career milestones at earlier stages in their careers have also been observed in Australian netballers (Bruce et al., 2013). In contrast, increases in the DT (i.e., time from first ATP ranking to first top 100 ATP ranking) of top 100 tennis players have been reported over time (Bane, Reid, & Morgan, 2014). Together these findings suggest shifts in generational trends may be domain specific, as changes to sporting landscapes likely occur at different periods of time. Shifts in generational trends may also be gender-specific (e.g., as suggested by Kovalchik et al., 2017), thus the current findings may only be relevant to male professional golfers.

With this in mind, different sports may benefit from appraising their own data for gender-specific generational shifts before using such data to inform AID programs. That said, our results highlight the need to continue to explore how generational effects influence our understanding of the development and maintenance of performance. Much of the previous literature has focused on generational changes in the age athletes in sports such as tennis, golf, swimming, running, and triathlon reach peak performance (Gallo-Salazar, Salinero, Sanz, Areces, & del Coso, 2015; Schulz & Curnow, 1988). For instance, in Olympic track and field and swimming the age athletes reached peak performance remained fairly consistent over time (Gallo-Salazar et al., 2015). However, our results emphasize that generational effects may be much more nuanced than previously investigated.

Importantly, our findings reflect the effect, not the cause of the developmental pathway differences observed amongst top 100 golfers from different generations. However, it is possible to speculate regarding the mechanisms that may be driving these changes. Since 1996, golf has experienced increases in both exposure and participation often attributed to the emergence of Tiger Woods, being referred to as the 'Tiger-effect' (Chatterjee et al., 2002; Herrington, 2016). Increases in exposure and cultural importance of a sport may lead to younger athletes having increasingly visible role models and enhanced opportunities to participate in the sport from the grassroots to professional level (Mutter & Pawlowski, 2014). Increased growth may also bring about the professionalization (i.e. sport resembling a professional environment such as increased practice time and intensity, access to specialised coaches and support teams, increased media attention, etc.) of junior and amateur/college golf, a trend reported in other sports such as basketball, baseball, and football (Brower, 1979; Gould 2009; Sheehan; 2000; Wheeler, 2004). Other influential changes in the sport that have occurred over the past few decades include advances in golf ball/club technology, and player support programs (i.e. increased funding, resulting in increased access to specialised coaching (technical, physical, and mental) (O'Connor & Hawkes, 2013). Accordingly, noticeable changes in player characteristics and training focuses concerning physical fitness abilities (with a shift towards a more physical/power game) have been observed (Torres-Ronda, Sanchez-Medina, Gonzalez-Badillo, 2011).

From a policy perspective, system changes in professional golf have also influenced the OWGR structure. For instance, more opportunities to earn ranking points are now available with 18 developmental tours added to the OWGR system since 2009. The growth of the OWGR and golf in general has contributed to more players being ranked. At the beginning of 1990, 733 athletes from 37 countries (16 athletes' countries not reported) obtained at least one ranking point; compared to 2005 athletes from 60 countries in 2018. These greater opportunities may allow golfers to be ranked at earlier ages. Further, as developmental tours offer less rankings points, this change may explain why higher (i.e., worst) first absolute rankings were observed in golfers from older cohorts. These factors may have enabled golfers from younger cohorts to obtain rankings and be better prepared to succeed in a professional environment at earlier stages of their careers.

The chief aim of this study was to determine whether data from previous generations is relevant to inform current and future AID programs. Applying outdated data may misinform AID programs moving forward, regardless of the context behind such changes (Kovacs et al., 2015). Rankings data have previously been used to inform AID programs in tennis and swimming. For instance, the career pathways of top 100 ranked male and female tennis players were outlined using the ATP/WTA rankings (Reid & Morris, 2013; Kovacs et al., 2015). Researchers have also examined whether these rankings can be used to aid in identifying athletes who have the potential for lower (i.e., better) rankings. Analyses revealed that both the men's and women's rankings may be used for this purpose, as the ranking trajectories of athletes who reached lower peak rankings were distinguishable from their higher ranked peers from early stages of their careers (Reid et al., 2014; Kovalchik et al., 2017). In swimming, it was found that leading up to the Olympics, athletes should be ranked in the top 10 for their respective discipline to be a realistic medal contender (Trewin, Hopkins, & Pyne, 2004). Similarly, future studies may employ the OWGR data of relevant cohorts to outline developmental trajectories and discriminate between skill-level differences of male professional golfers.

Despite the unique contribution of these analyses to understanding developmental trajectories of top 100 ranked golfers, several limitations exist. One limitation of this study was that the sample included athletes who were currently competing, which means that some cohorts may have an incomplete sample of athletes. Golf is unique in that athletes may remain competitive much later into their careers than those from other sports. On the Professional Golfers Association (PGA) rankings between 1948 and 1985, the average age of the 33 players who were ranked first during that period of time was 33.67 years (SD = 4.71), with a trend towards younger number 1 golfers closer to 1985 (Schultz & Curnow, 1988). When considering scoring average, PGA Tour players continue to improve their overall performance until around age 30, and do not see performance decrements until the age of 43 (Baker, Deakin, Horton, & Pearce, 2007). When applied to our sample, these findings suggest that some age cohorts may consist of an incomplete sample of athletes. For example, since golfers do not peak until ~30 years of age, athletes in cohort 1 who still have the opportunity to obtain a top 100 ranking at some point during their careers may not be included. As golfers maintain their performance until ~43 year of age, some of the relatively older cohorts may also be incomplete. With an incomplete sample of this nature, a conservative approach would be to include both cohort 1 and 2 data to inform golf AID programs at least until a more complete dataset is available.

Another limitation includes the possibility of a cut-point bias, as age cohort boundaries were assigned arbitrarily to the birth years of the sample. The cut-point of 10-year intervals between birth years were chosen to allow the sample to be split as evenly as possible while at the same time providing space for generational changes to be identified between the cohorts. It should also be noted that there was substantial intra-group variability for many milestones. This may be due to the fact that due to the cut-point bias, athletes at one end of the cohort may have been more affected by certain generational changes than others. Resulting in athletes having different developmental pathways than the rest of the cohort and skewing of the mean farther away from the median.

It should also be considered that athletes develop in a non-linear and nuanced fashion (Gulbin, Weissensteiner, Oldenziel, & Gagne, 2013) and future AID work using the OWGR for benchmarking should consider this variability with caution. Further, generational shifts may be dependent on a particular country/region, or effect different regions at different times. In order to determine whether these shifts and subsequent changes in developmental pathways were region-specific, the sample was split into four regions (Americas, Europe, Asia, and Oceania) and the original analysis replicated for each group. It was found that the generational trends observed in our original analysis were also present for each regional-group. While the overall trends of generational shifts were consistent across regions, the actual ages and times that athletes from different regions reached milestones fluctuated. Athletes from different regions may experience different developmental experiences and sporting systems (Bosscher et al. 2008; Bosscher, De Knop, & Heyndels, 2003). Future benchmarking work may benefit from independently analyzing the pathways taken by athletes from different regions.

Conclusion

The results of the current study indicate that the OWGR trajectories of top 100 male professional golfers have changed over time. A trend towards younger generations of golfers reaching milestones at earlier ages and in less time was observed. The following recommendations are provided:

- Golf NSOs and future researchers attempting to benchmark for their athletes using the OWGR data should use the data of athletes born after 1978
- Regardless of the sport in question, retrospective data being used to inform AID programs should be appraised for current relevance. Generational shifts may be unique to a specific sport and impact the data in a sport-specific manner. While the results of this study may only be applicable to inform male professional golf, the methods may be replicated by NSOs and researchers from other sports to inform their own practice.

- NSOs should continue to update and monitor their data in order to be aware of any potential change in generational trends so that policies may continue to be updated based on their findings. Models of AID should not remain stagnant for extended periods of time.

Collectively, these results highlight the pitfalls of using retrospective data to inform AID programs. However, when appraised and applied in an appropriate manner such data may still be useful to inform decision-making processes for current and future athletes.

	Cohort 1	Cohort 2	Cohort 3	Cohort 4
First absolute OWGR**	999.94 ± 207.82	836.71 ± 202.58	673.57 ± 150.33	598.20 ± 116.83
Phase One TT**	0.75 ± 1.20	1.56 ± 1.91	2.80 ± 2.23	4.49 ± 3.17
Phase Two TT[abce]	0.90 ± 0.96	1.62 ± 1.79	2.14 ± 1.90	2.69 ± 2.93
Phase Three TT[abc]	1.58 ± 1.60	2.97 ± 2.68	3.28 ± 3.18	3.54 ± 3.04
Overall DT**	3.22 ± 2.23	6.16 ± 3.56	8.22 ± 4.05	10.72 ± 4.65

Table 2.1. Descriptive statistics relating to First Absolute OWGR, DT and TT for Phase 1-3.

*Notes: **All groups significantly different from each other as determined by one-way ANOVA. Phase One (first turned professional to first top 1000 ranking); Phase Two (first top 1000 to first top 300 ranking); Phase Three (first top 300 to first top 100 ranking).*
[a]Cohort 1 significantly different from Cohort 2; [b]Cohort 1 significantly different from Cohort 3; [c]Cohort 1 significantly different from Cohort 4; [d]Cohort 2 significantly different from Cohort 3; [e]Cohort 2 significantly different from Cohort 4; [f]Cohort 3 significantly different from Cohort 4.

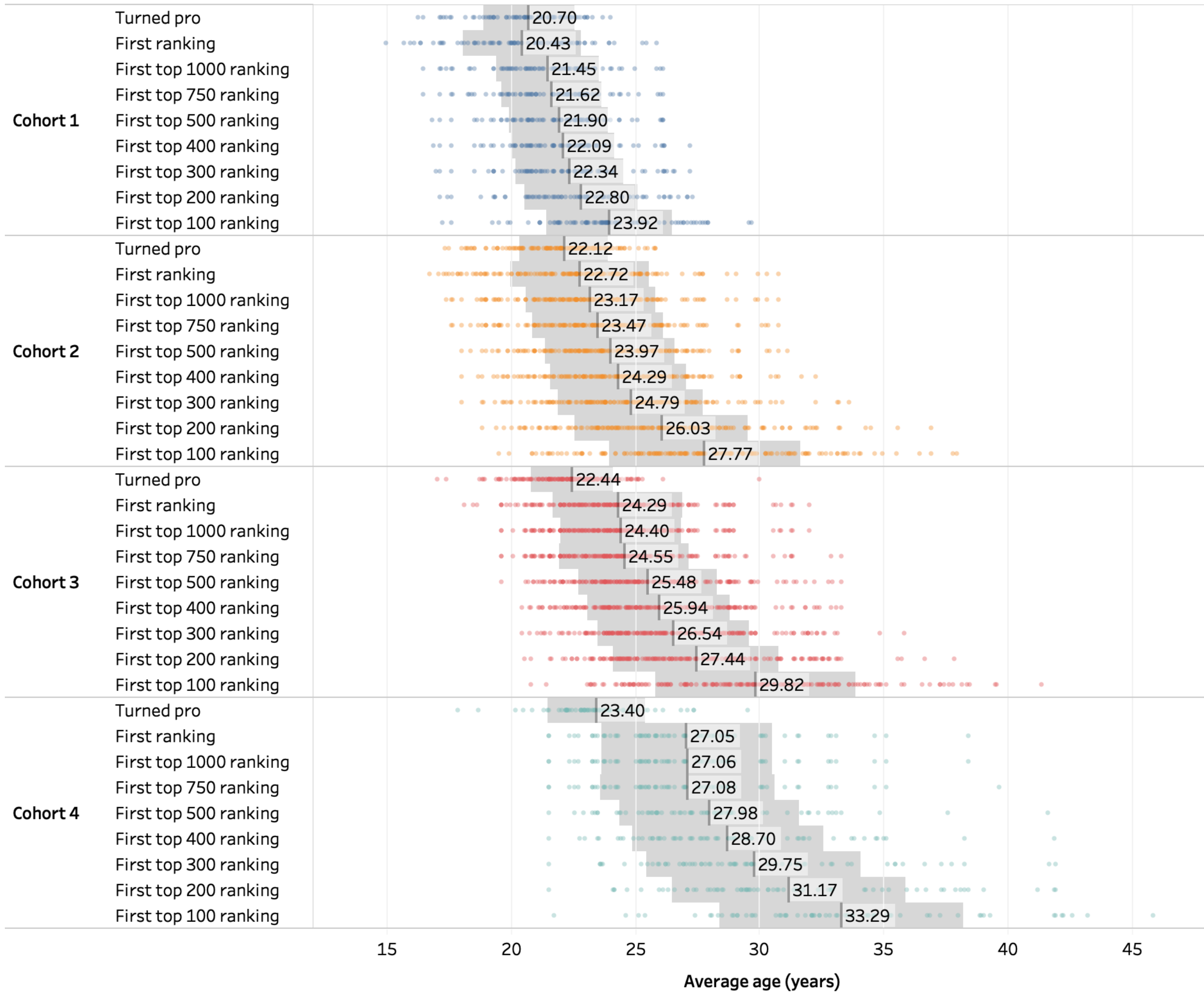

Figure 2.1 Mean ages that golfers from different cohorts reached career milestones. The shaded regions reflect the standard deviation and the individual dots show the specific ages that milestones were reached for each golfer.

3. General Thesis Discussion

Summary

The aim of this thesis was to investigate whether the overall developmental pathways of top 100 world ranked golfers have changed over time. Overall the data suggested players from more current generational cohorts reached career milestones at significantly younger ages than their relatively older peers. As well, progressive decreases for younger athletes in the total amount of time taken from turning professional to reaching a top 100 OWGR (DT) were observed. These results appear to reflect a combination of younger athletes both turning profession at earlier ages and transitioning between defined career phases at quicker rates than their older counterparts. Interestingly, it may be what is occurring at the beginning of these athletes' careers (i.e. phase 1) that is driving the overall effect of decreased DT. While linear declines in TTs were displayed for all younger cohorts during phases 2 and 3, the results were only significantly different when comparing athletes from cohort 1 to all others. Phase 1 was the only timeframe on the developmental pathway that saw all younger cohorts have significantly quicker TTs. Overall, top 100 athletes from younger cohorts were seen to move along the developmental pathway at quicker rates and reach career milestones at earlier ages than those from older cohorts.

While limited to a few studies, generational changes in other sports have been examined in the literature including netball, tennis, swimming, running, and triathlon (Bane et al., 2014; Bruce et al., 2013; Gallo-Salazar et al., 2015; Kovalchik, 2014; Kovalchik et al., 2017; Schulz & Curnow, 1988). However, in comparison to this study some studies have examined different phases of development (i.e. under 18/junior sport), and other sport-specific benchmarks. For example, while our study examined the pathway top 100 ranked golfers take from the amateur to professional level, others have focused on understanding whether the overall career lengths and ages of peak performance have changed over time (Kovalchik, 2014; Gallo-Salazar et al., 2015; Schulz & Curnow, 1988). Additionally, Bruce et al., (2013) examined whether the ages netball athletes reached specific developmental milestones during their formative years had changed between already professional athletes and their junior national team counterparts. While the specific milestones and phase of development under examination were different than those employed in our study, similar trends were observed. Overall, younger netball players reached many milestones at significantly younger ages than their older peers.

Our results are perhaps better compared to the generational changes examined within tennis. As previously discussed, similar to golf, the success of tennis players has been associated with the attainment of a top 100 ranking and is measured by a ranking scale that aggregates points from different professional events around the world to provide a relative ranking of professional tennis players (Reid & Morris, 2013). Contrasting our findings, the age at which top 100 ranked male and female tennis players obtain their first world ranking has stayed stable over time (Bane et al., 2014; Kovalchik et al., 2017). Further differences between the sports are present when comparing overall DT. On the male side of the game, DT for top 100 athletes has actually increased over time (Bane et al., 2014). While for top 100 female athletes, DT was seen to remain stable across generations (Kovalchik et al., 2017). This gives evidence to generational changes being sport-specific, as generational shifts (in policy, cultural importance etc.) that drive these changes may happen at different times and in different capacities for a particular sport. As well, different sports may have unique metrics for assessing performance, making it difficult to apply such findings to another domain (Brouwers et al., 2012). The findings in this study are novel to male professional golfers, as assessing generational changes to the developmental pathways of top 100 athletes in the sport had not previously been undertaken.

While the aim of our study was to investigate whether the overall developmental pathway of top 100 world ranked golfers had changed over time, another goal was to define a relevant sample of athletes to use when applying the OWGR data to AID programs in men's golf. However, before a sample could be defined, we had to address a limitation within our sample. That being, some cohorts may be incomplete, as athletes who have the potential to eventually obtain a top 100 ranking but have yet to reach that benchmark would not be included. Golf may be unique as a sport since players can remain competitive into a much later age than athletes from other sports. For example, tennis players reached the peak of their careers around the age of 25 (Reid & Morris, 2013) while golfers may not reach the peak of their careers until around the age of 30 (Baker, Deakin, Horton, & Pearce, 2007; Schulz & Curnow 1988). Additionally, it has been observed that decrements from peak performance may not occur until around the age of 43 (Baker et al., 2007). If we assume golfers can peak up to the age of 30 in our sample, cohort 1 (athletes aged 20 to 29 at the end of 2018) is likely incomplete because athletes in cohort 1 still have the opportunity to obtain a top 100 ranking at some point during their careers and may not be included in the current sample. What needs to be considered however, is the other end of that assumption - the fact that golfers can maintain their performance until around the age of 43. This assumption means that golfers, may still have the opportunity to obtain their first top 100 ranking between the ages of 30 and 43.

To assess the degree to which a cohort may be incomplete, the turnover rate of the OWGR may be assumed to be fairly stable over time, so that younger cohorts may be compared to older ones that are assumed complete. At 45-49 years of age the latter half of cohort 3 may be assumed complete (n=92). Cohort 2 for example consists of 82 athletes in the latter half and 71 in the early half of the cohort, while cohort 1 consists of 67 and 12 athletes in the later and early halves respectively. Clearly, cohort 2 is a more complete sample than cohort 1. Comparing these cohorts to the latter half of cohort 3, cohort 2 clearly consists of a more complete sample of athletes than cohort 1. With an incomplete sample of this nature, it is possible cohort 1 is comprised of relatively early achievers, and therefore, the results observed for athletes from cohort 1 may be a statistical artefact due to having an incomplete sample. With this in mind, it seems that until a more complete sample is available to reappraise the data, a conservative approach would be advisable, which would be to use both cohort 1 and 2 data to inform AID programs in men's golf.

Future Directions

With a generationally relevant sample now defined, the OWGR may be used to provide benchmarking data to inform AID programs. However, while the current analysis suggests an overall developmental pathway that players from both cohort 1 and 2 take to the top 100, the current data are not meant to be prescriptive. Further analyses need to be conducted on the relevant data in an appropriate manner before it may be applied to inform AID programs. Furthermore, ranking data have limited utility in practice and are simply a starting point to inform these programs. Understanding the mechanisms behind these ranking pathways of top 100 athletes would have greater value for informing the development of appropriate developmental pathways. Regardless, with limited knowledge to currently inform AID in golf, these ranking pathways serve as a first step to expanding these programs in the sport.

From an identification perspective, benchmarking current/future athletes against previous successful athletes can assist NSOs in identifying those who are tracking towards professional success (Allen, Vandenbogaerde, & Hopkins, 2014). Furthermore, an understanding of the benchmarks athletes need to reach in order to succeed at higher levels can aid with providing athletes the appropriate resources required to develop and reach such benchmarks (Cobley et al., 2012). It has been noted that many different athlete development scenarios exist, and accepted that their development is a non-linear and nuanced process (Gulbin et al. 2013). Such nuance is displayed in our data, as the intra-group variability for many milestones was quite large at certain points throughout the pathway. However, while nuance and outliers in athlete experiences may always exist, the overall goal of NSOs is to increase the probability of successful athlete outcomes (Gulbin & Weissenstiener, 2013). With this goal in mind, and the notion that NSOs have significant control over the selection and planning process of its athletes, objective data to inform decision-making seem warranted. However, objective data to inform selection and development decisions in professional golf is to our knowledge limited.

As previously noted, overall athlete performance in professional golf is assessed in similar ways to tennis, as both use a relative ranking list. While golf has the OWGR, tennis has the ATP and WTA rankings, which have both been previously used to inform the sport with benchmarking data. Reid and Morris (2013) outlined some general ranking guidelines (i.e. age at first ATP ranking, transition time from first ranking to first top 100 ranking, age at first top 100, correlation between first ranking age and peak ranking, etc.) for players who finished in the top 100 on the 2009 year-end ATP rankings. On the women's side, Kovacs et al. (2015) examined the ranking progression of athletes who were listed in the top 100 of the WTA ranking list in 2014. To examine ranking progression, the ages that athletes reached 5 key milestones (1000, 500, 300, 200, and 100) along with total time from first top 1000 ranking to first top 100 ranking were determined. In our analysis similar milestones were outlined which made up our overall development pathway. The first step to expanding the utility of the OWGR seems to lie with using the overall developmental pathway (as defined in our study) to carry out a descriptive analysis outlining the ranking progression for the generationally relevant sample.

In addition to understanding the ranking progression of top 100 male golfers, differences in trajectories between sexes (i.e. understanding the ranking trajectories of female golfers using the Rolex rankings) as well as athletes from different regions should be considered. Due to the differing rates of biological development for men and women, the ages they attain and transition between career milestones may differ (Schulz & Curnow, 1998; Kovalchik et al., 2017). It has been observed in track and field and swimming events, that women reach peak performance at younger ages than men (Schulz & Curnow, 1998). Furthermore, when comparing the ranking progression of male and female professional tennis players, females reached their first top 100 ranking at younger ages (Kovalchik et al., 2017).

Beyond developmental differences, distinctions in the policies that govern men's and women's competition within the same sport may also contribute to pathway differences. For instance, in tennis the WTA restricts the number of tournaments women under the ager of 18 can compete in, while on the men’s tour no such restriction exists (Kovalchik et al., 2017). It seems reasonable that gender differences should be taken into consideration when examining developmental trajectories. The ranking pathways of males ranked in the OWGR and women ranked in the Rolex rankings should be analysed in isolation, with potential differences displayed.

These sex differences may also be relevant for understanding generational changes within a sport. For instance, DT (defined for tennis professionals as the time from gaining a first ATP ranking to first top 100 ATP ranking) for male tennis players has increased over time (Bane et al., 2014). However, the same trend was not observed in females where DT has remained stable over time (Kovalchik et al., 2017). Therefore, males and females within the same sport may require independent generational analysis before applying their data to AID programs.

Developing golfers from different regions may also be susceptible to unique developmental experiences and sporting systems (Bosscher et al. 2008; Bosscher, De Knop, & Heyndels, 2003). For instance, the cultural importance of golf in a specific region may lead to athletes having different experiences in terms of available training, coaching, infrastructure, and competitive environments (Baker & Horton, 2004). As previously mentioned, the OWGR is a single ranking list that aggregate points from different tours to provide a relative ranking of male professional golfers (Broadie & Rendleman Jr., 2012). Professional golfers from a particular region may therefore play on a different tour than other athletes on their pathway to becoming a top 100 ranked golfer. These tours may have their own unique qualification pathways and offer different world ranking points. As well, the strength of the overall field may dictate how easily or quickly a player destined for the top 100 may gain the appropriate ranking points. For example, the OWGR system has been found to have a bias towards inflating the ranking of international tour players compared to those on the PGA Tour (Broadie & Rendleman Jr., 2013). This implies a player from Europe or Asia who is not as skilled as a player from the PGA Tour, will climb the ranking ladder at a quicker rate due to playing against easier competition. Due to such factors, future OWGR benchmarking work may benefit from considering the potential unique ranking trajectories of athletes from different regions.

Once the pathways of top 100 golfers are defined (with appropriate sex and regional considerations accounted for), the next step should be examining whether the OWGR and Rolex ranking trajectories have the ability to discriminate professional golfers at different skill levels. It has been previously observed in both men's and women's professional tennis that the ATP and WTA rankings could be used to aid in selecting athletes who have the most potential for future success. In two separate studies, professional male and female tennis players were grouped into "bands" of 1-10, 11-20, 21-50, 51-100, 101-175, and 176-250 according to their peak career ranking (Reid et al, 2014; Kovalchik et al., 2017). Players assigned to different ranking bands showed significant differences in their peak yearly rankings and these were distinguishable from an early age from early on in the player's careers. NSOs looking to use the OWGR and Rolex rankings to influence decision-making for AID purposes would benefit from conducting similar analyses. Whether or not the results show that such rankings can discriminate between skill levels will be informative to golf NSOs when deciding how much utility to give the ranking data in their decision-making processes. It should also be kept in mind that the ranking data explain the effect, not the cause of such rankings (Reid et al. 2014; Kovalchik et al., 2017). Future research also needs to focus on understanding the various factors (i.e. training and social support) that may also influence successful amateur to professional transitions in golf.

While the current findings are only generalizable to male professional golfers, the methodologies of the current study could be useful to inform the practice of NSOs and researchers in other sports; that is, setting guidelines for their appraisal of data for generational changes, prior to applying it to inform their AID programs. Different types of metrics within the same sport may also need to be appraised for generational changes independently. For example, performance statistics in golf (i.e. driving distance, scoring average, shot gained, etc.) may undergo changes at both different times and in different capacities than the OWGR trajectories. While this study allows us to identify a generationally relevant sample for applying OWGR data, different metrics may need to be reappraised using similar methods to the current study. For best practice, NSOs should regularly appraise the various types of data they use to inform AID programs. In sum, models of AID should use the most up to date data available in order to avoid remaining stagnant for extended periods of time.

Conclusion

Overall, the findings of this study will allow relevant data from the OWGR to inform AID programs in men's golf. However, on a wider scope, the contents herein should inform NSOs and researchers regarding the consequences of using outdated and possibly irrelevant data to inform AID programs. Additionally, the methodologies used in this study may offer solutions regarding how to effectively appraise sport-specific data for generational changes so that it may be applied responsibly to AID programs in the future.

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