Tampere University

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FAIRNESS IN ALGORITHMIC MULTI-DISCIPLINARY TEAM FORMATION

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Abstract

Shehani Nivanthika Athalage: FAIRNESS IN ALGORITHMIC MULTI-DISCIPLINARY TEAM FORMATION
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Fairness in team creation is becoming an increasingly important subject of study in computer science and artificial intelligence. As algorithms increasingly automate decision-making processes, ensuring these systems are fair and unbiased has become a key concern. Team formation is one area of study where algorithms are used to match individuals with complementary talents and expertise to establish productive teams. When it comes to the process of forming teams, fairness is an essential component. Based on the relevant research, the thesis proposes the Rule-Based Expert Extraction Method and the Group-project distance and Unfairness Optimization Method to improve fairness during the team-formation process. Additionally, To assess the unfairness, the two proposed approaches are compared with the Pair-round selection method, which was previously examined by Machado and Stefanidis (2019). The fairness improvement is evaluated and compared.

Several metrics were taken to assess the refined performance in the team formation process to create a balanced and fair team. The primary goal was to increase fairness when forming multidisciplinary teams. In terms of promoting fairness, the results reveal that the Group-project distance and Unfairness Optimization Method and the Rule-Based Expert Extraction Method perform slightly better than the Pair-round choosing method. The Rule-Based Expert Extraction Method has the most significant Group-project distance, followed by the Group-project distance and Unfairness Optimization Method, and the Pair-rounds choosing method. However, the new approaches have improved fairness and mitigated the increased Group-project distance. Overall, the experimental evaluation demonstrates the potential of the Group-project distance and Unfairness Optimization method and the Rule-Based Expert Extraction method to improve fairness in team formation, which has significant consequences for businesses and organizations that rely on team collaboration.

Keywords: team formation, fairness, group-project distance, skill variance, unfairness, multi-objective optimization

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1 Introduction

Algorithmic group formation has recently gained significant attention in computer science research, particularly in data mining and fair machine learning (Sahlgren and Laitinen 2020). Clustering algorithms, fairness-aware machine learning, social network analysis, and multi-objective group formation are some research topics linked with algorithmic group formation. Algorithmic group formation focuses on forming groups using algorithms that adhere to specific criteria or desiderata, such as optimizing utility or promoting diversity. How to verify that the algorithmic group formation process and the generated groups are fair is a significant question in this field. However, "fairness" is a complicated notion that can be challenging to define in group formation (Yorges n.d.; Sahlgren and Laitinen 2020). Thus, research in this field frequently investigates how various conceptions of fairness include in algorithmic group creation. Yorges n.d. describe the conception of procedural justice. Procedural justice refers to the observed fairness of the procedures used to choose the results or distribute the rewards. On the other hand, Sahlgren and Laitinen 2020 discuss multiple conceptions of algorithmic fairness, such as demographic parity, equal opportunity, and individual fairness. Demographic parity ensures that various demographic groups are proportionally represented in the algorithm's output. Equal opportunity means ensuring that individuals from diverse groups have an equal possibility of selection or inclusion. The ultimate objective is constructing algorithms that create optimal groups and enhance fairness. As activities get increasingly complicated, businesses need help building effective teams that can harness varied skills and collaborate towards a single objective. Creating a team entails evaluating various alternatives, such as diverse compositions of individuals with varying abilities, preferences, and levels of knowledge (Al-Taie et al. 2018). While choosing a team, companies must consider project requirements and organizational needs. For instance, project managers must consider the team's distributed location, technical proficiencies, and tools and technologies in a software development project.

Given the importance of forming a team capable of efficiently completing a project, researchers have attempted to measure team excellence using different criteria. While there is no universally accepted concept of the "best team", decision support systems can help summarize and visualize different metrics and rank teams based on end-user preferences. A variety of elements, including communication, cooperation, and collaboration, in addition to the technical skills of the users, influence the effectiveness of a team. As a result, it is crucial to create diverse teams with technical expertise and soft skills to work well together. Finding expertise for a project can be difficult in reality. For example, an organization might need to find conference paper reviewers, select software project consultants, or identify knowledgeable individuals to answer a question in an online forum. Researchers have explored various algorithmic approaches to group formation to address this challenge, including those based on generalized constraints and personality-oriented team recommenders (Lappas et al. 2009).

In organizations that work on collaborative projects, dividing tasks fairly is challenging. It is essential, when assigning jobs, to consider both the fitness of teams for each task and the fairness of the assignment to team members. This means that team members' workloads should be handled equitably, and nobody should be treated differently. However, maintaining track of each individual's workload and talents is challenging, necessitating the usage of automatic or semi-automatic assignment systems. However, there are concerns that these methods might result in unfair biases. Currently, most selection and matching processes focus solely on the technical skills and abilities of the applicants while overlooking the importance of their compatibility with other team members. A person's compatibility with other team members directly affects the team's performance. Therefore, it is crucial to consider the applicants' compatibility with job criteria and other team members to ensure better team effectiveness.(Malinowski et al. 2008).

In response to this challenge, researchers have explored various methods to enhance team formation by considering individual compatibility. Constructing teams involves integrating interpersonal factors such as communication abilities, personal traits, and social network structure. Social network analysis techniques have proven to be a helpful way of identifying potential candidates with similar interests and qualities to form a more united and harmonious team. These approaches help guarantee that the most qualified team is chosen for each task, considering both technical proficiency and compatibility with other team members, which ultimately results in improved performance and productivity (Anagnostopoulos et al. 2010; Barnabò et al. 2019). Therefore, large organizations must develop fair and effective assignment methods to improve project outcomes and cultivate a favorable work atmosphere.

Machado and Stefanidis 2019 have pointed out that allocating users to multidisciplinary projects while considering fairness as a critical concept has not been extensively researched in the literature until their recent study. Given the significance of multidisciplinary teams in addressing complex problems, enhancing the fairness of team formation is a pressing concern. However, more studies must examine how to allocate multidisciplinary teams considering fairness. The current study aims to close this gap in the literature by investigating methods that make recommendations for multidisciplinary teams fairer. This study will analyze the efficacy of various fairness-enhancing approaches in multidisciplinary contexts and the pertinent theoretical and practical aspects of fairness in team formation. What approaches may be used to make proposals for multidisciplinary teams fairer, and how effective are these approaches in enhancing the outcomes of multidisciplinary projects is the specific research question for this study. By creating a fair team creation process for multidisciplinary projects, the findings of this study can assist businesses in allocating resources more effectively.

Chapter 2 of this research presents an extensive overview of the existing literature on algorithmic team formation, fairness in team formation, and various methods to ensure fairness. The key objective of the chapter is to provide a better understanding of the situations that entail team allocation, the challenges that arise during the process, and the significance of producing fair teams. It emphasizes how prior studies impacted the current research and how it seeks to address the gap in knowledge by answering the question of how to improve fairness in multidisciplinary team recommendations. Additionally, the chapter explores various approaches applied to enhance fairness in team formation and assesses their effectiveness in the context of multidisciplinary teams.

Chapter 3 of the research advances a motivating problem, expounded formally. The study offers an insightful vantage point to appreciate the research question's significance and relevance. The chapter details the question model and formal definitions outlining the criteria for selecting users to form teams and measuring fairness. The problem statement and its formal definitions clearly understand the research question and lay the groundwork for developing the proposed solution. By defining the problem in a structured and precise manner, the research aims to provide a comprehensive and robust solution to the issue of fair team formation.

In Chapter 4, two divergent methods are provided for producing unbiased team recommendations and enhancing fairness in team formation, building upon the research done by Machado and Stefanidis 2019. This chapter furnishes a comprehensive description of the algorithms deployed in the study, seeking to offer a nuanced grasp of the proposed team formation approaches and their potential for enhancing fairness. By delving into the algorithms used, readers can gain insights into the underlying mechanisms that drive the team formation process and each approach's relative advantages and disadvantages. The chapter is a practical guide for developing and implementing fair team formation algorithms in real-world settings.

Chapter 5 of the research work provides a comprehensive description of the experimental evaluation conducted to test the efficacy of the team formation techniques proposed in Chapter 4. The study aims to assess the capability of the proposed methods in generating fair team recommendations. The chapter examines the obtained results and analyzes the effectiveness of the methods in enhancing fairness in team formation. Specifically, graphs are employed to compare the performance of the proposed methods with the existing ones.

Finally, Chapter 6 serves as a concluding section of the research, summarizing the research methods employed and the findings obtained from the experimental evaluation. Additionally, this section evaluates the degree of success achieved by the proposed methods in enhancing fairness in team formation. Furthermore, suggestions for future research are discussed, emphasizing the study's importance and relevance for advancing this field.

2 Related work

Establishing teams is a crucial component of many initiatives and organizations since it significantly affects the team's success. Since it impacts team members' satisfaction, motivation, and performance, fairness is vital to team formation. This literature review aims to analyze the notion of fairness in team formation critically by diving into its definition, essential characteristics, and empirical data. We hope to discover the numerous aspects that affect fairness in team formation by examining the existing literature on team composition. In this section, we will focus on how increasing fairness in the methods used to form teams, such as using objective criteria and involving team members in the selection process could affect the success of efforts to achieve equality. We will also investigate the effects of fairness in team formation on team performance and member satisfaction. Finally, this review will thoroughly grasp the significance of fairness in team formation and its possible impact on team outcomes.

2.1 Optimizing Team Formation and Player Assignment in Competitive Environments

Interest in creating algorithms and strategies for fair team creation that account for user diversity and equity has increased recently. In many virtual environments, such as online work sites, social networks, and community management platforms, putting together a team is an essential step. Assigning players or workers to fair, efficient, and effective teams is complex due to skill levels, preferences, and limits considerations. Bacon et al. 2001 systematically reviewed the various methods of assigning players to teams. Subsequently, they proposed a novel approach grounded on the "assignment game" model. Through their work, the authors demonstrated that the application of the assignment game could yield team formations that are both stable and efficient while simultaneously aligning with the preferences of the players involved. Key to the proposed model is the consideration of players' roles and team preferences, as well as the compatibility of their skills and personalities. Nevertheless, it is noteworthy that the model assumes players' full knowledge of their preferences and assumes that the team assignments do not influence such preferences.

Matthews et al. 2012 provide a research study investigating team formation in fantasy football, where teams consist of human and computer participants in broad, partially observable domains. The authors draw attention to the challenges in forming teams in this situation due to the difficulty of the game and the unawareness of participant identities. The authors offer a reinforcement learning-based approach to address this issue that optimizes team formation based on team dynamics, individual strengths, and weaknesses. A multi-agent reinforcement learning framework is used in the recommended method to allow agents to learn from one another and adjust to changing environmental conditions. The authors demonstrate that the suggested strategy outperforms existing approaches regarding team effectiveness, as evaluated by a team's performance in a fantasy football league. Overall, the study advances the literature on team building in complex, partially visible domains by suggesting a novel reinforcement learning approach that may use outside fantasy football. The report emphasizes the significance of evaluating individual strengths and weaknesses and team dynamics when establishing teams for such situations.

2.2 Team Formation in Large-Scale Community Systems

Employers are increasingly utilizing online labour markets to find workers for various tasks. As with any marketplace, concerns have emerged regarding the fairness of these platforms, particularly in terms of team formation. In their study, Barnabò et al. 2019 present algorithms for establishing teams considering several fairness criteria. These algorithms guarantee that teams are constructed in a manner that is fair to all employees, regardless of their abilities, and that they can balance the skills and expertise of team members while also considering their availability and desire to work. The approaches can be used to form fair teams for activities requiring collaboration and coordination among team members, such as software development, design, and data analysis.

Anagnostopoulos et al. 2010,Anagnostopoulos et al. 2012 and Lappas et al. 2009 researched the team formation processes in community systems and social networks. They concluded that forming an effective team needs to consider aspects such as social interactions, interests, team size, and composition. Lappas et al. 2009 have also stressed the significance of social context in selecting a competent team and suggested a model that considers competency and social network linkages. These studies have underlined the importance of cohesive and varied teams in social networks and community systems. However, past research has highlighted the limitations of team creation based exclusively on social relationships and shared interests. According to Anagnostopoulos et al. 2012, deploying algorithms to construct teams may be limited in such situations. Nonetheless, this research has contributed to a greater comprehension of team formation processes in community systems and social networks.

Olsson et al. 2020 investigated an alternate strategy for team formation based on professional social matching systems. They have stressed the benefits of matching individuals based on their skills and interests using social media platforms and online professional networks. The authors have emphasized the significance of user privacy and data protection as critical obstacles these systems pose. Professional social matching systems mainly rely on users' personal information; therefore, protecting their privacy and security is vital. The authors emphasize the importance of transparency and informed consent in data collection and utilization to address this issue. In addition, they have emphasized the potential advantages of personalization and user control in professional social matching systems, resulting in better matches and greater user satisfaction. Even though the research on social network-based team formation emphasizes the significance of social contacts and shared interests, it is constrained by the ambiguity of such linkages in specific settings. Professional social matching systems offer an alternate method for team development, but they must address privacy and data protection issues and provide users with control and customization options. Additional research is required to examine and improve these methodologies, and the papers mentioned above make essential contributions to this ongoing field of study.

2.3 Fairness and Bias in Team Formation Algorithms

In online job marketplaces, where individuals compete for opportunities and employers strive to form teams with diverse abilities, researchers have examined several methods for constructing diverse and fair teams. To limit potential biases and unfairness deriving from workers' demographic attributes and preferences, one method is the employment of algorithms that balance workers' abilities and traits, including gender and ethnicity. In a study conducted by Barnabò et al. 2019, algorithms were developed using matching and optimization techniques to balance the skills and characteristics of workers, including their gender and ethnicity. Using a large dataset of online jobs, the algorithms were evaluated and found both efficient and fair. Nevertheless, these algorithms may not be able to account for all forms of bias and individual perceptions of fairness.

Another key feature of online labour marketplaces is expert finding systems, which are used to locate and hire individuals with particular skills and knowledge. Al-Taie et al. 2018 provide an overview of the many expert-finding systems types and the strategies used to discover experts in their study. They divide expert finding systems into three categories: task-oriented, social network-oriented, and hybrid, and evaluate the benefits and drawbacks of each. In addition, the study includes a thorough examination of the various methodologies utilized in expert-finding systems, such as content-based, network-based, and hybrid approaches. The insights offered in this study are critical for understanding the status of expert-finding systems and the related issues, such as the need for more consistency in evaluating these systems and better user feedback integration.

Recommendation systems, which deliver individualized suggestions to users about jobs or workers that match their interests and requirements, are another significant part of online labour markets. Concerns exist, however, regarding the possibility of bias in these recommendation systems, especially regarding gender and other demographic characteristics. In their study, Beutel et al. 2019 propose using pairwise comparisons to increase the fairness of recommendations. This method permits the ranking of objects based on user preferences while ensuring the ranking is objective and fair. Using data from a popular online marketplace, the proposed method has been assessed and has shown promising results in improving the fairness of suggestions while retaining high levels of accuracy and relevance.

Kargar and An 2011 address locating top-k teams of specialists in social networks with or without a leader. They offer an algorithm that takes both the knowledge and social relationships of team members into account. The method uses a combination of network analysis and optimization approaches to identify expert teams that can collaborate efficiently. The proposed method has been evaluated using real-world data from social networks, and the outcomes confirm its efficacy in identifying high-quality expert teams with or without a leader. This study is essential for selecting expert teams that can interact effectively, especially for activities requiring high coordination and communication degrees.

Barocas and Selbst 2016 studied big data analytics as an additional method for promoting diversity and fairness in team creation. Using big data analytics, they investigated the concept of “disparate impact,” which refers to algorithmic decision-making’s unintentional and disproportionate effects on particular categories of individuals. They stated that team-building algorithms might perpetuate or exacerbate pre-existing biases and inequalities due to their reliance on demographic or behavioural data about sensitive factors such as race or sexual orientation. To solve these problems, the authors proposed enhancing data quality and transparency, integrating affected groups in decision-making, and developing more inclusive and varied algorithms. In addition, to these approaches, Dwork et al. 2012 advise considering individual preferences and striking a compromise between precision and fairness. They contended that fairness should be based on individual choices and that algorithms should strive for a balance of precision and fairness. This is especially true regarding team formation, when individual preferences and qualities can substantially impact team relationships and performance.

Meulbroek et al. 2019 created a method for assembling teams that use recommender systems to pair people according to their skills and interests while accounting for factors like gender balance, workload, and distribution of expertise. This strategy promotes cooperation and teamwork, which results in more effective and successful group outputs. It also aids in avoiding frequent problems like workload inequality and groupthink. The authors stressed the benefits of their approach, noting that it not only promotes better teamwork and communication but also prevents common problems like groupthink and unequal workloads.

Lastly, Cachel and Rundensteiner 2022 provided a system for assessing subset selections' fairness that promotes greater representativeness and diversity within groups, hence promoting optimal results. This approach recognizes the importance of diverse teams in achieving success in group tasks. They exhibit more significant levels of creativity and innovation due to their diverse perspectives and methodologies. Overall, it is impossible to emphasize the importance of good team formation for success in group tasks. These studies provide vital insights into how to accomplish fairness, variety, and efficiency in team formation.

2.4 Fairness in Team Formation and Decision Making

Researchers have paid more attention to team formation in recent years because of its importance in producing desirable results in fields as diverse as business, sports, and science. Various stakeholders' differing value systems and goals have made fairness in the team create a more complex and nuanced issue.

The FASTT approach proposed by Bulmer et al. 2020 leverages concepts of fair division to construct teams. This strategy considers user preferences, team size and diversity, and the stability and fairness of assignment distribution. When evaluated on synthetic and real-world datasets, the authors found that FASTT offers fairness, efficiency, truthfulness, and incentive compatibility. Despite its success, scalability may be limited when dealing with complex scenarios and vast datasets. Friedler et al. 2021) tackle the critical topic of the subjective nature of fairness. According to the authors, fairness is a highly customized term dependent on various groups' settings, value systems, and interests. They provide a comprehensive framework for fairness that considers multiple value systems and demonstrate that different techniques may be required to achieve fairness in different settings. This underlines the importance of incorporating many value systems into decision-making to attain fairness.

Similarly, Lee and Floridi 2021 examine algorithmic fairness and the trade-offs between absolute and relational fairness in mortgage financing. In cases where obtaining absolute fairness may not always be possible, they propose that a relational fairness trade-off may be a more appropriate alternative. The authors stress the significance of understanding the many types of fairness and the necessity of weighing opposing values when making judgments.

Machado and Stefanidis 2019 offer a unique method that considers individual preferences, skills, and fairness constraints for recommending teams for multidisciplinary projects. Establishing an efficient team is vital in multidisciplinary projects where individual preferences and expertise must be addressed. Individual preferences and fairness constraints are incorporated into the suggested mathematical model to maximize team formation. This method has been evaluated using data from a multidisciplinary project, and the study demonstrates its effectiveness in delivering fair team formation recommendations. The suggested method considers individual preferences and fairness limitations critical to team success and member happiness.

Bulmer et al. 2020 presented the Fair and Stable Team Formation (FASTT) technique, which forms teams using equitable division principles. The authors considered player job preferences, team size and diversity, assignment consistency, and fairness. The objective was to develop an algorithm for team building with high fairness, efficiency, veracity, and incentive compatibility. The authors utilized FASTT to both synthetic and real-world datasets to evaluate their strategy. They found that FASTT effectively establishes fairness, but its scalability may be limited when dealing with massive datasets or complex circumstances in which player preferences and limitations alter.

Fairness in team creation is a challenging and nuanced problem since it depends on various parties' value systems and interests. According to Friedler et al. 2021, fairness is subjective and varies based on different groups' situations, value systems, and goals. To address this, they presented a complete framework for fairness that considers numerous value systems and asserts that different techniques may be required in different contexts to attain fairness. This study underlines the significance of integrating multiple value systems in decision-making.

Lee and Floridi 2021 explored the topic of algorithmic fairness in the context of mortgage lending. They examined the advantages and disadvantages of establishing absolute vs. relational fairness.

The authors stated that absolute fairness standards might only sometimes be attainable, especially in the mortgage lending area, and recommended that a relational fairness trade-off may be more appropriate. This study emphasizes the significance of recognizing the many types of fairness and the necessity of weighing opposing values when making decisions or establishing teams.

In a recent paper, Machado and Stefanidis 2019 introduced a novel technique for team creation that overcomes this issue by considering individual preferences and fairness restrictions. When building teams, the authors considered individual preferences, expertise, and fairness limitations. Effective team creation is crucial for attaining project goals in the growing era of collaboration between various disciplinary fields. Creating an appropriate team composition that satisfies individual preferences within the limits of fairness can be difficult. The authors created a mathematical model to solve this issue that optimizes team formation by factoring in individual preferences and fairness constraints. Using data from a multidisciplinary project, they examined their approach and verified its efficacy in delivering fair recommendations for team formation. This study emphasizes the significance of considering individual preferences and fairness limitations, which still need to be thoroughly addressed in the previous literature on team formation. Overall, the suggested method offers a workable and reliable option for generating impartial team suggestions in multidisciplinary projects.

2.5 Machine learning techniques for group formation and team building

Mehrabi et al. 2021 conducted a comprehensive study emphasizing the significance of addressing bias and fairness problems in machine learning and team creation to prevent biased algorithms from producing unfair team compositions. The authors suggested incorporating ethical principles and openness into algorithmic decision-making to promote team formation and discover and resolve biases. In contrast, Yilmaz et al. 2015 suggested a personality-oriented team recommender system for software development organizations that uses machine learning algorithms to identify the personality traits of individuals and link them with compatible teammates. By matching employees with complementary personality qualities, the strategy can improve team cohesion and performance, thereby increasing team productivity and reducing conflicts.

The methodology put forth by Yilmaz et al. 2015 was based on the idea that personality qualities significantly influence how well a team works together. The approach can adapt recommendations to the needs of specific software development organizations by learning from previous data and using machine learning algorithms, leading to more precise and unique recommendations. Investigating how groups change over time and how leadership, communication styles, and task organization affect group outcomes are possible future research topics. Future research should also look at how technology influences group formation and how design choices affect the success of groups. Future studies must also examine varied populations and their effects on group dynamics. Harris et al. 2019 recommended researching how excluded or marginalized groups collaborate when using technology and the influence of social networks, cultural norms, and other elements on group formation. In conclusion, further study is necessary to enhance fairness and equality in team formation and machine learning, resulting in more productive teams and project outcomes.

The publications discussed in this literature review provide vital insights into team creation. They indicate the need for additional study to solve the different obstacles connected with this endeavour. The ideas described in these papers offer prospective solutions to ensure that teams are established reasonably and efficiently. Further study is needed, however, to design fair team formation and decision-making mechanisms that facilitate the establishment of diverse and inclusive teams. In conclusion, forming a team is a challenging and complex endeavour involving carefully considering numerous elements. Essential to team development, online communities, and decision-making mechanisms is fairness. Building fair team formation and decision-making mechanisms is crucial to prevent exclusion and discrimination based on a person's qualities. Although computational methods have demonstrated promise in this subject, significant effort remains to ensure fairness, reduce bias, and develop more effective tools and systems.

3 Methodology

The team formation issue, which has been identified as a crucial problem in numerous industries and organizational contexts, is addressed methodically in this chapter. To illustrate the difficulties of this issue and the demand for a methodical strategy to address it, we offer an example. We then describe the fundamental ideas and terminologies underlying our methodology, including a comprehensive framework for examining team formation and a collection of research models that can direct empirical studies in this field. We aim to offer researchers and practitioners a rigorous and valuable method for addressing this complex and multifaceted problem by utilizing these tools and insights.

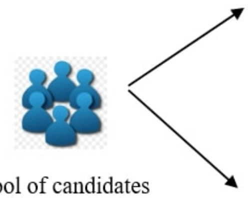
3.1 Motivating Example

The company is about to launch a mobile phone application and needs individuals assigned to satisfy the requirements within a specific deadline. The project consists of three major tasks:

1. Design the application
2. Develop the application environment
3. Release it in the market

Since each activity is unique, it cannot be developed simultaneously. The first assignment necessitates a team of mobile phone developers and visual designers, while the second task necessitates developers knowledgeable in back-end and front-end development. Finally, the application's release requires individuals with digital marketing and social media knowledge. Assuming a pool of users with relevant capabilities exists, a subset must be chosen to work on the project. We want to ensure the following:

- All tasks are fulfilled in all their requirements
- Users can be associated with more than one task
- Tasks are equally important and require the same amount of work
- The best users are selected according to their skills
- The workload is balanced along the personnel, so no one is sub or super loaded
- Fairness regarding sensitive attributes such as race, gender, and nationality



Pool of candidates

Mobile Application Development

Skills		
User 1	User 2	User 3
Software development	Programming	Cybersecurity
Back-end computing	Music	Programming
Agile development	Software development	Networking
	IoT	

Smart Home Automation System

Skills		
User 1	User 2	User 3
Programming	Electronics	Networking
UX design	Security	Home Automation
Project Management	Data Analytics	Database Management
Testing and Quality Assurance	IoT	Programming

Figure 3.1 *Motivating example of a team formation problem*

Figure 3.1 provides an example of team formation for two projects: Mobile Application Development and a Smart Home Automation System. These particular teams consist of three users, each of which possesses a unique set of skill sets. Similarly, our purpose is to discover the users who are the most qualified for each project out of a bigger pool of potential candidates while ensuring that the selection process is fair at the same time.

3.2 Model

The projects are defined as requirements for sets of skills and other attributes D that constrain team assembly. D includes non-protected attributes $S \in D$ (e.g., skills or personalities). Protected attributes are denoted with A (e.g., race, gender, nationality). Each user has a set of protected attributes, $A \in D$, regardless of whether it is used explicitly as a factor. Attributes in D can have binary, categorical, or continuous values. U refers to a set of users, i.e., the user pool. Each $u \in U$ is a vector of length $|D|$. $Y = 0, 1$ refers to whether u is selected into a team, $Y = 0$ being negative, and $Y = 1$ positive. Augmenting and optimization systems compute the best teams $g \in G$ suitable for each related project that satisfies its requirements D. Self-assembly and team-staffing systems allow different degrees of control over what is included in D, or how users are selected into teams from U, for example.

Let us assume $s \in S = s_1, \ldots, s_m$ as a set of skills and $u \in U = u_1, \ldots, u_n$ as a set of users. Each user profile is defined as a histogram of skills through $f : S \times U \to [0, 1]$ for every skill s. f is defined as returning the strength of a particular skill observed for one specific user normalized by the maximum value observed in the particular skill. For example, $u = (f(s_1, u), f(s_2, u), \ldots, f(s_m, u))$ represents one user according to their expertise in skills $s_1, s_2, \ldots, s_m \in S$. We also define a binary version of the user profile in such a way that $u' = (f'(u, s_1), \ldots, f'(u, s_m))$. Where f' is defined as:

$$f'(u, s_i) = \begin{cases} 0 & \text{if } f(u, s_i) = 0 \\ 1 & \text{otherwise} \end{cases}$$

The binary version of the profile does not contain information about the level of expertise of a user in a specific skill but, instead, describes simply if the user has any experience on that topic. We define a project p through $\varphi : S \times P \to \{0, 1\}$. A project has the same dimension as a user profile, and the number of skills available $|P| = |u| = m$. For example, a project can be represented as $p = (\varphi(s_1, p), \varphi(s_2, p), ..., \varphi(s_m, p))$. Now φ returns 1 or 0, in the case the project requires a skill or not, respectively. A subset of users are allocated to the project in a group $G \subset U$, whose sizes will be defined according to the project's requirements. The distance between a group and a project is defined as:

$$\text{Dist}(G, P) = \frac{1}{|G|} \sum_{i=1}^{|G|} \text{dist}(u_i, P) \tag{3.1}$$

Where $dist(u, P)$ is the distance between a user and the project and is defined as:

$$\text{dist}(u, P) = \frac{1}{|P|} \sum_{\forall \phi(s_i, P)=1} (\phi(s_i, P) - f(s_i, u)) \tag{3.2}$$

The $\text{dist}(u, P)$ function's purpose is to calculate how close a user is to a project based on their skills pertinent to the project's criteria. The degree of alignment between the user's skills and the project's requirements is indicated by the score this function generates, which ranges from $[0, 1]$. The score is a factor in user selection for a project since it makes it possible to identify people with the most relevant abilities.

In addition, after a group has been formed, the $\text{Distance}(G, P)$ function calculates the distance between the group and the project. This parameter determines which group is best for a particular project.

3.3 Fairness-aware Team Formation

Creating fair teams is a crucial component of managing projects successfully. It guarantees equitable resource distribution and gives every team member an equal chance to contribute to the project's success. While building teams, several factors must be considered, including the users' knowledge, experience, and availability. The building of teams must also be done in a way that values diversity and gets rid of any potential prejudices based on delicate characteristics like colour, gender, and nationality.

The idea of Multi-Objective Optimization (MOO) is essential for encouraging fairness consciousness when forming teams. Solving mathematical optimization problems with several concurrently-optimized objective functions is a subfield of multiple-criteria decision-making. MOO is used in team building to ensure that multiple goals, including enhancing user skills, eliminating workload inequality, and fostering diversity, are optimized simultaneously.

For instance, project managers can guarantee that teams are constituted in a way that increases the possibility of project success while fostering fairness and equity by using MOO during team creation. This strategy can result in more vital teamwork, more productive team members, and higher levels of job satisfaction, all of which improve project outcomes.

Definition 3.3.1 *Group average skills*

To ensure fairness, we define $\mathrm{sim}(u', P) = |u' \cap P|$ as the number of matches between a user profile and a project. The average number of skills users within a group have for one project is:

$$\mathrm{MS}(G, P) = \frac{1}{|G|} \sum_{u' \in G} \mathrm{sim}(u', P) \tag{3.3}$$

Definition 3.3.2 *Skill variance*

This measures the skill variance of the users within the group for the required skills of the project.

$$\text{Skill variance}(G, P) = \frac{1}{|G|} \sum_{i=1}^{G} (user\ skill_i - group\ skill_{avg})^2 \tag{3.4}$$

The group skill average is calculated after groups are formed. The team members' skills value is added and divided by the number of total members to obtain the group skill average.

Definition 3.3.3 *Unfairness*

unfairness counts the variance observed for group members regarding the number of matches between user skills and project requirements.

$$\text{Unfairness}(G, P) = \frac{1}{|G|} \sum_{u' \in G} (sim(u', P) - MS(G, P)) \tag{3.5}$$

where $|G|$ is the cardinality of the group G, $sim(u', P)$ is the similarity between user u' and project requirements P, and $MS(G, P)$ is the mean similarity between the group G and project requirements P. The goal is to select a group G that minimizes the multi-objective condition:

$$\underset{G}{\operatorname{argmin}} \, (Distance(G, P), Unfairness(G, P)) \tag{3.6}$$

4 Methods

This chapter discusses the two proposed methods for creating fair team recommendations. The support functions, the fundamental building blocks of the suggested approaches, are discussed in Section 4.1 of the study. These functions are required for calculating the distances between users and projects, sorting and selecting people based on their skills, and assessing the quality of the created groups. Section 4.2, on the other hand, introduces the paper's two key methods: the Group-project distance and Unfairness Optimization Method and the Rule-Based Expert Extraction method. Using the Pair-round choosing method, the Group-project distance and Unfairness Optimization Method establishes a big group of individuals and divides them into smaller random groups for evaluation. On the other hand, the Rule-Based Expert Extraction method chooses the best people for each required skill and then fills the remaining spots with people with the highest skill levels in other areas. Both techniques are implemented using the support functions outlined in Section 4.1.

4.1 Support functions

Using the definition presented in Chapter 3, Algorithm 1 computes the function dist(u, p), which gives the distance between the user u and the project p.

Algorithm 1: Function dist(u, p)

Input: A user u and project p
dist=0
Skills = Get the skills mentioned in the project
  for each user in group **do**
    distance += calculate distance between the individual and the project
  distance/number of skills in the project
  end

Output: Distance between a user and the project

Table 4.1 *Function dist*(u, p)

Algorithm 2 implements the function dist(G, p), which calculates the distance between group G and project p.

Algorithm 1 calculates the distance between a user and a project, while Algorithm 2 calculates the distance between a group and a project. First, the required skills mentioned in the project are identified using binary comparison. Then for everyone, his set of skill values is compared with the

Algorithm 2: Function dist(G, p)
Input: A set of users, a set of project requirements
Skills = Get the skills mentioned in the project
for each user in group **do**
distance += dist(u, p)
distance/number of people in the group
end
Output: Distance between a group and the project

Table 4.2 *Function dist*(G, p)

project skills, and the difference is added according to a non-linear function to get the final distance value. The non-linear function is the quadratic function $x^2 - 2x + 1$. This function calculates the distance compared to a linear function like $1 - x$ because this allows the distance value to be lower if a person at least has some experience with a particular skill. This is an intuitive decision taken during the implementation.

Algorithm 3: The Concept of Dominance
Input: dominated array = array of zeros, dominant array = array of zeros
for each $x_1 = 0$: size of vectors along axis=0 **do**
for each $x_2 = 0$: size of vectors along axis=0 **do**
If $x_1 == x_2$ **do**
Continue
end
If vectors[x_2] dominates vectors[x_1] **do**
dominatedarray[x_1] += 1
dominantarray[x_2] += 1
end
end
Output: Arrays containing the number of dominated instances and dominant instances for each vector given

Table 4.3 *The Concept of Dominance*

Algorithm 3 introduces the "Concept of Domination", which involves identifying the most suitable users for each group using a multiobjective optimization (MOO) method to optimize the required skills for the project. The MOO method utilizes the Paretosearch algorithm to generate the *dominant* and *dominated* arrays. Specifically, the dominant array comprises individuals with superior or equal skills in all required areas relative to the other individuals. The dominated array contains persons with lower or equal skills in at least one required area.

The Concept of Dominance is essential for identifying the most qualified individuals for the group-formation process. In this method, dominant users are called "Pareto-fronts" the best users among the entire dataset. These people can be chosen to form optimal groups based on their skills and abilities. The dominance strategy ensures the final groups are established utilizing the most qualified

members. Utilizing the MOO method and the Paretosearch algorithm, the domination approach can identify the top performers among the users in the dataset. This results in the development of appropriate groups and ensures that the persons chosen for each group have the necessary skills and competencies, resulting in enhanced project outcomes.
Below is an illustration of the Concept of Dominance.

Input $X1$: An individual with skill values

Input $X2$: An individual with skill values

$X1$ dominates $X2$ if;

- $X1$ is no worse than $X2$ in all objectives AND
- $X1$ is strictly better than $X2$ in at least one objective

In that case, $X1$ is the dominant user, while $X2$ is the dominated user.

Algorithm 4: Function Check Feasibility (G, p): Check whether the group is fair in terms of the number of skilled individuals

Input: A group (set of individuals with skill levels) and a project of required skills
binskills = An array of binarized skill levels for the entire group
numskills = An array of the total users for each skill
threshold = Group size divided by the number of skills required by the project
if (for all skills: numskills $\geq$ threshold) **do**
  return True
else
  return False
end

Output: A binary value indicating whether the group is fair or not regarding the number of skilled individuals

Table *4.4 Function Check Feasibility*

Algorithm 4 describes the procedure for determining the viability of a group based on the number of qualified members in each needed skill. To do this, the algorithm determines how many individuals possess the necessary talents for the project. This is accomplished by analyzing the ability levels of each individual and identifying those with competency in the necessary skills above zero.

Once the number of talented persons has been determined, the algorithm creates a *threshold* value representing the minimal number of skilled individuals per skill required for a group to be fair. This threshold value is established by dividing the group members by the number of skills required for the project. For instance, if a project requires four skills and a group comprises 12 people, the threshold value would be $12/4 = 3$. This means that at least three group members must possess proficiency in each needed skill to form a fair group.

The feasibility check function is essential for ensuring that each group's talent distribution is fair. By selecting a minimum threshold value for each ability, the algorithm may find groups that fulfill the requisite skill standards and remove those that do not, resulting in more efficient and effective team creation.

4.2 Proposed methods in team formation problem

Definition 4.2.1 *Group-project distance and Unfairness Optimization Method*

Algorithm 5 presents a novel algorithm for generating a set of fair groups for a given set of projects. To begin, a group is obtained for each project using the Pair-round choosing method, but with a slightly larger group size (e.g., 100 individuals if the final group size is 10).
Pair-round choosing method: Allocating team members involves $k/2$ rounds, where k is the required team size. During each round, $\text{dist}(u, p)$ is used to calculate the distance between each user u in the set U and each project p in the set P. Users u_1 and u_2 with the lowest $\text{dist}(u_i, p)$ values for p are then selected as team members and deleted from the set of available users U. This approach is repeated until each project has a member of the k-team. In the final round, just one team member is chosen if k is an odd number.

Next, the Group-project distance and Unfairness Optimization Method is employed, utilizing the multiobjective optimization (MOO) technique. Specifically, 10,000 random groups are formed from the available individuals for the project, and algorithm 4 is applied to ensure the feasibility of each group by checking if each required skill has a sufficient number of experts. Feasible groups are evaluated based on $\text{dist}(G, p)$ and $\text{Unfairness}(G, P)$. The ultimate aim is to find the best group that minimizes $\text{dist}(G, p)$ and $\text{unfairness}(G, P)$. To accomplish this, the Pareto front is calculated using the dominated array, and the best group from the Pareto front is determined using the dominant array. The final output is the optimized fair group for the given project.

The next expert to the team will be chosen from the **Recommendation** as it has the minimum sum.

Definition 4.2.2 *Rule-Based Expert Extraction method*

Algorithm 6 presents a methodical strategy for building a group for a particular project based on

Algorithm 5: Group-project distance and Unfairness Optimization Method to generate team recommendations

Input: array containing the required skills for the project (This is a binary 1d array), interim group obtained by using the Pair-round choosing method
for each p = 0: 10000 **do**
randomidx = Get a random vector of size ngroup within range of size(expert group)
localgroup = Get group from expert group according to randomidx
if (localgroup is feasible) **do**
dist local, var local, fairness error = calculated distance, variance and unfairness
append randomidx to allgroups append [dist local, var local, fairness error] array to allvectors
end
reducedleaderdomarr = select best element from a set using MOO with allvectors sortidx = Get best group index from sorted reducedleaderdomarr array (from last column
bestexpertgroupidx = best group indices from reducedleaderdomarr using sortidx finalgroup = expertgroup[bestexpertgroupidx]
min local distance, min local variance, min local fairness error = calculated distance, variance and unfairness
end

Output: Best group for the project, distance, variance and fairness error statistics Additional: selecting the best element from a set using multiobjective optimization dominatedarr, dominantarr = pareto numdom 2(allvectors) leaderdomarr = columnwise concatenate allgroups, dominatedarr and dominantarr reducedleaderdomarr = keep only the first pareto front of leaderdomarr

Table 4.5 *Group-project distance and Unfairness Optimization Method to generate team recommendations*

the sorted skill levels of the accessible users. A system based on rules ensures that the group is fair. This system iteratively adds to the group the individuals with the highest skill values for the requisite skills. Here are the stages for this method:

- First, the best available member is selected and joins the group for each required skill. To do this, the users are ranked according to their skill levels for each required talent, and the best individual is chosen for each skill

- Then, the sum of each skill's values is calculated to determine which skill has the lowest sum. The following best user is then selected for this skill, and the procedure is continued until the required number of experts for each skill has been reached

This procedure guarantees that the team members spread the essential skills fairly. This method can assemble an impartial and knowledgeable team for the given assignment. This method provides a systematic and transparent method for selecting team members based on their skills, ensuring that the group is balanced and capable of completing the project quickly.

Table 4.6 represents an example of the Rule-based Expert Extraction Method. After User 0001 and User 0002 are selected for the team, the next user will be selected from the skill *Recommendation* as it has the minimum sum from the skill values.

User ID	Database	Recommendation
User 0001	1.0	0.0
User 0002	0.2	1.0
Sum	1.2	1.0

Table 4.6 *Example of Rule-Based Expert Extraction method*

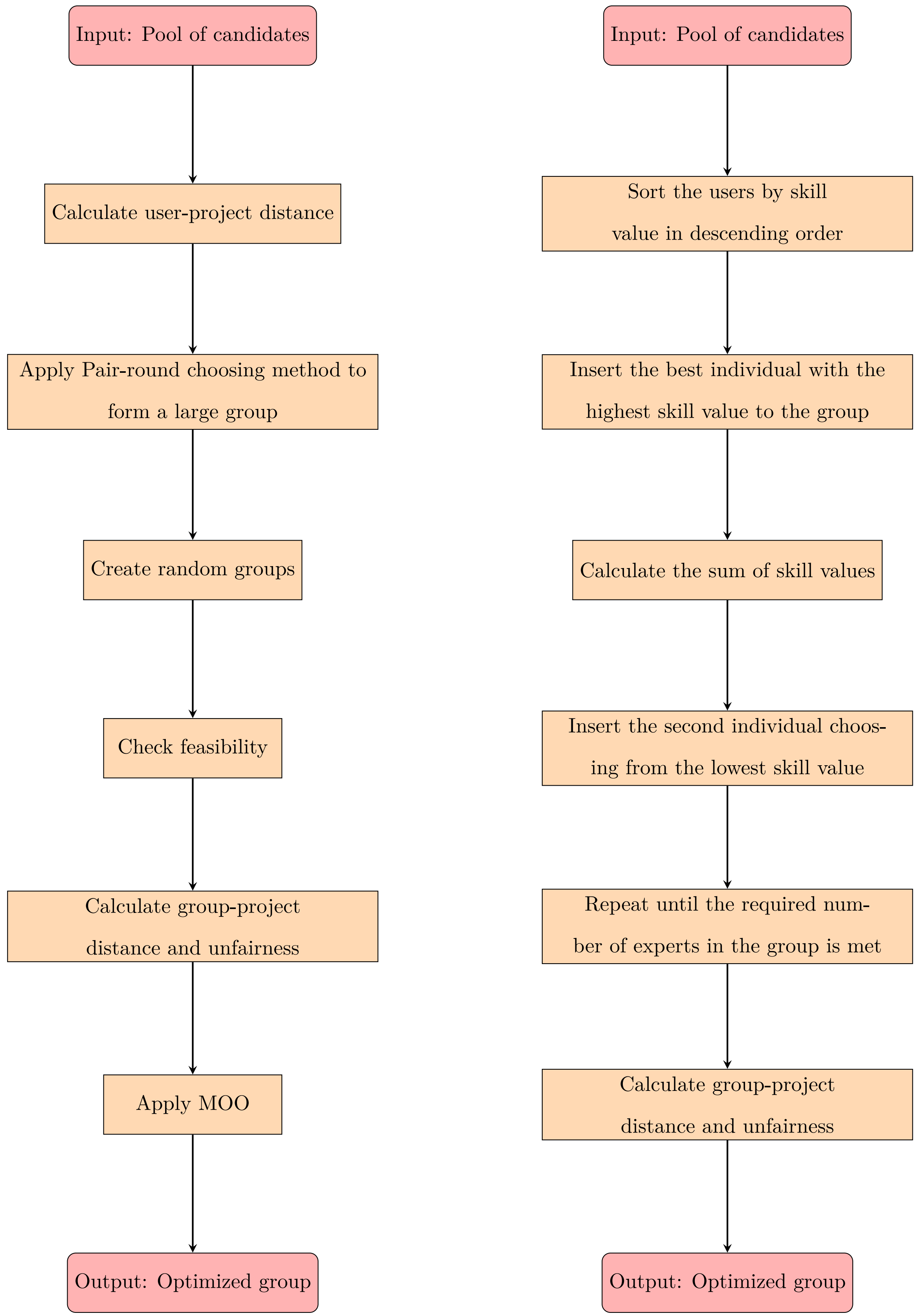


Figure 4.1 *Architecture of the Rule-Based Expert Extraction method(Left) and the Group-project distance and Unfairness Optimization Method (Right)*

Algorithm 6: Rule-Based Expert Extraction method to generate team recommendations

Input: Skill levels of individuals, the array containing sorted individuals for each skill, skills required in the project, Required group size
group = empty vector
Skills = indices of skills required by the project
for each skill in Skills **do**
   Append maximum skilled individual for the particular skill to group
end
remain = Required group size − length(Skills)
for each p = 0:remain **do**
      minskillidx = Check for which skill the group skill level (sum) is minimum
      append maximum skilled individual for the minskillidx skill to group
end

Output: expert group for the project

Table 4.7 *Rule-Based Expert Extraction method to generate team recommendations*

5 Experimental Evaluation

This chapter presents an experimental evaluation to compare the performance of the existing Pair-round selecting method with the two proposed methods: *The Group-project distance and Unfairness Optimization Method* and the *Rule-Based Expert Extraction method* stated in Chapter 4. This experiment's major objective is to analyze the effectiveness of the three approaches based on Group-project distance, skill variance, and unfairness. In terms of enhancing the fairness of team formation, the Group-project distance and Unfairness Optimization Method and Rule-Based Expert Extraction approach are anticipated to perform better than the Pair-round selecting method. In Section 5.1, the experiment's data are discussed. The following section, Section 5.2, focuses on the three main measurements used to evaluate the performance of the proposed methods. Sections 5.3 to 5.6 delve into Group-project distance, skill variance, unfairness, and the harmonic mean. Scatter plots and box plots are used to compare the performance of the Pair-round choosing method, Group-project distance and Unfairness Optimization Method, and Rule-Based Expert Extraction method.

5.1 Dataset

The dataset utilized in the experiment is a modified version of the online bibliography database DBLP, which organizes computer science publications. Trier University compiled the initial dataset, which contains many records. 2015's X. Wang et al. developed the experiment's adjusted dataset, which consists of 7428 lines of CSV text. Each record in the DBLP dataset represents an author and includes the author's name and a variable number of skill tags connected with the author. It's worth noting that every author possesses at least one skill, and there are 4,480 separate skills shared by all persons, with some skills duplicated for the same person numerous times. This dataset is appropriate for the experiment since it contains a wide variety of talents and individuals, which is necessary for assessing the performance of the proposed team creation approaches.

The following example depicts a data line associated with an author with the user ID 0000-0001-9940-1821 who holds five competencies.

e.g. (A line from the preprocessed dataset) 0000-0001-9940-1821, database, recommendation, networks, social, web

Authors frequently employ keywords in their scientific publications to represent their abilities and areas of expertise. Hence, the skill tags associated with each author in the dataset may not be an exact reflection of their entire skill set but rather a near approximation based on the keywords they employed. However, these skill tags are pertinent to their competence and can be considered an adequate approximation for the experiment's purposes.

5.2 Measurements

The three main measurements used in this study are described in Table 5.1.

Key Measurement	Description
Group-project distance	Skill level difference between the chosen group and the requirements of the particular project
Skill variance	Skill level variance within the group for required skills
Unfairness	A parameter denoting the unfairness, depending on equal distribution of skill values

Table 5.1 *Key Measurements to evaluate the performance of the proposed methods*

5.3 Group-project distance

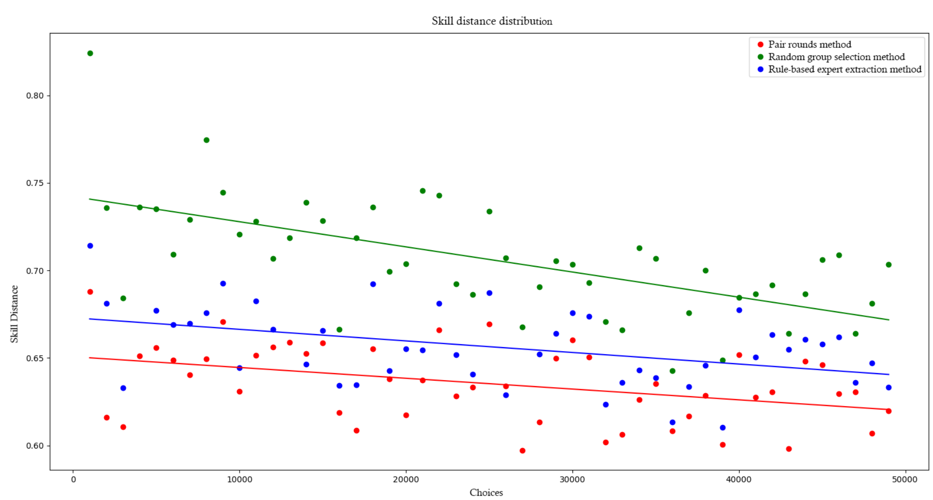


Figure 5.1 *Group-project distance distribution*

The performance of the three group creation strategies is shown in Figure 5.1 in terms of Group-project distance and the number of options. As the scatter plot shows, the Pair-round selection approach has the smallest Group-project distance. The Rule-Based Expert Extraction approach closely follows the next lowest Group-project distance. However, despite having a more significant Group-project distance, the Group-project distance and Unfairness Optimization Method is still comparable to the other two methods. According to the scatter plots, the Pair-round choosing method has the lowest Group-project distance, which means it performs better than the other two methods. However, the Rule-Based Expert Extraction method is still comparable.

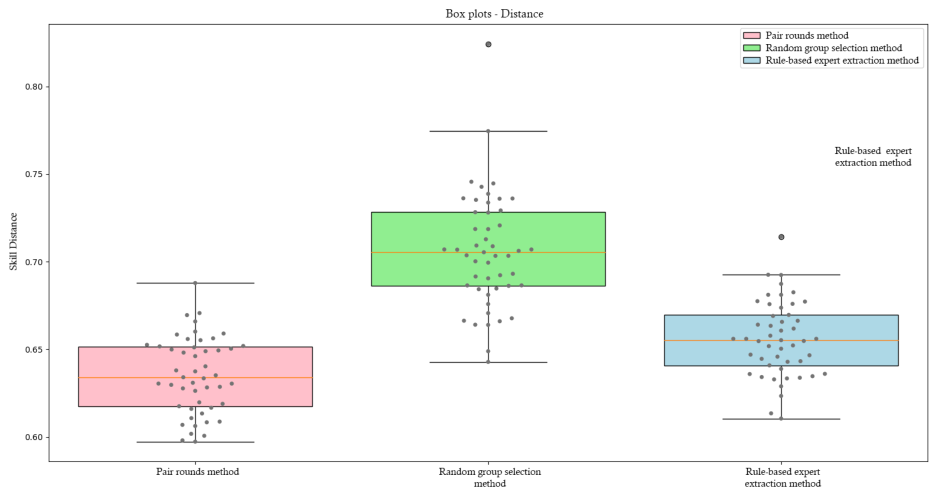


Figure 5.2 *Box plot:Group-project distance*

Figure 5.2 illustrates the variation in Group-project distance between the three approaches. The Rule-Based Expert Extraction method has a Group-project distance variation comparable to the Pair-round choosing method. On the other hand, the Group-project distance and Unfairness Optimization Method has a higher mean value and a broader range, showing that it is less suitable than the other two ways of establishing groups with the appropriate skill set. Based on the box plot, the Rule-Based Expert Extraction method is more effective than the Group-project distance and Unfairness Optimization Method at producing groups with a closer match to the desired skill set.

5.4 Skill Variance

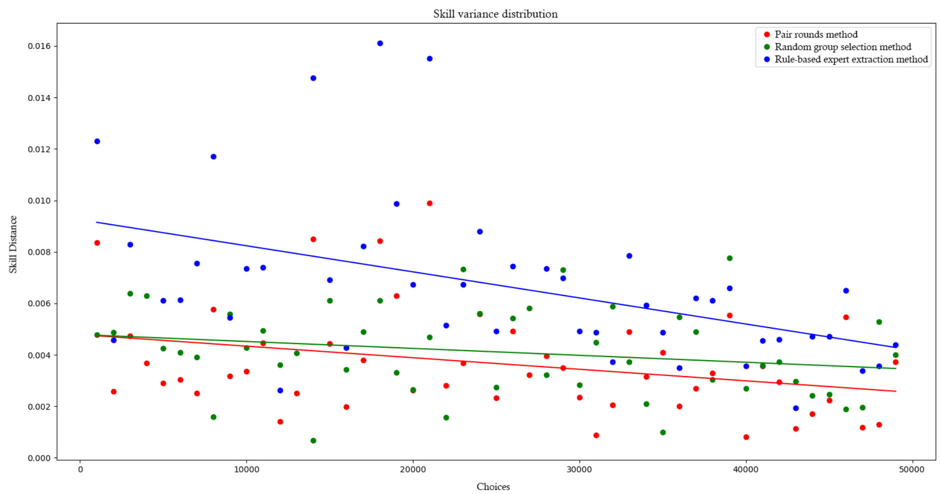


Figure 5.3 *Skill variance distribution*

Figure 5.3 compares the skill variance performance of the three group creation strategies based on the number of choices. The scatter figure reveals that the Pair-round approach has the lowest skill variance compared to the other two methods. Group-project distance and Unfairness Optimization Methodclosely follows the method with the next-lowest skill variance. When the number of options is limited, the skill variance trends of the Group-project distance and Unfairness Optimization Methodand Pair-round picking methods are relatively comparable. On the other hand, the Rule-Based Expert Extraction method has a higher skill variance, especially when the number of options is significant, but it approaches the other two methods. The Group-project distance and Unfairness Optimization Methodapproach and the Rule-Based Expert Extraction method have obtained marginally higher skill variances than the Pair-round selecting method, but the difference is not statistically significant.

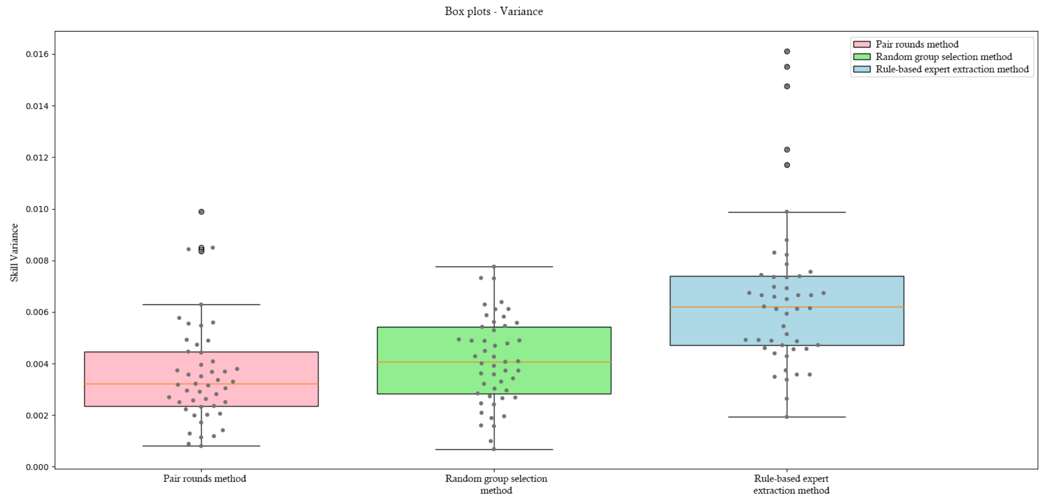


Figure 5.4 *Box plot:Skill variance*

Figure 5.4 depicts the variation in skill variance among the three techniques of group construction. The Group-project distance and Unfairness Optimization Methodapproach and the Rule-Based Expert Extraction method have comparable skill level variations regarding the range. Despite outliers, the Rule-Based Expert Extraction method delivers data points more closely clustered around the mean. In contrast, the Group-project distance and Unfairness Optimization Method produces a more extensive distribution of data points, indicating a greater variety in skill levels between groups. The Pair-round selection approach continues to have the lowest mean skill variance among all methods. Nonetheless, the ranges of the three approaches converge and overlap. Overall, this indicates that the Rule-Based Expert Extraction approach and the Group-project distance and Unfairness Optimization Method have equivalent skill variance performance; however, the Pair-round selecting method remains the most effective technique for reaching the lowest skill variance.

5.5 Unfairness

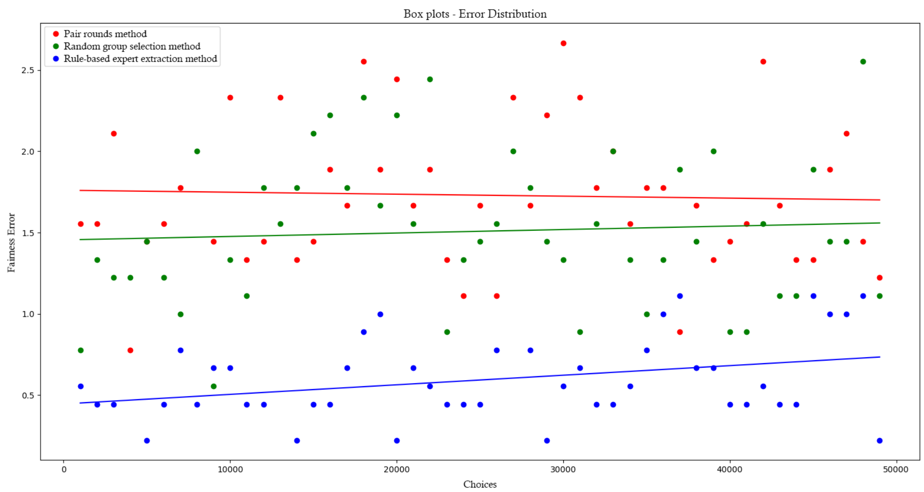


Figure 5.5 *Unfairness distribution*

Figure 5.5 depicts the performance of the three group creation strategies regarding unfairness according to the number of options. The Rule-Based Expert Extraction method has the lowest unfairness(fairness error) among the three methods, as Figure 5.5 indicates. The following lowest fairness error is that of the Group-project distance and Unfairness Optimization Method, close to the fairness error of the Pair-round choosing method. The Rule-Based Expert Extraction method produced the lowest fairness error, indicating that this method is more suitable for constructing groups with a more equitable distribution of skill levels.

Fairness error is a crucial metric to consider while constructing groups, as it quantifies the degree of imbalance in the distribution of talents among group members. The lower the fairness error, the more evenly distributed skills are across the group's members. In this regard, the Rule-Based Expert Extraction method is the most appropriate for forming groups with a more equitable and balanced distribution of skill levels.

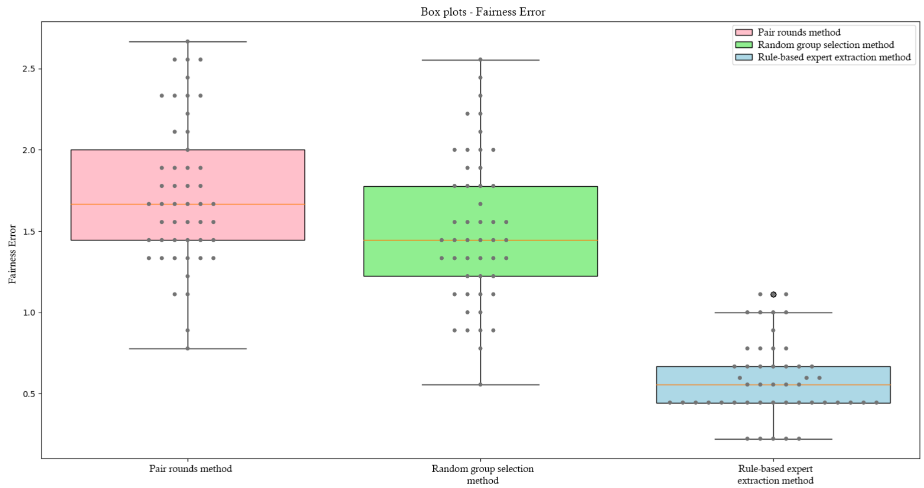


Figure 5.6 *Box plot: Unfairness*

Figure 5.6 illustrates the difference in fairness error between the three group formation strategies. The closest clustering of data points around the mean value implies that the Rule-Based Expert Extraction method has the lowest fairness error of the three methods. However, Rule-Based Expert Extraction has the lowest mean value of all techniques. In contrast, the Group-project distance and Unfairness Optimization Method and the Pair-round choosing method have a greater mean value and a more comprehensive range than the Rule-Based Expert Extraction method. The Rule-Based Expert Extraction method consistently provides groups with lower fairness errors despite outliers. Consequently, the Rule-based strategy for extracting experts is more dependable for establishing groups with an equitable distribution of skill levels.

5.6 Harmonic Mean

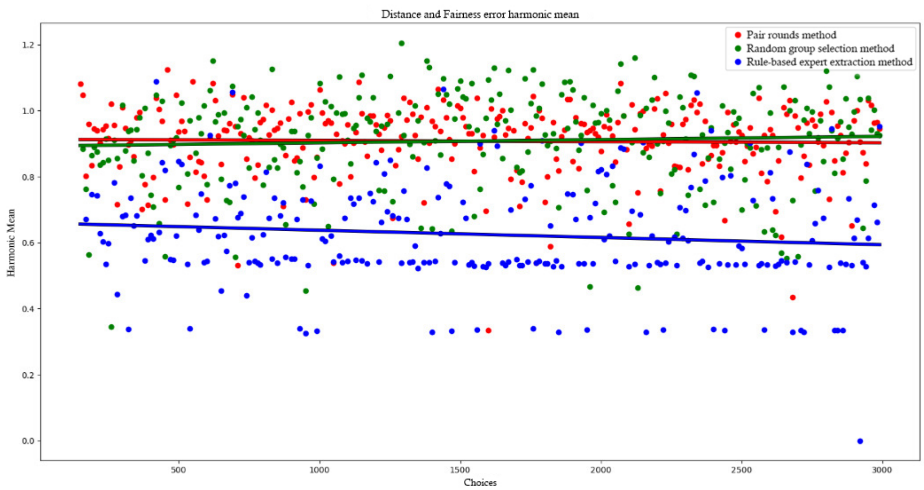


Figure 5.7 *Group-project distance, skill variance and unfairness Harmonic mean*

Figure 5.7 displays the harmonic mean values for the three group formation strategies. The Rule-Based Expert Extraction approach has the lowest harmonic mean value among the three methods, as shown in the graph. When the number of options increases, the Group-project distance and Unfairness Optimization Method tends to be slightly higher than the Pair-round selecting method. This demonstrates that the Rule-Based Expert Extraction method generates skill-balanced groups most effectively. The harmonic mean is essential because it considers the group's most significant and lowest skill levels, providing a more accurate measurement of its overall performance.

In the study, we emphasized the Group-project distance parameter because it was a critical aspect in establishing the compatibility of users or user groups with a given project. It indicates how well a team's talents align with the project's requirements. The measurement of Group-project distance was deemed relevant since it increased the number and quality of applicants whose abilities matched the project's criteria. In addition, based on the $Distance(G, P)$ and $MS(G, P)$ values, the $Unfairness(G, P)$ measure evaluates the equal distribution of users among the projects. The team's overall quality could be enhanced by lowering Group-project distance, skill variation, and unfairness.

The example output from a test case that calculates the values of $Distance(G, P)$, $Skillvar(G, P)$, and $Unfairness(G, P)$ for two projects is shown in Table 5.2. The output is from two projects names A and B which are;

	Project A			Project B		
	Distance(G,P)	Skill var(G,P)	Unfairness(G,P)	Distance(G,P)	Skill var(G,P)	Unfairness(G,P)
Method 0	0.665847	0.001205	0.888889	0.661621	0.000773	1.111111
Method 1	0.744536	0.001645	0.444444	0.765345	0.003867	0.444444
Method 2	0.668725	0.002376	0.444444	0.686449	0.004712	0.444444

Table 5.2 *Output of the measurements of a test case*

$ProjectA = \{\text{Cloud}, \text{Web}, \text{Software}\}$ and $ProjectB = \{\text{Software}, \text{Graphs}, \text{Networking}\}$

Method 0: Pair-round choosing method

Method 1: Group-project distance and Unfairness Optimization Method

Method 2: Rule-Based Expert Extraction method

Group-project distance: For both Project A and B, Method 0 and Method 2 has the lowest Group-project distance values, indicating that they form teams with more equal skill levels among team members. This is significant because team members with similar skill levels are more likely to collaborate effectively and efficiently, improving team performance. However, the Group-project distance values of Method 1 are still comparable to those of Method 0 and Method 2.

Skill variance: For both Project A and B, Method 0 and Method 2 has the lowest skill variance values, creating teams with fewer skill levels across team members. This is significant because when there is less difference in skill levels across team members, one member has less potential to dominate the team, and all team members have an equal opportunity to contribute to the team's success. Although Method 1 has somewhat greater skill variance values than the other methods, this difference might be considered insignificant.

Unfairness: For both Project A and B, Method 1 and Method 2 have the lowest unfairness scores, indicating that it creates teams with a more even distribution of skills across team members. This is significant because when team members' skills are distributed fairly, each team member has a better opportunity of contributing to the team's success and feel valued for their contributions. Furthermore, it encourages diversity and inclusivity in team creation.

As a result of these findings, Method 1 and Method 2 are effective approaches for team formation since it produces teams with similar skill levels, less fluctuation in ability levels, and a more equitable distribution of skills across team members. It should be noted, however, that these results are only based on Group-project distance, skill variance, and unfairness metrics. Other aspects, such as team dynamics, individual strengths, and communication styles, should also be addressed

User ID	Cloud	Web	Software
334X	1	0	0
6117	0	0	0.94
7672	0	0.84	0.01
107X	0	0.76	0.02
5639	0.75	0	0 0.01
1859	0	1	0.07
4197	0	0	1
4660	0.85	0	0.01
0712	0.8	0	0
9856	0	0.76	0

Figure 5.8 *Project A: Team formed by Method 0*

User ID	Cloud	Web	Software
6675	0.45	0	0
6869	0.5	0	0.01
4926	0	0.46	0.01
471X	0.45	0.15	0.08
1706	0	0	0.5
8556	0	0.15	0.2
4195	0.45	0	0
5584	0	0.15	0.47
4442	0	0	0.47
6418	0.55	0	0.01

Figure 5.9 *Project A: Teams formed by Method 1*

User ID	Cloud	Web	Software
334X	1	0	0
1859	0	1	0.07
4197	0.85	0	0.01
4660	0	0.85	0.01
7672	0	0	0.94
6117	0	0.76	0
9856	0.8	0	0
0712	0.05	0	0.55
7230	0.1	0	0.55

Figure 5.10 *Project A: Teams formed by Method 2*

in the team formation process.

Figures 5.8, 5.9, and 5.10 depict the three approaches used to construct the teams for Project A. Since many users have higher levels of competency in the cloud than in the web or software, it can be shown that Method 0 gives cloud skills more weight. Contrarily, Method 1 has an equal distribution of skills amongst Cloud, Web, and Software. In Method 2, there is a mix of high and low skill levels throughout all three domains, with some users being less skilled than others in one or more domains.

Figure 5.11, 5.12, 5.13 depict the teams formed for Project B using three alternative ways. Method 0 highlights networking capabilities, with numerous individuals scoring high in that area but low in the other two. Methods 1 and 2 have a more even distribution of skills across the three domains, with some users excelling in one and lower in another. Overall, the results indicate that Methods 0 and 2 may be effective for building teams based on specific skill requirements, whereas Method 1 may be more helpful in forming more balanced teams.

User ID	Software	Graphs	Networking
7594	0	0.07	0.89
5756	0	0.84	0.02
6398	0.8	0	0.006
1455	0.05	0.69	0.04
200X	0.75	0	0.01
2640	0	0	1
7119	0	0	0.93
2148	0.85	0	0
0868	0	0.07	0.72
1793	0	0	0.76

Figure 5.11 *Project B:Team formed by Method 0*

User ID	Software	Graphs	Networking
9222	0.1	0	0.56
1059	0	0.23	0.36
9223	0	0.07	0.27
6617	0.55	0	0.006
2529	0	0.07	0.48
1292	0.4	0	0
7369	0	0.07	0.38
2942	0.35	0	0
8453	0.5	0	0.04
4096	0.35	0	0.006

Figure 5.12 *Project B: Teams formed by Method 1*

User ID	Software	Graphs	Networking
2148	0.85	0	0
5756	0	0.84	0.02
2640	0	0	1
1455	0.05	0.69	0.04
6398	0.8	0	0.006
7119	0	0	0.93
3716	0	0.38	0.01
200X	0.75	0	0
3369	0	0.38	0
7594	0	0.07	0.89

Figure 5.13 *Project B: Teams formed by Method 2*

6 Conclusion

In conclusion, the effectiveness of three distinct methods for forming groups is compared using various criteria. First, we looked at the concept of *Group-project distance*, which quantifies the degree to which individual members of a group have varying levels of expertise. The Rule-Based Expert Extraction, Group-project distance, and unfairness optimization methods performed well enough to achieve a smaller Group-project distance. The Group-project distance was more significant for the Group-project distance and Unfairness Optimization Method when the number of choices increased but performed similarly to the Pair-rounds choosing and Rule-Based Expert Extraction methods. The box plot showed how the Group-project distance varied between the three methods, while the scatter plots provided an overall picture of the performance.

Skill variance, a measure of the distribution of individual skills within a group, was evaluated next. The Rule-Based Expert Extraction and Group-project distance and Unfairness Optimization Methods yielded lower skill variances. When the number of choices was large, the Rule-Based Expert Extraction method's skill variance was highest, but it was still competitive with the other two approaches. The box plot showed how the skill variance varied between the three approaches, while the scatter plot offered an overview of the skill variance performance of the three ways.

Thirdly, we looked at *unfairness*, which measures how unequally people's skills are distributed in a group. The Rule-Based Expert Extraction approach had the smallest fairness error, followed by the Group-project distance and Unfairness Optimization Methodand Pair-round choosing methods. The scatter plot summarised the three ways' fairness error performance, while the box plot showed how the fairness error varied between the three approaches to grouping.

Harmonic mean, the fourth and last metric examined, measures group performance that averages out the highest and lowest scores. The harmonic mean value was lowest for the Rule-Based Expert Extraction method, followed by the Group-project distance and Unfairness Optimization Method. The Rule-Based Expert Extraction method has the lowest mean value and the closest clustering of data points around the mean value, constantly outperforming the other two methods regarding unfairness.

The study found that the Rule-Based Expert Extraction strategy and the Group-project distance and Unfairness Optimization Method, with its low fairness error and low harmonic mean, were the most successful method for forming groups with a balanced distribution of skill levels. But, when establishing groups with similar skill levels, the Pair-round choosing method had the smallest Group-project distance and skill variance. This study aimed to make the team creation procedure more equitable. We presented two cutting-edge methods to encourage fair team formation to achieve this goal. We also considered the Pair-round choosing method to compare the efficacy of these novel techniques. Our findings show that the suggested approaches successfully promoted the fairness of team formation. The research sheds light on the various group formation tactics that can be employed and stresses the need to consider multiple criteria when assessing their efficacy. Forming more effective and efficient groups better equipped to achieve desired outcomes may be feasible by adopting a group creation method that matches the unique goals and criteria of a specific task or project.

There are several constraints of fairness in challenges involving team formation:

Subjectivity: Fairness is frequently subjective and varies from person to person. What one person considers fair may not be regarded as fair by another
Limited data: Getting complete and accurate information about a person's skills and abilities could take time, making it hard to assemble fair teams
Competing goals: Fairness may not always be compatible with other goals, such as improving team performance or attaining specific goals. In some cases, promoting justice may result in poor results
Lack of diversity: Teams that prioritize fairness based on specific criteria, such as knowledge or skill level, may lack diversity in other areas, like gender, race, and socioeconomic status
Changing circumstances: Projects usually start with team formation. However, team members may leave, or skill requirements may vary. Maintaining impartiality might take a lot of work
Complexity: When team formation difficulties become more complicated, with more individuals and criteria to consider, balancing fairness and other factors becomes more difficult

It is essential to recognize these constraints when planning and implementing team formation procedures to guarantee that fairness is prioritized effectively and consistent with the specific requirements and objectives of the project or job.

Bibliography

Al-Taie, M. Z., S. Kadry, and A. I. Obasa (2018). "Understanding expert finding systems: domains and techniques". In: *Social Network Analysis and Mining* 8, pp. 1–9.

Anagnostopoulos, A. et al. (2010). "Power in unity: forming teams in large-scale community systems". In: *Proceedings of the 19th ACM international conference on Information and knowledge management*, pp. 599–608.

— (2012). "Online team formation in social networks". In: *Proceedings of the 21st international conference on World Wide Web*, pp. 839–848.

Bacon, D. R., K. A. Stewart, and E. S. Anderson (2001). "Methods of assigning players to teams: A review and novel approach". In: *Simulation & Gaming* 32.1, pp. 6–17.

Barnabò, G. et al. (2019). "Algorithms for Fair Team Formation in Online Labour Marketplaces ". In: *Companion Proceedings of The 2019 World Wide Web Conference*, pp. 484–490.

Barocas, S. and A. D. Selbst (2016). "Big data's disparate impact". In: *California law review*, pp. 671–732.

Barreto, A., M. d. O. Barros, and C. M. Werner (2008). "Staffing a software project: A constraint satisfaction and optimization-based approach". In: *Computers & Operations Research* 35.10, pp. 3073–3089.

Berkovsky, S. and J. Freyne (2010). "Group-based recipe recommendations: analysis of data aggregation strategies". In: *Proceedings of the fourth ACM conference on Recommender systems*, pp. 111–118.

Beutel, A. et al. (2019). "Fairness in recommendation ranking through pairwise comparisons". In: *Proceedings of the 25th ACM SIGKDD international conference on knowledge discovery & data mining*, pp. 2212–2220.

Bhattarai, S. et al. (2018). "A comprehensive survey on expertise retrieval". In: *Information Processing & Management* 54.6, pp. 961–977.

Bulmer, J. et al. (2020). "Fastt: team formation using fair division". In: *Advances in Artificial Intelligence: 33rd Canadian Conference on Artificial Intelligence, Canadian AI 2020, Ottawa, ON, Canada, May 13–15, 2020, Proceedings 33*. Springer, pp. 92–104.

Buolamwini, J. and T. Gebru (2018). "Gender shades: Intersectional accuracy disparities in commercial gender classification". In: *Conference on Fairness, Accountability and Transparency.* PMLR, pp. 77–91.

Cachel, K. and E. Rundensteiner (2022). “FINS Auditing Framework: Group Fairness for Subset Selections”. In: *Proceedings of the 2022 AAAI/ACM Conference on AI, Ethics, and Society*, pp. 144–155.

Caramia, M. et al. (2020). “Multi-objective optimization”. In: *Multi-objective Management in Freight Logistics: Increasing Capacity, Service Level, Sustainability, and Safety with Optimization Algorithms*, pp. 21–51.

Chen, L. et al. (2020). “A Survey on Expertise Retrieval”. In: *IEEE Access* 8, pp. 13314–13330.

Coello, C. C. (2006). “Evolutionary multi-objective optimization: a historical view of the field”. In: *IEEE computational intelligence magazine* 1.1, pp. 28–36.

Datta, A., J. T. T. Yong, and S. Braghin (2014). “The zen of multidisciplinary team recommendation”. In: *Journal of the Association for Information Science and Technology* 65.12, pp. 2518–2533.

Deb, K. et al. (2002). “Scalable multi-objective optimization test problems”. In: *Proceedings of the 2002 Congress on Evolutionary Computation. CEC’02 (Cat. No. 02TH8600).* Vol. 1. IEEE, pp. 825–830.

Dwork, C. et al. (2012). “Fairness through awareness”. In: *Proceedings of the 3rd innovations in theoretical computer science conference*, pp. 214–226.

Friedler, S. A., C. Scheidegger, and S. Venkatasubramanian (2021). “The (im) possibility of fairness: Different value systems require different mechanisms for fair decision making”. In: *Communications of the ACM* 64.4, pp. 136–143.

Frikha, M., M. Mhiri, and F. Gargouri (2017). “Using social interaction between friends in knowledge-based personalized recommendation”. In: *2017 IEEE/ACS 14th International Conference on Computer Systems and Applications (AICCSA).* IEEE, pp. 1454–1461.

Golshan, M., L. Tamine, and M. Boughanem (2019). “A Survey of Expertise Retrieval in Academia”. In: *Journal of Information Science Theory and Practice* 7.4, pp. 42–60.

Gómez-Zará, D., L. A. DeChurch, and N. S. Contractor (2020). “A taxonomy of team-assembly systems: Understanding how people use technologies to form teams”. In: *Proceedings of the ACM on Human-Computer Interaction* 4.CSCW2, pp. 1–36.

Gunantara, N. (2018). “A review of multi-objective optimization: Methods and its applications”. In: *Cogent Engineering* 5.1, p. 1502242.

Gutiérrez, J. H. et al. (2016). “The multiple team formation problem using sociometry”. In: *Computers & Operations Research* 75, pp. 150–162.

Hafiz, R. et al. (2021). “Pairwise Ranking-Based Fairness Measures for Multi-Criteria Recommender Systems”. In: *Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR ’21)*. ACM, pp. 2267–2271.

Haghani, A. et al. (2020). “Multi-Objective Optimization of Fairness and Accuracy in Classifiers”. In: *Proceedings of the AAAI Conference on Artificial Intelligence*. Vol. 34, pp. 3937–3944.

Hardt, M., E. Price, and N. Srebro (2016). “Equality of opportunity in supervised learning”. In: *Advances in neural information processing systems* 29.

Harris, A. M. et al. (2019). “Joining together online: the trajectory of CSCW scholarship on group formation”. In: *Proceedings of the ACM on Human-Computer Interaction* 3.CSCW, pp. 1–27.

Huang, K. et al. (2020). “Expertise Retrieval via Heterogeneous Information Networks: A Survey”. In: *ACM Transactions on Intelligent Systems and Technology* 12.1, pp. 1–34.

Hwang, Y., S. Kim, and S. Park (2018). “Modeling player retention in massive multiplayer online games: A survival analysis approach”. In: *Information Processing & Management* 54.5, pp. 778–790.

Karduck, A. (1994). “TeamBuilder: a CSCW tool for identifying expertise and team formation”. In: *Computer Communications* 17.11, pp. 777–787.

Kargar, M. and A. An (2011). “Discovering top-k teams of experts with/without a leader in social networks”. In: *Proceedings of the 20th ACM international conference on Information and knowledge management*, pp. 985–994.

Koivunen, S., E. Olshannikova, and T. Olsson (2021). “Understanding matchmakers’ experiences, principles and practices of assembling innovation teams”. In: *Computer Supported Cooperative Work (CSCW)* 30, pp. 589–616.

Konak, A., D. W. Coit, and A. E. Smith (2006). “Multi-objective optimization using genetic algorithms: A tutorial”. In: *Reliability engineering & system safety* 91.9, pp. 992–1007.

Konert, J., D. Burlak, and R. Steinmetz (2014). “The group formation problem: an algorithmic approach to learning group formation”. In: *Open Learning and Teaching in Educational Communities: 9th European Conference on Technology Enhanced Learning, EC-TEL 2014, Graz, Austria, September 16-19, 2014, Proceedings 9*. Springer, pp. 221–234.

Langlois, J. and L. Schmidt (2019). “Machine learning methods for player selection and draft decision making in the NFL”. In: *Journal of Sports Analytics* 5.3, pp. 153–169.

Lappas, T., K. Liu, and E. Terzi (2009). “Finding a team of experts in social networks”. In: *Proceedings of the 15th ACM SIGKDD international conference on Knowledge discovery and data mining*, pp. 467–476.

Lee, M. S. A. and L. Floridi (2021). "Algorithmic fairness in mortgage lending: from absolute conditions to relational trade-offs". In: *Minds and Machines* 31.1, pp. 165–191.

Machado, L. and K. Stefanidis (2019). "Fair team recommendations for multidisciplinary projects". In: *IEEE/WIC/ACM International Conference on Web Intelligence*, pp. 293–297.

Malinowski, J., T. Weitzel, and T. Keim (2008). "Decision support for team staffing: An automated relational recommendation approach". In: *Decision Support Systems* 45.3, pp. 429–447.

Marler, R. T. and J. S. Arora (2010). "The weighted sum method for multi-objective optimization: new insights". In: *Structural and multidisciplinary optimization* 41, pp. 853–862.

Marques, A. B. et al. (2013). "An ontology for task allocation to teams in distributed software development". In: *2013 IEEE 8th International Conference on Global Software Engineering*. IEEE, pp. 21–30.

Matthews, T., S. Ramchurn, and G. Chalkiadakis (2012). "Competing with humans at fantasy football: Team formation in large partially-observable domains". In: *Proceedings of the AAAI Conference on Artificial Intelligence*. Vol. 26. 1, pp. 1394–1400.

Mehrabi, N. et al. (2021). "A survey on bias and fairness in machine learning". In: *ACM Computing Surveys (CSUR)* 54.6, pp. 1–35.

Meulbroek, D. et al. (2019). "Forming more effective teams using catme teammaker and the gale-shapley algorithm". In: *2019 IEEE Frontiers in Education Conference (FIE)*. IEEE, pp. 1–5.

Minto, S. and G. C. Murphy (2007). "Recommending emergent teams". In: *Fourth International Workshop on Mining Software Repositories (MSR'07: ICSE Workshops 2007)*. IEEE, pp. 5–5.

Ngatchou, P., A. Zarei, and A El-Sharkawi (2005). "Pareto multi objective optimization". In: *Proceedings of the 13th international conference on, intelligent systems application to power systems*. IEEE, pp. 84–91.

Ntoutsi, E. et al. (2012). "Fast group recommendations by applying user clustering". In: *Conceptual Modeling: 31st International Conference ER 2012, Florence, Italy, October 15-18, 2012. Proceedings 31*. Springer, pp. 126–140.

Olsson, T., J. Huhtamäki, and H. Kärkkäinen (2020). "Directions for professional social matching systems". In: *Communications of the ACM* 63.2, pp. 60–69.

Pan, R. et al. (2020). "Effective Team Formation via Multi-objective Optimization in Task-Based Crowdsourcing". In: *Journal of Intelligent Information Systems* 54.3, pp. 557–580.

Pedreshi, D., S. Ruggieri, and F. Turini (2008). "Discrimination-aware data mining". In: *ACM Transactions on Knowledge Discovery from Data* 2.4, p. 13.

Sahlgren, O. and A. Laitinen (2020). “Algorithmic Fairness and its Limits in Group-Formation”. In.

Sener, O. and V. Koltun (2018). “Multi-task learning as multi-objective optimization”. In: *Advances in neural information processing systems* 31.

Stefanidis, K. and E. Pitoura (2013). “Finding the right set of users: generalized constraints for group recommendations”. In: *arXiv preprint arXiv:1302.6580*.

Tamaki, H., H. Kita, and S. Kobayashi (1996). “Multi-objective optimization by genetic algorithms: A review”. In: *Proceedings of IEEE international conference on evolutionary computation*. IEEE, pp. 517–522.

Tonoike, M. et al. (2020). “Toward high-performance teamwork in esports: Understanding team coordination in a first-person shooter game”. In: *International Journal of Human-Computer Studies* 137, p. 102392.

Vakulenko, S., A. Bröring, and M. Tietz (2019). “Expertise Retrieval in the Enterprise: A Survey and Future Directions”. In: *Information Processing & Management* 56.6, pp. 1–23.

Wang, J. and Y.-I. Lin (2003). “A fuzzy multicriteria group decision making approach to select configuration items for software development”. In: *Fuzzy Sets and Systems* 134.3, pp. 343–363.

Wang, W. et al. (2016). “Toward efficient team formation for crowdsourcing in noncooperative social networks”. In: *IEEE transactions on cybernetics* 47.12, pp. 4208–4222.

Yildirim, P. et al. (2021). “Pairwise Fairness for Learning-to-Rank”. In: *Proceedings of the 14th ACM International Conference on Web Search and Data Mining (WSDM ’21)*. ACM, pp. 793–801.

Yilmaz, M., A. Al-Taei, and R. V. O’Connor (2015). “A machine-based personality oriented team recommender for software development organizations”. In: *Systems, Software and Services Process Improvement: 22nd European Conference, EuroSPI 2015, Ankara, Turkey, September 30–October 2, 2015. Proceedings 22*. Springer, pp. 75–86.

Yorges, S. L. (n.d.). “The Impact of Group Formation and Perceptions of Fairness on Organizational Citizenship Behaviors 1”. In: *Journal of Applied Social Psychology* 29(7) ().

Zhang, L. et al. (2020). “Multi-Objective Optimization for Fair Recommendation”. In: *Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR ’20)*. ACM, pp. 1173–1176.

Žliobaite, I. (2017). “Measuring discrimination in algorithmic decision making”. In: *Data Mining and Knowledge Discovery* 31.4, pp. 1060–1089.