Golf and GameForge: Innovative Analytics for Recommender Systems

A Technical Report submitted to the Department of Engineering Systems and Environment

Presented to the Faculty of the School of Engineering and Applied Science

University of Virginia • Charlottesville, Virginia

In Partial Fulfillment of the Requirements for the Degree

Bachelor of Science, School of Engineering

Rachel Kreitzer

Spring, 2022

Technical Project Team Members

Rose Dennis

Zachary Kay

Jerry Lu

Sam Roberts

Thomas Twomey

Steven Wasserman

On my honor as a University Student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments

William Scherer, Department of Engineering Systems and Environment

Golf and GameForge: Innovative Analytics for Recommender Systems

Rachel Kreitzer, Rose Dennis, Steven Wasserman, Zachary Kay, Jerry Lu, Sam Roberts, Thomas Twomey, William Scherer

Department of Engineering Systems and the Environment, University of Virginia, Charlottesville, United States
rak2cy@virginia.edu, rad7wgg@virginia.edu, stevenwasserman@virginia.edu, zmk2ud@virginia.edu, zl5bf@virginia.edu, scr3ar@virginia.edu, tlt7pg@virginia.edu, wts@virginia.edu

Abstract **–The college sports industry has grown tremendously over the past decade, with NCAA athletic departments recruiting almost half-a-million students to 19,866 teams in 2019 and generating $18.9 billion of revenue the same year. Identifying and selecting the best student-athletes is critical to maintaining the power of these sports programs, aggrandizing the recruitment pipeline and necessitating the demand for novel use of existing technologies. Sports analytics is one response to these growing needs, as its primary use in junior recruitment has presented fruitful for college basketball and football teams across the nation. Golf analytics firm GameForge aims to provide the same insights to college golf coaches, streamlining the recruitment of junior golfers to U.S. universities from around the world. GameForge seeks to develop a two-sided recruiting system that provides similar insights to junior players and their coaches as well as strengthen its predictive models with the inclusion of new data. A systems-based approach was taken to develop data-driven machine learning models that would provide (a) a proprietary ranking system that compares junior athletes to one another; (b) a relative SWOT analysis that highlights each player's strengths and skill gaps; and (c) a recommender system to suggest potential recruits to college coaches and to recommend colleges of best fit to junior players.**

Keywords – sports analytics, student-athlete recruitment, big data modeling, systems integration

I. Introduction

Emerging digital transformation in the sports industry has escalated the role data analytics plays in recruiting and maintaining talented players across a variety of sports. The $620 billion global sports industry is accelerating faster than the entire global gross domestic product, arising from innovative customer experiences that take advantage of consumer technology and broad access to Internet connectivity [1][2]. Professional sports leagues like the National Football League and the National Basketball Association now capture fan engagement through over-the-top (OTT) platforms that offer live streaming, virtual reality experiences, and social media content on personal mobile devices, "leverage[ing] digital media to build direct connections with fans… [and] broaden content reach for sports organizations" [3]. More recently, new companies such as FanDuel and DraftKings have sought to capture market share in the $165-billion American sports betting industry that yielded $44 billion during the pandemic in 2021 [4][5].

The college sports industry is no stranger to this explosive growth – the U.S. Department of Education reported $14.4 billion in revenue for American colleges in 2019, an increase of approximately $750 million every year since 2004 [6]. The National Collegiate Athletic Association (NCAA) is one of the most powerful sports organizations in the country, whose top twenty-five programs are projected to grow in revenue by 116% over the next ten years, a factor more than double the NBA, NFL, NHL, or MLB [7]. And following regulations regarding name, image, and likeness (NIL) recently passed by the NCAA and upheld by the Supreme Court, student athletes have found new opportunities to promote themselves in a burgeoning college sports sponsorship market valued at $100 million, where athletes can earn $1,000 to $10,000 on average annually [8][9].

While private industry and policymakers rush to keep up with the ever-expanding student athlete market, colleges across America are employing data analytics to recruit and retain top talent to NCAA teams. This is further extrapolated between sports of different apparent retail values – U.S. universities spend far more on recruitment in football and basketball compared to other sports because of the demonstrated difference in consumer demand [10]. Junior athletes in other sports, like golf, must rely on specially segmented platforms, like rankings published by the American Junior Golf Associations (AJGA), to demonstrate their value to recruiters.

GameForge Golf, a Virginia-based analytics firm, provides a data-driven platform that seeks to ameliorate the junior recruiting process by streamlining information sharing between junior players, college players, and collegiate coaches [11]. Currently, the company offers college students and coaches an online portal that features thorough athlete analyses comprised of relevant descriptive statistics and golfer rankings comparable to different college conferences [12]. However, with the apparent market opportunity entertained by new options for student-athletes and by the sports industry at-large, GameForge seeks to expand their services to better serve the recruitment of junior players. In conducting research in coordination with GameForge, our objective is to develop complex statistical inference and machine learning models that can deliver insight on identifying and recruiting junior golfers as well as provide strategic guidance on the development of a two-sided recruiting system for both junior and collegiate stakeholders. As the magnitude of the college sports industry rises, GameForge can deliver unique golfer tracking capabilities that proffers novel sports analytics techniques and manages junior recruitment practices for its customers.

II. Background

The current approach in collegiate golf recruitment overlooks many golf players that have the potential to improve team performance. Top golfers are easily identified at tournaments and other major golfing events, but mid-level players are rarely considered due to an absence of a tangible platform to demonstrate their strengths. In addition to this, there is no current way for players to identify teams that are good matches based on metrics beyond rank, such as

qualitative factors and personal preferences. This results in both colleges losing out on players that may strengthen their team and players not being able to find a team that will foster their skills and optimize their performance. The absence of a centralized setting that addresses the current recruitment concerns led GameForge, a golf analytics firm, to develop a data-driven platform. GameForge currently provides features that allow its users to understand their individual performance and identify training needs. We outlined 3 specific features to help improve the college golf recruiting experience - a high school player ranking, a method of outlining a player's specific strengths and weaknesses, and a college recommender system for matching junior players and collegiate coaches.

A. Player Rank

Current popular golf associations, such as the American Junior Golf Association (AJGA) and Golfstat, are the standard for ranking players. However, these ranking systems do not allow for direct player comparison across different associations from junior golf to college to the Professional Golfers' Association (PGA) tour [13]. It is a common complaint amongst college coaches that current rankings do not fully capture all talent and potential in the player recruitment pool [14]. Our objective was to develop a proprietary ranking that outperforms the current systems, while allowing coaches to compare an individual player to the current recruitment pool and obtain a projected college rank based on player performance with less bias than current ranking systems [15].

B. Player-Field Performance

An inherent part of comparing athletes is to consider their specific strengths and weaknesses. No two sports players are the same or play their sport the same way. A challenge for many sports analysts is to quantify the strengths and weaknesses of different players to compare them overall. The approach of identifying a golfer's individual skill sets has been brought to golf on a limited scale at the PGA Tour level; however, their statistical measures are not practical for golfers at the high school and college level [16][17]. At the high school and college level, metrics to identify the strengths and skill gaps of a golf player or team do not exist. Coaches that express interest in a specific player often use qualitative decision factors to pinpoint player strengths. This results in golf players being overlooked and players not always committing to a college where their skill set could be optimized. The goal was to provide quantitative metrics that objectively identify how players perform compared to industry levels and other players by using hole variances and means of individual players. Similarly, utilizing the proprietary GameForge metrics for the driving, irons, short game, and putting aspects of a player's performance allows the system to identify specific areas to target for improvement. Identifying skills and skill gaps in comparison to the current field allows coaches to analyze specific components of a player's performance. Coaches are then given the opportunity to identify their overall team skill gaps and recruit players that may fill the existing skill gaps.

C. Player Recruitment

Collegiate golf recruiting, like many other university level sports, is a fragmented and inefficient process for both coaches and athletes for several reasons. There is misunderstanding in the requirements to be recruited, poor communication between golf players, recruiters, and coaches, and most importantly there is an absence of a centralized setting for addressing these issues [18]. Current recruitment for junior golf players consists of creating an online profile, contacting college coaches, competing in tournaments that will gain them recognition, and potentially hiring a private consultant [19]. This creates a confusing, labor-intensive, and sometimes expensive process that can be incredibly overwhelming for high school athletes. In addition to this, it is difficult for coaches and players to identify mutual interest based on player performance and preferences. The objective was to identify various factors that go into selecting a college and generate a list of potential player and college pairs. This will serve to reduce stress and streamline the recruiting process for both players and coaches. Various factors that could impact an individual's choice to commit to a college were explored: student body size, college golf team rank, distance from hometown, geographic regions, social factors and academic factors [20][21][22].

D. Previous Work

GameForge has been working in past years to enhance their analysis and add new features to their platform in order to better serve their users [11][23]. Previous research efforts utilized disparate datasets without clear organization or accessibility, in stark opposition to the now available GameForge database. The GameForge database includes player tournament scorecards for AJGA and PGA tours; rankings from AJGA, Golfstat and WAGR; proprietary, user-inputted GameForge metrics; and collegiate team and player information. With this new resource, the objective was to aid GameForge by generating data-driven insights to provide players and coaches metrics beyond current ranking systems and prestige when committing to a team.

III. PLAYER RANK: PROPRIETARY GAMEFORGE RANKING

In chess, the Elo system allows for direct comparison of any two players by their rating [24]. In tennis, the ATP point system provides a numerical system to compare performances within the calendar year [25]. Current golf rankings, however, lack features that allow for head-to-head player comparison while capturing player performance variability due to segmentation of tournaments and rankings. AJGA, for example, only includes tournaments that are invitationals, open tournaments, senior events, all-star series, and preview series [26]. To combat these issues, we developed current rank and projected college rank using GameForge metrics so that current player performance and future potential can be measured more accurately. Both newly-developed, proprietary GameForge ranks outperform the leading industry rankings generated by AJGA after analysis.

A. GameForge Current Rank and Projected College Rank

TABLE 1. OVERVIEW OF PREDICTIVE MODELS

Player Name	Tournament Outcome	Golfstat	GameForge
Player A	4	5	1
Player B	5	4	2
Player C	3	1	3
Player D	6	12	4

*For privacy reasons, player names have been obfuscated

Using GameForge metrics and player scorecards, a stepwise regression model was created to determine significant golf metrics and generate an index-based scoring model for ranking players. The regression was completed using historical GameForge metric data as the independent variables and the latest tournament score as the dependent variable. The model computes factor loadings on the significant metrics and creates a weighted sum that results in an index score for each player. These index scores are then ranked to generate the GameForge current rank, which is organized as a "1224" standard competition ranking (SRC). For head-to-head comparisons, higher-ranked players have greater scores and are estimated to outperform a lower-ranked player. Analysis of the GameForge current rank found it outperformed 20% better than published AJGA rankings and 17% better than Golfstat rankings, as exemplified in TABLE 1. . The same regression methods employed to create current rank were employed to develop the projected college rank. The change was the dependent variable: college ranking. The model for projected college rank accurately predicts the top 25 players with greater than 70% accuracy.

B. *Dynamic Rankings*

For both rankings, as new tournament data is available, the GameForge metrics are recalculated with the added scorecards, leading to different factor loadings. The dynamic nature of the factor loadings allows the current rank and predicted college rank to better capture variability in performance and predict head-to-head player comparisons more accurately than existing golf ranking systems.

IV. Player-Field Performance: SWOT Analysis

Another important aspect of evaluating players is examining their performance throughout golf rounds to scrutinize their beneficial functional strengths and hindering skill gaps. Collegiate coaches often face challenges in creating well-functioning teams for tournaments arising from a lack of tools that evaluate combinations of golfers in a simple manner. Additionally, traditional golf research does not provide comprehensive feedback to players on their strengths as well as potential areas for improvement [16]. The player-field performance tool provides a succinct overview of each player's course performance through a transfigured SWOT analysis that examines mean score for each par as player strengths and weaknesses as well as unique GameForge metrics as player opportunities and threats.

This tool accomplishes two distinct goals. First, it provides quantitative information for coaches to analyze both their teams and their potential recruits. A coach could analyze their team and see if all their players have a specific strength or weakness; if there are no players who meet a threshold for a current criterion, that could be an important factor they could use when recruiting players for the next year. In addition, it could allow them to shape the lineups for their current team; if the coach knows that a specific type of hole is prevalent or an aspect of the overall golf game is especially important in an upcoming tournament, then they could look at which of their players are strong in those fields when determining the golfers they will take to that tournament. In addition, the tool allows individual players to identify their own strengths and weaknesses to better target areas for training. Since this data is also available to the player to which it pertains, they can see where their game may be lacking and practice specific skills that can help raise their scores.

A. *Par Performance*

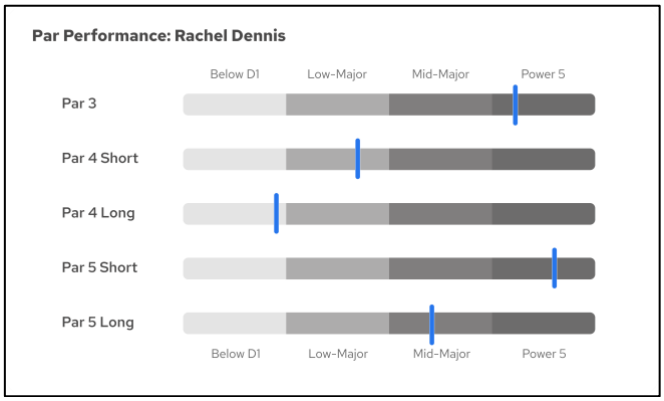

Fig. 1. Analysis of Mean Score Relative to Par for Generic Player, compared to Conference Thresholds

Player performance relative to par is determined using data acquired from high school and collegiate tournament performance, divided by player and subdivided by the hole par associated with the score. This subdivision is required for accurately evaluating a player's consistency in scoring relative to the average number of strokes expected on a given hole. Both junior and college golfers will typically play holes with a par of 3, 4, or 5. Concurrent with previous analyses of the effects of hole yardage on player score relative to par, designations of "short" and "long" for par 4 and 5 are used for holes shorter and longer than the calculated mean yard length, used throughout analysis and shown in Fig. 1 above [11].

After adjusting for player improvement in college, we compare a player's current performance to calculated benchmarks in order to separate them into one of four skill levels for each of the five types of holes. Players are compared to four major categories, including: the Power 5 Conferences schools, which incorporate the most elite conferences of the NCAA; the Mid-Major schools that are considered the "middle-of-the-pack" colleges in Division 1; and the Low-Major schools, which reflect the less competitive Division 1 colleges in the NCAA. Fig. 1 displays a typical analysis of the player's consistency in scoring par for each hole type and includes additional information that allows users to analogize each player to established thresholds of collegiate performance. Similar analyses are performed on the average scores of an entire college team, which evaluates players within teams and determines frequencies of player types represented on a given team.

B. *Players Skills and Gaps*

Comprehensive comparison of player performance relative to par is beneficial to recruiting and sustaining competitive golf teams, but it does not aid in directly improving player skills through regimented practice and directed training. GameForge maintains sixteen proprietary metrics that are inputted by users and describe diverse player skills. Metrics are categorized into four areas relevant to different aspects of gameplay (driving, irons, short game, and putting), and aggregate score are calculated for each. These insights suggest

areas for improvement for players as well as competitive thresholds for performance on a skill-by-skill basis. Furthermore, it allows collegiate recruiters to distinguish key attributes from one player to another, supporting colleges in developing rosters of diverse talent.

V. Player Recruitment: Recommender System

Due to the fragmented golf recruitment process, it is important that efforts and resources are directed where there is mutual interest between players and coaches. The recommender system provides players and coaches quantitative confidence when pursuing a potential commitment and gives guidance to both parties during the recruitment process. The system is based on a multifactor model that incorporates various elements a player may consider when selecting a school. In addition, the recommender system integrates junior player strengths and skill gaps from previous analyses to bolster recruitment decision-making, by providing insight into the utility a player and collegiate team can provide each other.

A. Phase I: Individual Predictive Models

Five machine learning models, summarized in TABLE 2. predict various factors that a player considers when selecting a college. The data used to develop these models came from either the GameForge database or was collected from an outside source. The GameForge database data includes player tournament scorecards and AJGA rank. AJGA ranks are composed of junior players who have competed in at least six premier junior golf tournaments in the United States. Other data acquired include hometown size, hometown location, Niche grades, and National Golf Foundation data.

Niche Schools Rankings are a widely recognized college rank system that generates an overall grade for each college based on student survey data. The Niche grades include factors such as academics, athletics, social life, diversity, and safety. Niche grades range from D to A+ with D being the worst and A+ being the best. After testing several binning methods for Model 1, the Niche grades were binned into a high-grade bucket (A+, A, and A-) and a low-grade bucket (B+ and lower). Each athlete's AJGA rank, hometown location, and hometown size were used as independent variables to predict the Niche grade bucket of the college that the player will attend. The best performing method to predict Niche grade was a random forest model. Methods similar to those employed for Model 1 were used to create Models 2 through 5. Each of the models predict values that are indicative of which college a player will select and all models were fitted using ten-fold cross validation.

TABLE 2. Overview of Predictive Models

Model	Predicting Values	Method	Data
Model 1: Niche Grade	High: A+ to A- Low: B+ and lower	Random Forest	Niche Grade, AJGA rank, hometown location, hometown size
Model 2: Geographic Region	South West Midwest Northeast	Random Forest	Player scorecards, AJGA rank, hometown location, hometown size
Model 3: College Size	Students: < 3000 3000-10K > 10,000	Voting Ensemble: Random Forest, Rule Induction, kNN	Player scorecards, AJGA rank, hometown location, hometown size
Model 4: Team Rank	<50 50-100 100-150 >150	Voting Ensemble: Random Forest, Rule Induction, kNN	Player scorecards, AJGA rank, hometown location, hometown size
Model 5: Distance from Hometown	< 250 Miles < 250 Miles	Voting Ensemble: Random Forest, Naive Bayes	AJGA rank, Number of holes played, hometown data

B. Phase II: Multi-Factor Model

A generalized linear model was created using the model outputs from A. Phase I: Individual Predictive Models. Second order interaction terms were significant but did not add predictive power when suggesting player-college pairs. The model outputs scores for all colleges a player can attend and then recommends the schools with the top 15 scores. The list generated by the final ensemble model accurately captures the college a player attended 80% of the time. The multi-factor model is based on optimizing data we have on where high school students have attended college in the past. In order to account for player preferences and constraints that were not analyzed the recommender system would be implemented with the option for players filter based on the predictive values we determined.

VI. Deliverables And Outcomes

A. Proposed GameForge Dashboards

The proposed GameForge Dashboard utilizes the information generated by the machine learning models discussed to aid coaches and junior players. The dashboard would consist of four components: a player profile, college profile, player recommender, and a college recommender. The player profile is an overview of player metrics. This includes current rank, college predicted rank, and player-field performance comparisons. The college profile displays the same information as the player profile but metrics of members on a given college team are aggregated. The player recommender suggests junior players to college team coaches based on the multi-factor model, strengths, and skill gaps. The college recommender uses the same information as the player recommender but suggests colleges to junior players.

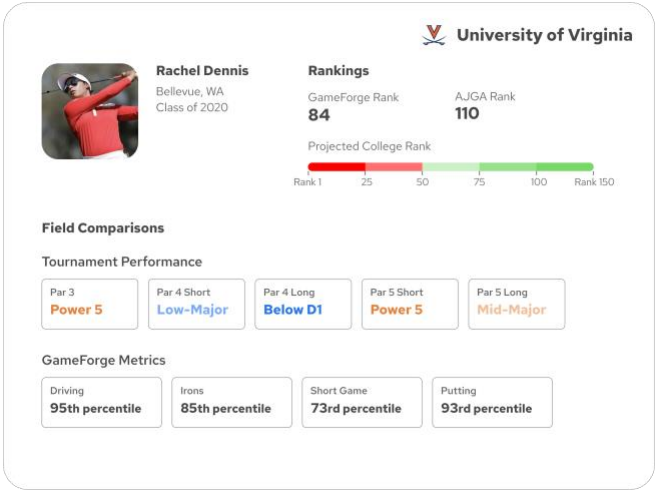

Fig. 2. Player Profile Dashboard

In Fig. *2* above, the tournament performance section indicates the level at which the player performs for par 3, 4 and 5. There are four levels of performance: power 5, mid-major, low-major, and below D1. Rachel Dennis' strengths include that she plays par 3 and par 5 short at a Power 5 level. The GameForge Metrics section at the bottom of the dashboard summarizes the percentile, compared to all junior players, that the player falls in for each of the four categories of GameForge Metrics: driving, irons, short game, putting. Rachel Dennis' driving and putting metrics are above the 90th percentile compared to other players in the field, making those her strengths.

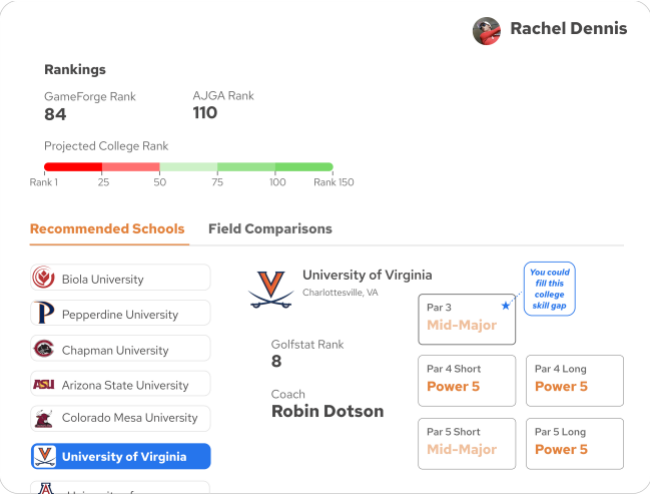

Fig. 3. College Recommender

In Fig. *3* above, the player college recommender displays the top 1 colleges recommended by the multi-factor model to the player. For all of the recommended schools, a player can view the college team's information, strengths, and skill gaps. Rachel Dennis was recommended the University of Virginia as her sixth match. The blue star icon for par 3 indicates that Rachel, who plays par 3 at the Power 5 level, could fill UVA's par 3 skill gap as the team performs at a mid-major level.

B. Sandbox

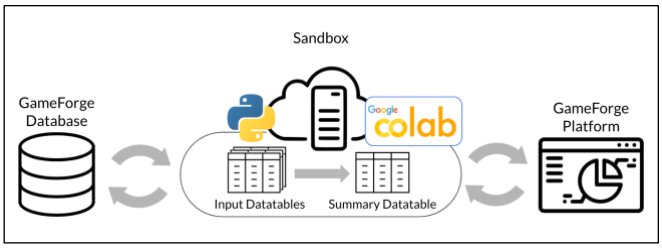

Fig. 4. Sandbox cloud application interacting with GameForge systems

One key distinction in our research and development compared to previous years has been the employ of controlled data management in model research and development. In previous capstone work between the Department of Engineering Systems and the Environment at UVA and GameForge, research teams relied on disparate datasets to develop and operate statistical models through instance-based execution [11][23]. Since then, GameForge compiled a MySQL database to house research-related data that could be pulled from on an ongoing basis. This inspired the development of Sandbox: a fluid, dynamic environment where the statistical and machine learning models generated now could be re-run at any point in the future, providing GameForge the opportunity to recalibrate models based on new data and permit ongoing data monitoring without complete instantiation of the models. A simplified Extract-Transform-Load (ETL) pipeline was initialized in a Google Colab file using Python, and models created during the research period were re-created accurately within the environment. Sandbox calls on the GameForge MySQL database, re-runs the models after loading information onto the platform, then pushes data back to the database. This end-to-end product provides the backend information aggregation necessary to compute values given in the proposed GameForge dashboard, and benefits players and coaches alike with streamlined, up-to-date institutional knowledge.

VII. Conclusion

A. Discussion

Through machine learning model creation and product deliverable development, we discovered that junior golfer performance could be modeled to predict eventual collegiate recruitment and college player scoring could be analyzed to increase tournament success. The proprietary GameForge ranking system provides a unique classification of golfers that compares selected junior players to the entire recruiting pool and predicts eventual college performance. The player-field performance analysis identifies player strengths and weaknesses through aggregated mean par scoring as well as opportunities and threats through targeted golf metrics that describe hole performance, both to bolster athlete training by recommending areas for improvement and enhance player recruitment by recommending players with distinct characteristics that can field diverse collegiate lineups. Finally, the player recruitment system combines a variety of descriptive data, including player performance metrics, university ranking factors, and geographic information, to

match players with colleges, aiding both college coaches and junior players in finding the best fit for college teams.

The dynamic interaction between these data-intensive systems provides a wide-ranging, comprehensive view of the field of golf players that permits GameForge users access to key insights on field-wise performance. Conversely, the interwoven use of data allows for a narrow view on an individual basis for close scrutiny of player strengths and skill gaps that can dictate training and recruitment.

B. Limitations and Future Work

When considering the recommender system multi-factor model, incorporating additional factors, such as weather, that a student athlete might consider when selecting a college could increase accuracy in matching players and college. Additionally, incorporating the player-field performance results into the algorithm for the recommender system could aid in aligning player skills with college skill gaps. One limitation of the recommender system is the unavailability of personal information about the athletes such as SAT score or family history, which could provide more insight into school selection. Due to privacy concerns, this data is unattainable but potentially in the future, athletes using GameForge could opt into providing this kind of information to improve their college recommendations as well as future golf prospects through mor historical data. One next step for player-field performance is to quantify the consistency of each player. Golf is characterized by exceeding amounts of variance from round to round, so player consistency could be an important metric for coaches to consider. One limitation of the player skill gaps methodology is its reliance on user-inputted data. This data is limited to players who are users of the GameForge system and input their own data for each of the proprietary metrics, which results in less data to analyze than that found online of all golf players and is subject to self-reporting errors.

ACKNOWLEDGMENT

We would like to extend our sincerest appreciation to GameForge for sponsoring this project, and to Mark Sweeney and Brian Bailie for their continuous support, advice, and engagement over the past eight months.

REFERENCES

[1] Kearney. (2022, April). *The sports market.* Kearney. https://www.kearney.com/communications-media-technology/article?/a/the-sports-market

[2] Hsia, R. (2018, June 28). *The long game – sports analytics and social media insights.* Harnham. https://www.harnham.com/us/post/2018-2/the-long-game-sports-analytics-and-social-media-insights

[3] Giorgio, P., Ohri, L., & Marzin, K. (2018). *A whole new ball game: Navigating digital change in the sports industry.* Deloitte Consulting LLP. https://www2.deloitte.com/us/en/pages/technology-media-and-telecommunications/articles/digital-transformation-and-future-changes-in-sports-industry.html

[4] How much money do americans bet on sports? (2022) *LegalSportsBetting.com*. https://www.legalsportsbetting.com/how-much-money-do-americans-bet-on-sports/

[5] Yakowicz, W. (2021, August 10). *U.S. gambling revenue to break $44 billion record in 2021.* Forbes Media LLC. https://www.forbes.com/sites/willyakowicz/2021/08/10/us-gambling-revenue-to--break-44-billion-record-in-2021/?sh=7c8d1685677b

[6] Office of Postsecondary Education. (2019). *Equity in athletics data analysis* (17th ed.). U.S. Department of Education. https://ope.ed.gov/athletics/Trend/public/#/answer/6/601/trend/-1/-1/-1/-1

[7] Barakat, C. (2017, June 21). The business of athletic recruiting. *Sparks Rowing.* https://sparksrowing.com/blog/the-business-of-athletic-recruiting

[8] Derdenger, T. (2022, February 10). Can you quantify the economic worth of celebrity endorsements? *Carnegie Mellon University Tepper School of Business.* https://www.cmu.edu/tepper/faculty-and-research/research/videos/celebrity-endorsements-tim-derdenger.html

[9] Maestas, A., & Belzer, J. (2020). *How much is NIL worth to student athletes?* AthleticDirectorU. https://athleticdirectoru.com/articles/how-much-is-nil-really-worth-to-student-athletes/

[10] Wittry, A. (2019) *An analysis of college football recruiting costs.* AthleticDirectorU. https://athleticdirectoru.com/articles/an-analysis-of-football-recruiting-costs/

[11] Bassilios, M., Jundanian, A., Barnard, J., Donnelly, V., Kreitzer, R., Adams, S., & Scherer, W. (2021, April 29-30). *Developing a recommendation system for collegiate golf recruiting.* 2021 IEEE Symposium on Systems and Information Engineering Design, Charlottesville, VA, United States. https://doi.org/10.1109/SIEDS52267.2021.9483777

[12] Golf Academy at Heritage Point (2021). Future junior champions. Paul Horton Golf. https://www.paulhortongolf.com/future-junior-champions/

[13] Leivenberg, W. (2013, August 14). *Breaking down the biggest problems with the official world golf rankings.* Bleacher Report, Inc. https://bleacherreport.com/articles/1738273-breaking-down-the-biggest-problems

[14] Johnson, A. (2017, January 7). *A systematic problem: Golf digest's golf course rankings.* The Fried Egg. https://thefriedegg.com/bad-golf-digest-rankings

[15] Broadie, M., & Rendleman, Jr., R. (2013, February 26). Are the official world golf rankings biased? *Journal of Quantitative Analysis in Sports, 9*(2), 127-140. https://mba.tuck.dartmouth.edu/pages/faculty/richard.rendleman/docs/owgr_20130226a.pdf

[16] Broadie, M. (2012). Assessing Golfer Performance on the PGA Tour. *Interfaces*, *42*(2), 146–165. http://www.jstor.org/stable/41472743

[17] Lutes, M. F. (2012). *Power vs. precision: How have the determinants of PGA tour golfers' performance-based earnings evolved since the 1990's?* [Master's thesis, Dalhousie University]. http://hdl.handle.net/10222/15439

[18] Three major mistakes commonly made in todays' college recruiting process (2019, May 31). *ForeCollegeGolf.* https://www.forecollegegolf.com/blog-posts/three-major-mistakes-commonly-made-in-todays-college-recruiting-process

[19] Men's college golf recruiting guide. (2021). *NCSA Sports.* https://www.ncsasports.org/mens-golf

[20] Czekanski, W. A., & Barnhill, C. R. (2015). Recruiting the student-athlete: An examination of the college decision process. *Journal for the Study of Sports and Athletes in Education, 9*(3), 133-144.

[21] Pauline, J. (2010). Factors influencing college selection by NCAA division I, II, and III lacrosse players. *ICHPER-SD Journal of Research*, *5*(2), 62-69. https://files.eric.ed.gov/fulltext/EJ913334.pdf

[22] Huntrods, K. (2019). *Analysis of factors influencing college choice decisions of mid-major NCAA division I swimmers*. [Master's thesis, South Dakota State University]. https://openprairie.sdstate.edu/etd/3171/

[23] Rohrer, K., Ziller, J., Flores, A., Scherer, W., Kaylor, C., Jimenez, O., & Adams, S. (2020, April 24) *Developing state-based recommendation systems for golf training*. 2020 IEEE Symposium on Systems and Information Engineering Design, Charlottesville, VA, United States. https://doi.org/10.1109/SIEDS49339.2020.9106646

[24] Kovalchik, S. (2020). Extension of the elo rating system to margin of victory. *International Journal of Forecasting, 36*(4), 1329-1341. https://doi.org/10.1016/j.ijforecast.2020.01.006

[25] ATP rankings. (2022) *Association of Tennis Professionals Tour.* https://www.atptour.com/en/rankings/rankings-faq

[26] Rolex AJGA rankings. (2022) *American Junior Golf Association*. https://www.ajga.org/rankings#:~:text=What%20are%20the%20rankings%3F