DEVELOPING A RECOMMENDER SYSTEM FOR COLLEGE GOLF RECRUITING

IMPACT OF UNETHICAL BIASES ON RECOMMENDER SYSTEMS

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By
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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.

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Currently, the college golf recruiting process is one that is very tedious and fragmented for both college coaches and junior golfers, many of whom are international. A junior golfer is a golfer that is in middle school or high school, and is considering playing collegiate golf. There is great difficulty in determining which school would be a good fit for a particular junior golfer, and vice versa, based on a number of influencing factors. To help simplify this process, GameForge, a website that helps golfers improve their game, desires to develop an online college golf recruiting recommender system that has two main tasks: i) to give college coaches a list of potential junior golfers that may fit on their team and ii) to provide recommendations to the junior golfers about which school may be a good fit for them. The technical project will consist of determining factors that make a player and school a good fit, analyzing datasets to build predictive models, and ultimately including these factors and models in a robust, online recommender system that can be used by players and coaches.

These recommender systems, however, can come with a variety of biases that can have a negative effect on the recruiting process, and these biases therefore must be recognized and guarded against. The tightly coupled STS research will look to identify common biases that affect recommender systems, and display the harmful effects that these biases can have on both the recruit and recruiter. The motivation for doing this STS research is because recommender systems are becoming more popular, but they can come with a variety of biases, and it is vital to raise awareness of these biases and their implications. My teammates on the technical portion of this project include four other undergraduates: Ava Jundanian, Vienna Donnelly, Josh Barnard, and Rachel Kreitzer. This project will be carried out over the course of a two-semester capstone advised by Professor William Scherer of the Engineering Systems and Environment department. He will be assisted by Stephen Adams, who is a Senior Research Scientist in the same department. For the STS research, my advisor is Professor Catherine Baritaud of the Department of Engineering and Society. Deliverables for the technical project include: a project scope in October, 2020; an interim report in December, 2020; a SIEDS abstract in early 2021; a technical report in Spring 2021; and a SIEDS paper and presentation in April, 2021. Deliverables for the STS research are: this prospectus in November, 2020; a sociotechnical synthesis in early 2021; an STS research paper in Spring 2021; and a complete thesis portfolio in April, 2021.

DEVELOPING A RECOMMENDER SYSTEM FOR COLLEGE GOLF RECRUITING

College golf recruiting is and has been a dysfunctional and disorganized process for junior golfers and college coaches. This is especially a problem for golf in particular for two main reasons: i) golf is not as popular of a sport in the United States as some other major sports, such as football. Gaines (2016) shows that NCAA Division 1 college football makes nearly $30 million, while college golf makes just over $300,000, meaning that college golf earns about 1% of what college football does. Therefore, college golf teams have less funding available that they can use for scouting, recruiting, and scholarships. ii) College golf contains more international players than other sports. According to the database of the National Collegiate Athletic Association (2020), about 22% of all college golfers are international students, while that number is only about 8.5% for college basketball players. International players are usually harder to recruit, and therefore there is a greater need for a top-quality online recommender system since there is less in-person evaluation that can be done. According to Hernando, Bobadilla, Ortega, and Tejedor (2013) recommender systems are generally, “based on a filtering technique that attempts to reduce the amount of information available to the user" (p. 1). Essentially, recommender systems attempt to simplify the matching process for the users involved, and in our project, the main users are the junior golfer and the college coach. Figure 1 displays the basics of how a recommender system should work for the golf recruiting process. Recruits form their own

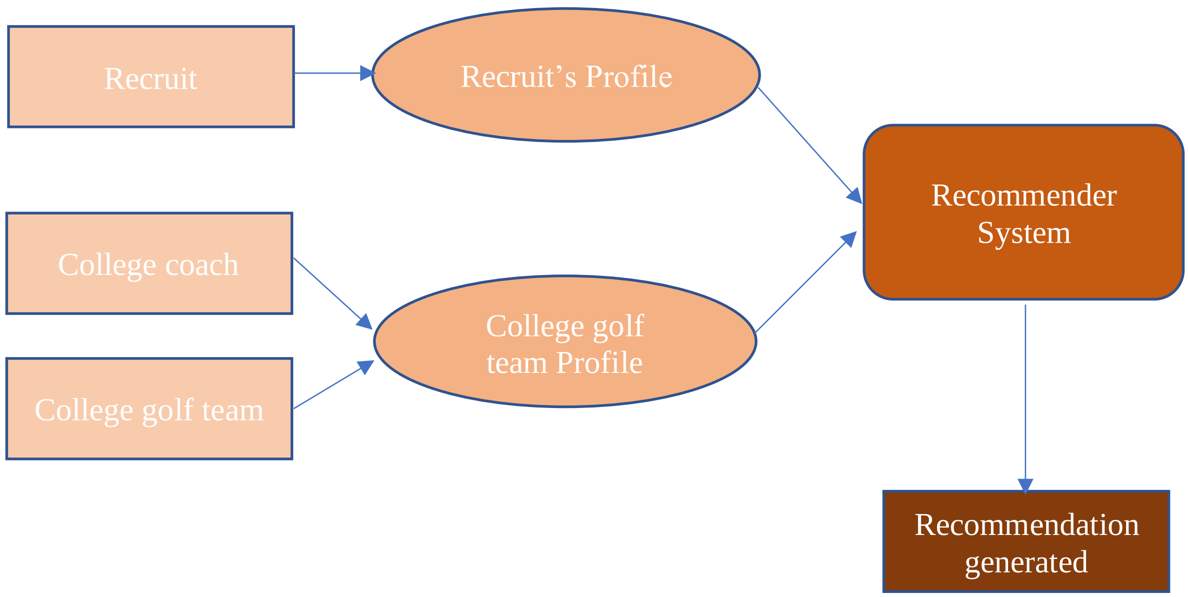

Figure 1: Basic Process of a Recruiting Recommender System. A sequential diagram showing the general process to match a recruit and recruiter through a recommender system (Bassilios, 2020).

profile based on their golf statistics and preferences, and the college team and coach have their own profile as well. These two profiles are inputted into the recommender system, and it finds the best matches and generates recommendations.

OBJECTIVES

There are many subobjectives for this project for both the junior golfers and college coaches. For the junior golfers, one objective is to allow them to be able to enter their personal preferences, such as financial, geographic, and if they have a desire to go pro after college golf. Another objective is that they be able to specify what the strengths and weaknesses of their golf game are, so that they can find the right college coach for them. Finally, junior golfers should be able to get noticed by recruiters and understand the recruiting process, even if they are not one of the top golf recruits in the world. At the moment, junior golfers are responsible for researching college golf schools with minimal help available to them besides their parents. This is, of course, in addition to managing their academic requirements, finding a school that works for them academically, and applying to colleges. The Next College Student Athlete (2020) explains that, "student-athletes should build a list of target schools that meet their academic expectations, athletic ability and personal preferences" ("Researching Golf Schools," para. 1). That is undoubtedly very challenging, overwhelming, and potentially discouraging for the junior golfer; therefore, our main objective for the student-athletes is for them to have a recommender system that they can utilize that will not only focus on their golfing skills, but also on helping them narrow down and connect with schools based on their preferences.

For the college teams and coaches, one objective is to improve their team as a whole, as well as help the individual golfers on their team to develop their skills. Another objective for them is to be able to improve their team during the recruiting season each year. Lastly, college coaches should be aware of and follow all rules and regulations from the NCAA, and be Health Insurance Portability and Accountability Act (HIPAA) compliant. This act protects sensitive, private information of the players. Ultimately, the main, overall objective of this technical project is to develop a novel online recommender system that can help junior golfers and college coaches be able to better match up with each other.

APPROACH

The first step in developing this recommender system is to determine a player's and team's fit. One's fit is composed of a variety of factors such as: details and statistics of the athlete's golf scores, geographic region, academic performance, etc. These factors will also be applied to the college team as well, and using as many of these factors as possible will lead to a stronger matching system between player and coach. As Ryan (2017) describes, many problems arise "when parents and students become ego oriented, focusing on scholarship or brand of school, instead of fit" (p. 25). In other words, Ryan explains that there are many other important factors to consider besides golfing skills and school name, and these factors help determine fit. After determining these factors, the next step will be to analyze large datasets about junior and college golfers in order to focus specifically on their golfing skills. Our approach to do this analysis can be broken down into four main methods. First, we will look into current college golf teams as a whole, determine what the best teams are based on their rankings, and identify golf statistics that make them stand out or outperform other, lower-ranked teams. Second, we will focus on the top college players individually, and determine certain golf metrics that they dominate. Our goal with this method is to see if there are potential patterns or trends shown by top college golfers that can be applied to current junior golfers. Third, we will then find the golf statistics of those top college golfers when they were junior golfers to formulate predictive models that attempt to capture which aspects of their junior game led them to be successful college golfers. As Isinkaye, Folajimi, and Ojokoh (2015) describe, this predictive modeling is a crucial step of what they call the information collection phase because, "accurate models are indispensable for obtaining relevant and accurate recommendations from any prediction techniques" (p. 263). This method will help us forecast a player's golf scores in college based on their current junior scores. Lastly, we will apply these predictive models to current junior golfers to help determine which junior golfers could potentially become great college golfers. A visual summary of our proposed approach is shown in Figure 2 below. Overall, the main goal of our

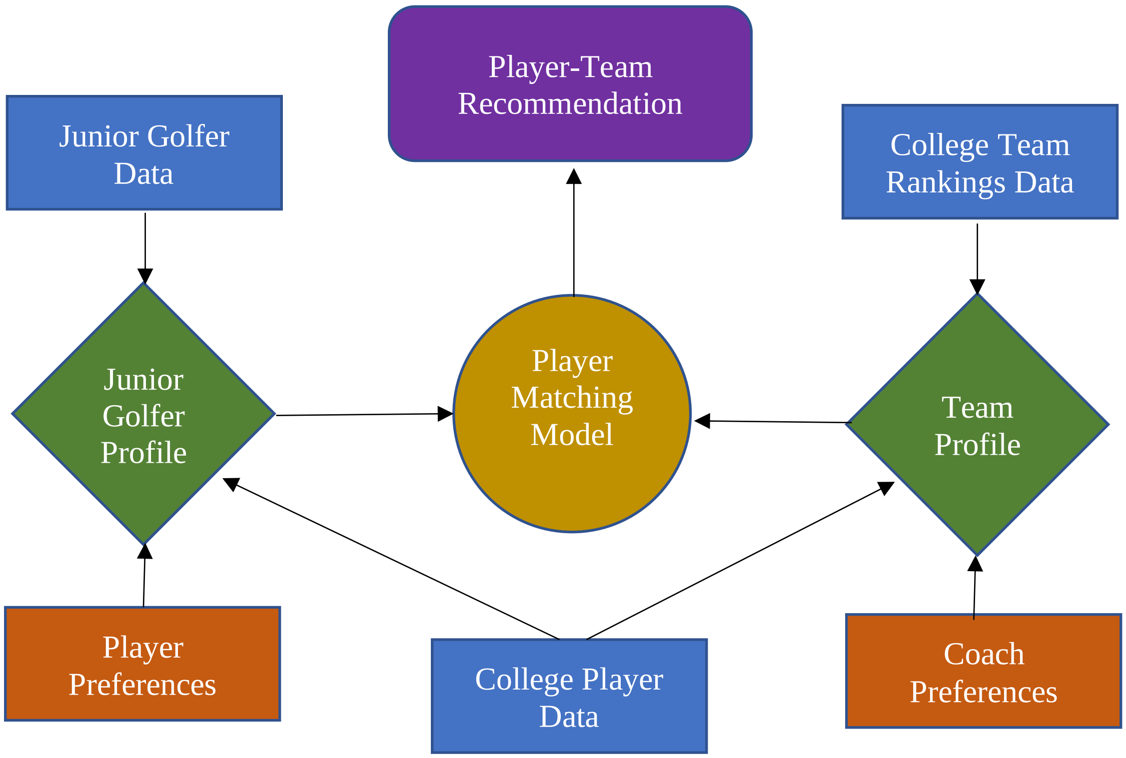

Figure 2: Data and Model Organization. A diagram showing our proposed approach and the information we will use in order to generate a recommendation (Adapted by Bassilios (2020) from Barnard 2020).

approach will be to use a combination of both current and retrospective college and junior golf data to find a predictive model or hidden metric that can be included in our recommender system.

DESIRED OUTCOMES

Upon completion of this technical work, our team hopes to achieve a few outcomes.

Firstly, we want to characterize and define college golf teams and junior golfers to determine their fit based on their preferences and statistics. As a basic example, a high-ranked junior golfer with a very strong high school GPA who has no interest in playing professional golf after college will probably focus on attending a top academic school, even if it does not have the best golf team. Secondly, we want to be able to find some metrics from the data to create predictive models that can more accurately forecast which junior golfers are expected to become above average players. This is crucial because many times in sports, the best college or professional player was not a top recruit out of high school. We want to know why those players were overlooked, and find some of those hidden metrics they excelled in that allowed them to become top players. Finally, by accomplishing the first two outcomes, we hope to develop an online recommender system that incorporates both the fit of players and teams, and the predictive models so that junior golfers and college coaches can use this system to simplify the process of finding the best potential matches.

The main resource that our team will be using to complete this technical project is a robust database that can handle large datasets, and allow us to work together and analyze the data simultaneously. The required funding will be a monthly cost to access the database. For this project, our team will be writing a conference paper that will be presented at the Systems and Information Engineering Design Symposium (SIEDS).

IMPACT OF UNETHICAL BIASES ON RECOMMENDER SYSTEMS

Unfortunately, as technology has increased and developed over time, biases in these technologies have also been introduced, and that is no different for recommender systems. Recently, many companies and institutions have started to use more recommender systems to help them with a particular process, such as the hiring process. Not only does the use of these systems help them save time in narrowing down potential candidates or recruits, but these companies may also wrongly feel that this automatically makes the process fairer since humans are not involved in the system's selections, and so human bias is removed. While recommender systems have become a useful and efficient way to help match a recruit with a recruiter, there are many common biases that exist within these systems that must be recognized and prevented. Adomavicius, Bockstedt, Curley, and Jingjing (2019) state that "biases can contaminate the recommender system's inputs, weakening the system's ability to provide high-quality recommendations" (p. 1322). This is a significant problem because these biases can ultimately be a determining factor for which candidate gets selected by the recruiter.

One of the most common biases that appears in these systems is known as popularity bias. Abdollahpour, Burke, and Mobasher (2017) define this bias as "collaborative filtering recommenders emphasize popular items…much more than other [items]" (p. 42). Popularity bias is shown through the example of online shopping, where the highest-rated items with lots of reviews are listed first. This bias can also be seen in a different way through the recruiting process. The recommender system may be more likely to recommend candidates or recruits that are similar to ones that have previously been reviewed or hired by the company. Thus, the main issue with popularity bias is that many times, the best recommendation is one of the less popular items, so the selected candidate may not be the best possible one. Furthermore, the biases are difficult to perceive because many of them are unintentional, which is why it is vital to bring awareness to their existence. One example that displays unconscious bias comes from the Race

Implicit Association Test (IAT), which shows racial bias. According to Marcelin, Siraj, Victor, Kotadia, and Maldonado (2019), this test was taken over four million times from 2002 to 2017, and 75% of participants showed automatic white preference, which associates white people with good and black people with bad (p. S64). In addition to racial bias, other types of unconscious biases include gender, sexual, and disability bias. Hsu (2020) provides a clear example of gender bias when Amazon recently stopped using an AI hiring tool because the system, "had learned to prefer male job candidates while penalizing female applicants" (p. 9). Hsu goes on to explain that this happened because the AI training originally consisted of mostly male candidate applications. This improper AI training is detrimental because the best candidate may have been a woman, but she might not have gotten the job because the system is biased in favor of men. Clearly, humans' unconscious bias as displayed through the Race IAT, though likely unintentional, can seep into recommender systems, which leads to destructive effects on the system and its users.

What complicates matters further is that recommender systems are designed and developed by people, and "people have a lot of different and unusual biases, which is fascinating but also quite terrifying" (Fleming, 2019, para. 14). Terrifying indeed, because the systems are therefore bound to have some bias in them by default. Buranyi (2017) puts it bluntly: "Computers don't become biased on their own. They need to learn that from us" (para. 10). The topic of biases in recommender systems is an important one to research because "as the algorithms learn and adapt from their original coding, they become more opaque and less predictable" (Buranyi, 2017, para. 11). Therefore, it is imperative to understand how this technology works and what its inputs are in order to understand how it produces a recommendation.

Some basic objectives of this research include: identifying common biases that influence recommender systems, showing how biases in these systems can affect both the recruit and recruiter, and providing some potential solutions that may be beneficial in reducing biases in these systems. Ultimately, the primary objective of this research is to ensure that the main benefit of using recommender systems is not simply to save time for the company or user, but rather to produce an accurate, unbiased recommendation that truly finds the best possible match.

RECOMMENDER SYSTEMS THROUGH THE LENS OF ACTOR-NETWORK THEORY

A good framework for looking at recommender systems and ensuring their impartiality and success in the long run is Actor-Network Theory (ANT), which breaks down a technology into its social groups, problems faced by those groups, and possible solutions (Law and Callon, 1988). One benefit of using this framework is that it focuses on the entire network, which can be composed of both human and non-human actors. Figure 3 shows the distinct social groups that can influence the recommender system in some way. Additionally, this figure can then be broken

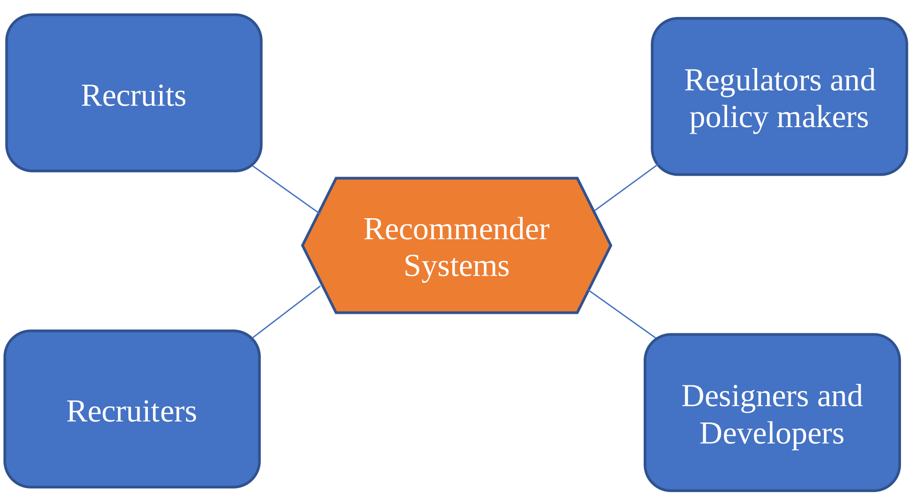

Figure 3: Relevant Social Groups for Recommender Systems. Four main actors who in some way impact or shape the recommender system (Adapted by Bassilios (2020) from Carlson 2009).

down further by honing in on each of the particular social groups and describing some problems that that particular group may face using the system. These problems can range from issues with the system itself, to potential conflicts with other actors in the network, to negative effects of using the system. An example of this is provided in Figure 4, which looks at some problems that designers and developers of recommender systems may run into. Finally, each of these problems

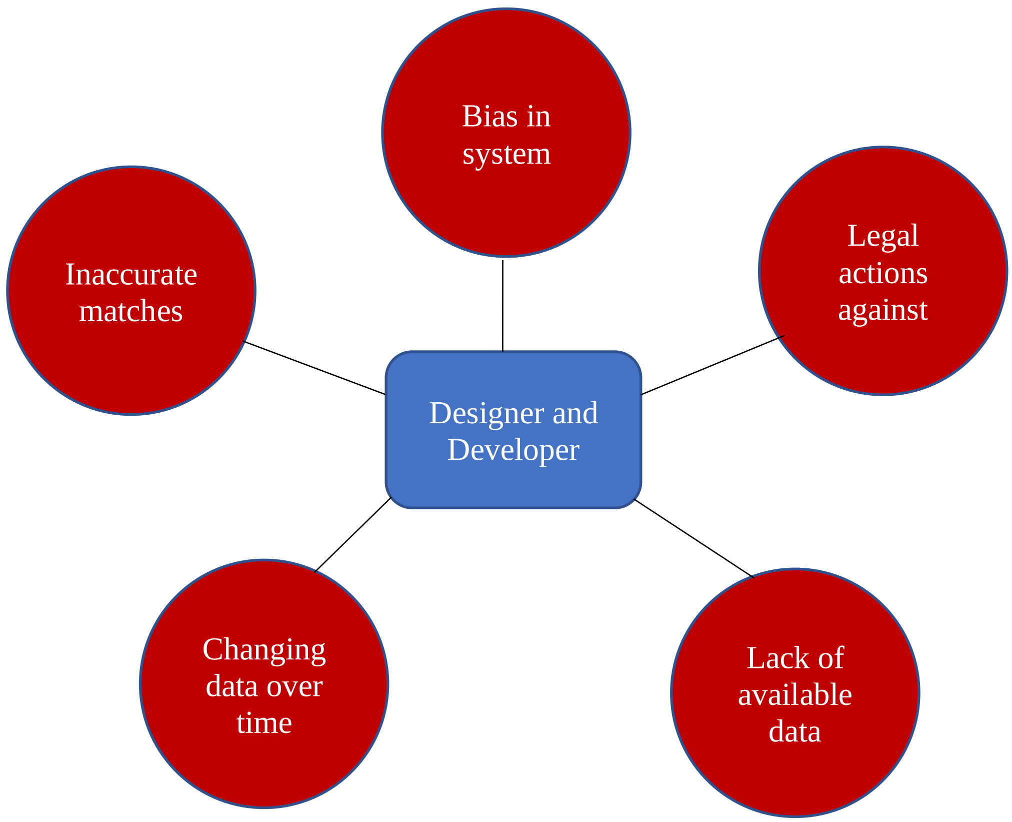

Figure 4: Potential Problems for a Social Group. Five possible issues that designers and develops, a main social group, may face when forming recommender systems (Adapted by Bassilios (2020) from Carlson 2009).

can then be broken down into potential solutions, and this is represented in Figure 5 below, which shows some general solutions to the problem of bias in the system. This is a common

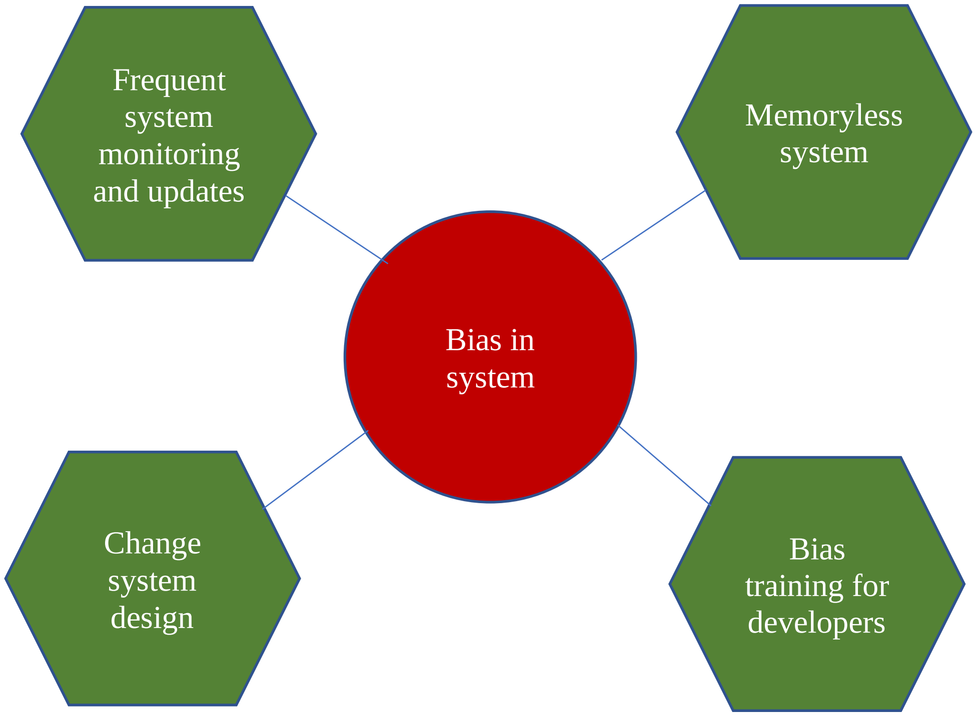

Figure 5: Potential Solutions for a Recommender System Problem. Four possible, general solutions to bias in the system, a major issue that its designers and developers face (Adapted by Bassilios (2020) from Carlson 2009).

problem that designers and developers of the system face, and a main goal of this STS research is to provide additional details about each of these solutions and how they can be implemented. The use of Actor-Network Theory to look at recommender systems provides a strong method of analyzing the relationship between different actors in the network. These various actors will naturally have different or even conflicting ideas about how a recommender system should be designed and developed. These varying opinions lead to the concept of framing, which is defined by Jolivet and Heiskanen (2010) as, "the process through which a common world is established between different actors that allows them to achieve a collective scenario of a desired outcome" (p. 6748). Thus, framing is an integral part of the development and use of recommender systems when viewed through the lens of actor-network theory because it requires the actors to come together, negotiate, and compromise in order to find a common ground.

RESEARCH OBJECTIVES

By doing this research, I will write a scholarly article that will show what types of biases exist among recommender systems and how they affect both the recruit and the recruiter. This research is extremely important because there are many cases of recommender systems and similar technologies that quite clearly show bias, even in major companies. For instance, a few years ago, LinkedIn's search engine displayed gender bias. Day (2016) explains that, "searches of popular female first names…bring up LinkedIn's suggestion to change 'Andrea Jones' to 'Andrew Jones,' 'Danielle' to 'Daniel,' 'Michaela' to 'Michael,' and 'Alexa' to 'Alex'" (para. 4). Day goes on to explain that the opposite did not happen, meaning that if one were to search 'Daniel', there would be no suggestion to change to 'Danielle'. This example and the Amazon example described earlier show why biases in recommender systems is a significant topic to research, especially considering that this technology is continuing to be used more and more. Additionally, the research will provide some potential solutions that can be implemented in recommender systems in order to reduce bias in them. By writing this research paper, I want to bring awareness to the impact of biases in these systems, and to hopefully greatly reduce or eliminate them from these systems. This research topic is tightly coupled with my technical project because they both look at recommender systems and how strongly they can influence a recruiting process.

REVIEW AND RECAP

Overall, the technical project will attempt to simplify the college golf recruiting process through the use of a recommender system. This will help junior golfers and college coaches be able to better match up with each other based on both golf related information and a number of other important factors. The tightly coupled STS research topic will look at the potential biases that may arise in recommender systems, and how they can impact both the recruit and the recruiter. Through my STS research, I hope to display the harmful effects of these biases so that they may be eliminated from the system. Recommender systems can be a very useful technology that can have a positive impact on both the recruit and recruiter. However, their main goal should not be to save time for the users, or to make searches easier. While those are certainly valuable goals, the main goal should be to provide an accurate, unbiased match between the users. For that to occur, the level of bias in these systems must be greatly reduced from where they are today.

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