Systematic Literature Review on the Team Formation Problem

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The success of any team project is heavily influenced by its effective formation. However, assembling teams requires careful consideration and is often time-consuming due to the high number of aspects that must be taken into account such as candidates' background, skill sets and other relevant attributes. The focus of this research is the Team Formation Problem (TFP) which is of critical importance to modern society. It is a complex issue which aims to allocate people from a large set of potential candidates to form an effective team. This study aims to perform a Systematic Literature Review (SLR) to identify and classify the most commonly used optimization techniques based on their application domains (e.g., education, sports, healthcare). Additionally, it contributes to the field by providing a taxonomy of these optimization techniques and algorithms. In this review, 3539 papers were retrieved from the Scopus and Web of Science databases. After duplicate removal, initial screening and eligibility assessment, 405 papers were reviewed and classified. The findings revealed that **(1)** the most used optimization techniques are Genetic Algorithms (GA) applied in 23% of the cases, followed by Greedy-based algorithms (9%) and Integer Linear Programming (ILP) approaches (8%). **(2)** The techniques are categorized into three major classes – Exact, Approximation and Hybrid approaches. Additionally, each class is further divided into multiple subclasses, creating a comprehensive taxonomy. **(3)** The most common application domains are General (60.5%) and Education (30.6%) with other domains (Sport, Healthcare, Software development, Game teams) constituting 8.9%.

Additional Key Words: team formation, team composition, group formation, group composition, heuristic, metaheuristic, optimization, algorithm, exact algorithm, approximation algorithm, systematic literature review

1 INTRODUCTION

Forming effective teams plays a vital role in the success of every project or task. A recent study suggests that effective team composition contributes to increased productivity, motivation, work satisfaction and positively impacts project success [221]. It is a complex topic, fundamental in many areas of our society such as education, healthcare, sports, software projects and everywhere where groups are composed to solve a certain task. Unfortunately, teams often do not perform as expected despite the best efforts of their members. Numerous factors may lead to unsuccessful projects, including lack of communication, disagreement, improper knowledge aggregation, unclear goals and poorly defined roles and responsibilities [221].

The Team Formation Problem (TFP) is a complex optimization problem which aims to form effective groups while considering many factors. To begin with, it is complicated to define what an effective team in any given context. For instance, in some projects, maximizing the aggregate prior knowledge (team skill set) might be a priority, while in others, minimizing the chance of conflicts or increasing adaptability might be the main concern. Depending on the task, one might be interested in composing heterogeneous or homogeneous teams based on various attributes such as demographics, Belbin roles, previous performance, or personality traits. Furthermore, scalability adds another layer of complexity to the TFP. For smaller pools of available candidates, we simple techniques or even manually team formation might suffice. However, as the size of available candidates or the number of constraints increases, the computational complexity also increases, making the TFP an NP-hard problem, which cannot be solved in polynomial time.

Numerous solutions exist for the TFP from basic brute force algorithms to complex metaheuristics. Popular algorithms include Particle Swarm Optimization (PSO), Genetic Algorithms, Greedy Algorithms, Integer Linear Programming, Dynamic Programming, Simulated Annealing, Hill Climbing, and many more.

This research aims to contribute to the field of team formation by classifying the most applied optimization techniques that solve the TFP based on their approach (exact, approximation, hybrid) and application domain (e.g. education, sports, healthcare). Despite the emergence of numerous studies over the past two decades, the results are so varying that we still do not have a clear and composite view of the existing literature. By synthesizing and evaluating the literature, this review highlights the most effective and commonly used techniques available. Moreover, the classifications provide by this literature can help professionals select suitable algorithms for their projects or tasks based on the application domain.

To achieve these goals, the paper focuses on the following research questions:

RQ1: What are the most used optimization techniques or algorithms applied in the field of the Team Formation Problem (TFP)?

Sub-RQ1.1: How can these techniques be classified?

RQ2: In which application domains are the techniques identified in RQ1 mostly applied?

The rest of this paper is organized as follows: Section 2 describes the methodology applied during this review, including the risk of bias assessment. Section 3 reports the results of the systematic literature review and answers the research questions. It contains a taxonomy of the most used optimization techniques and concludes by highlighting some points for the top three most applied algorithms. Finally, section 4 proposes some future directions and discusses the limitations, while section 5 draws the conclusion.

2 METHODOLOGY

This review follows the guidelines of the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) methodology for systematic reviews and analysis. PRISMA allows researchers to systematically reproduce this work, verify the results, and use it as a foundation for other studies [125]. The following section details all the steps taken during the research and concludes with an assessment of the risk of bias.

2.1 Information Databases and Research Criteria

For this review, the Scopus and Web of Science databases were chosen due to their extensive collection of peer-reviewed, high-quality literature across various disciplines.

2.1.1 *Inclusion and Exclusion Criteria*

IC1: Only peer-reviewed articles, conference papers, reviews and book chapters are included.

IC2: Only papers written in English are included.

IC3: No specific date range is utilized.

To create a comprehensive literature review that can serve as a foundation for future work, no specific date range was applied. Additionally, to answer RQ1, the author is interested in the most applied optimization techniques used to solve the TFP since its inception. This approach will show how techniques have evolved and the direction in which the field is moving.

2.2 Search Formula

The search was conducted in April 2024 in both databases using the string shown in Table 1. Papers that only focus on reviewing the team formation literature are not of interest. Therefore, an additional search condition was introduced to limit the scope to records containing optimization techniques or algorithms. As this paper aims to provide an extensive review regardless of the application domain, readers who wish to narrow the research to a specific domain should add an additional category to the search formula.

Table 1. Key words and search formula

Category	Synonyms
Team Formation	team formation, team composition, team forming, formation of team, group formation, group composition, group forming, formation of group
Algorithm	algorithm, exact algorithm, optimization, optimization, heuristic, metaheuristic, local search, operations, research, MILP, Mathematical Model, ILP, combinatorial optimization, linear programming, integer programming, mathematical programming, game theory, algorithmic framework, decision support, search, optimization model, optimisation model, approximate approach, approximate algorithm, decision-making
Search formula	
("team formation" OR "group formation" OR "team composition" OR "group composition" OR "group forming" OR "team forming") AND ("algorithm*" OR "optimization" OR "heuristic*" OR "metaheuristic*" OR "meta-heuristic*" OR "local search" OR "exact algorithm" OR "MILP" OR "Mathematical Model" OR "ILP" OR "optimisation" OR "operations research" OR "combinatorial optimization" OR "linear programming" OR "integer programming" OR "mathematical programming" OR "game theory" OR "algorithmic framework" OR "decision support" OR "search" OR "optimization model*" OR "optimisation model*" OR "approximate approach*" OR "approximate algorithm*" OR "decision-making")	

2.2.1 *Refinement of the Search Formula*

To ensure the effectiveness of the search formula, a simple and highly effective strategy was employed. A "gold list" of highly relevant articles that cover the aspects of the research question was manually created. The author searched for papers containing the term "Team Formation Problem" on Google Scholar. After reviewing the first few pages of results, 18 admissible papers were added to the list. Next, the formula was tested in Scopus and Web of Science simultaneously. After careful refinement, the string shown in Table 1 was chosen. It successfully retrieved 72% of the highly relevant articles from the gold list, demonstrating the formula effectiveness. Additionally, it retrieved 2107 records in Scopus and 1432 in Web of Science, which was sufficient given the time limits of this paper.

2.3 Papers Selection

The following section outlines the inclusion and exclusion criteria for each stage of the PRISMA methodology. It describes the process of paper selection during the Identification, Screening and Eligibility stages.

2.3.1 *Duplicates Removal*

A total of 3539 papers were retrieved and combined from Scopus and Web of Science. Duplicate records were removed according to the following exclusion criteria:

EC1: If two records are duplicated, the one from Scopus is removed.

EC2: If two records from the same database are present, the newly published one is excluded.

2.3.2 *Screening*

After duplicates were removed, a total of 2374 unique papers (from the year 1971 till 2024) were identified for screening based on their title, abstract, and keywords. During this stage, the following exclusion criteria were applied:

EC3: Articles without basic data such as author, year, title, or source are removed (Total = 3).

EC4: Articles with fewer than three author or indexed keywords are removed (Total = 145).

EC5: Articles unrelated to the TFP are removed.

EC6: Articles that do not use algorithms, optimization, or mathematical techniques are also removed.

2.3.3 *Eligibility*

After the screening stage, 519 papers were selected for full-text reading based on following eligibility criteria:

EC7: Systematic literature reviews are excluded.

EC8: Reports that do not use an algorithm, optimization, or mathematical technique to solve the TFP are excluded.

EC9: Articles describing, developing, or reviewing a team formation tool or its user interface are excluded. This criterion also applies to papers that evaluate algorithms of a specific tool (e.g., CATME) but do not describe their attributes, objectives, or functionality.

Table 2. Example of a paper categorization

ID	Title	Technique	Domain
id_1	…	Genetic Algorithm (GA)	education
id_2	…	exact algorithm	general
Id_3	…	DISCARDED - *reason*	

Table 2 above demonstrates how the 519 papers retrieved after the screening stage are categorized in a spreadsheet based on the following criteria:

C1: Optimization technique or Algorithm

C1.1: If an article uses an algorithm to solve the TFP, the name of the algorithm is recorded (e.g., id_1).

C1.2: If the name is unspecified but the (sub)class of optimization technique is mentioned, then the (sub)class is recorded (e.g., id_2).

C1.3: If the paper falls under one of the exclusion criteria EC7 – EC9, it is marked as DISCARDED and a reason is provided.

C2: Domain - Identified application domains for this review include General (not specified), Education, Sport, Healthcare, Software Development, Game Teams, Military and Space (e.g., id_1, id_2).

The full article selection process from retrieval to classification, according to PRISMA guidelines is presented in Figure 1.

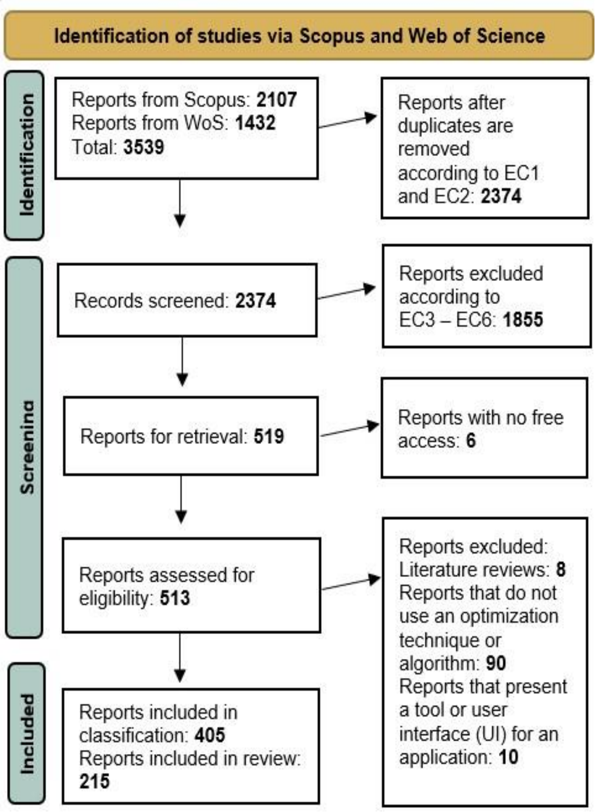

Figure 1. Selection flow adopted by the PRISMA methodology

2.4 Risk of Bias Assessment

Since the screening stage was performed by a single reviewer, there is a risk of bias in this study. To address it, two independent reviewers (including the author) systematically coded the same 75 randomly selected articles following the exclusion criteria EC3 – EC6. The matrix below demonstrates the agreement between the two coders.

The matrix (Table 3) reveals a high prevalence in the data. The high majority (71%) of the papers exhibit the same characteristic - being excluded. Therefore, the Kappa statistic, which measures the interrater agreement between coders might be influenced by this prevalence [216]. Consequently, the Kappa statistic cannot be calculated in this case, as it might lead to misleading results [217].

Table 3. Agreement matrix between the reviewers

	Included	Excluded
Included	17	4
Excluded	1	53

K.A. Hallgren suggests using an alternative to Kappa, called PABAK (Prevalence-Adjusted Bias-Adjusted Kappa) [217]. PABAK accounts for the prevalence in the data and adjusts for bias between reviewers accordingly.

The observed agreement with PABAK is calculated as follows:

$$P_o = \frac{17 + 53}{17 + 4 + 1 + 53} = 0.933$$

$$PABAK = 2 \times P_o - 1 = 0.866$$

As a result, the two reviewers agreed on 86.6% with each other, which significantly reduces the risk of bias.

3 RESULTS

After the eligibility stage, 405 papers (from 1996 to 2024) were successfully classified according to their optimization technique and application domain.

3.1 On Research Question 1

Research Question 1 (RQ1) focuses on the most used optimization techniques and algorithms applied in the field of TFP and their classification. This section begins by addressing Sub-RQ1.1, which is interested in the classification of these techniques and algorithms.

Figure 2 below provides a taxonomy of optimization techniques and algorithms used in the field. These can be divided into three major categories – Exact, Approximation, and Hybrid algorithms.

Exact algorithms: These algorithms are designed to find the best solution to a problem. In comparison to other popular techniques, they exhibit a deterministic nature, which means that they always return the same output for the same input. Given the NP-hardness of the TFP, Exact algorithms are less frequently applied due to being more computationally expensive. This review shows that Approximation algorithms are used four times more frequently than Exact algorithms, as illustrated in Figure 3. Additionally, this

EXACT				Approximation															Hybrid
Mathematicial Programming		Dynamic Programming	Others (Constraint Progr., Goal Progr., etc.)	Heuristic				Metaheuristic										Others	
				Constructive	Improvement		Others	Single			Population-based						Other MHs		
											Evolutionary algorithms			Animal-inspired	Swarm-based				
ILP	Others (INLP, MIP, Binary IP)			Greedy algorithm	Local search	Hill climbing		Tabu search	Simulated Annealing	Neighbourhood search algorithm	Genetic	Cultural	Others		PSO	Others			
32	13	7	11	36	7	5	9	5	9	5	93	3	5	11	13	7	20	28	5

Figure 2. Classification taxonomy per optimization technique

class of algorithms can be further categorized into two main subclasses: Mathematical Programming (MP) and Dynamic Programming (DP). MP includes various types of Integer Programming (IP) such as mixed, linear, non-linear, or binary. Additionally, Exact algorithms can be subdivided into Constraint Programming, Goal Programming, and others.

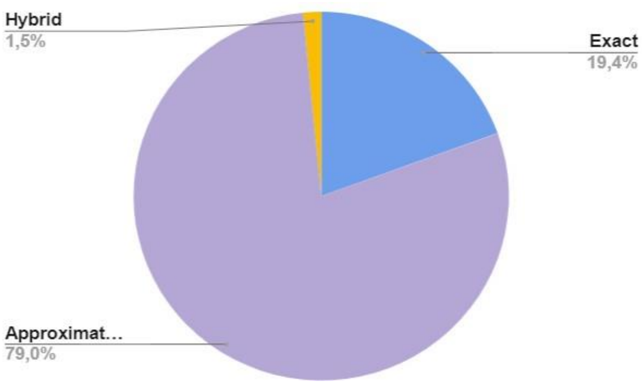

Figure 3. Distribution of algorithms per classes

Approximation algorithms: This is the largest class of techniques used to solve the TFP due their lower computational complexity. Rather than looking for the best solution, Approximation algorithms look for an optimal one. They are non-deterministic and often run in polynomial time, making them preferred in cases with a large pool of possible solutions. As illustrated in Figure 3, 79% of the articles use this type of algorithms. This class can be divided into two major subclasses: heuristics and metaheuristics (MH). Metaheuristics are further categorized into single-solution MH and population-based MH. Single-solution algorithms modify one solution each iteration and aim to converge to a local optimum around this solution [218]. These are suitable single-team formation problems. In contrast, population-based algorithms modify different solutions simultaneously. Even though they converge more slowly than single-solution algorithms, they are more suitable for multi-team formation problems (e.g., project groups in collaborative learning) [218]. Population-based techniques can be further divided into Evolutionary algorithms, where one of the most popular algorithms – the Genetic Algorithm – resides, Swarm-based or Animal-inspired algorithms such as Ant Colony Optimization (ACO), Bee Colony Optimization (BCO), and Crow Search Algorithm (CSA).

Hybrid algorithms: This class refers to algorithms that combines elements of Exact and MH or different MH techniques. For instance, [219] proposes a hybrid Particle Swarm Optimization – Genetic Algorithm (PSO-GA) approach. The evaluation of this algorithm demonstrates its effectiveness and suitability for heterogeneous groups.

Out of the 405 papers that passed the eligibility criteria and were selected for classification, 324 articles were successfully categorized according to the taxonomy provided in Figure 2. The remaining 81 papers did not specify the names for their algorithms or a classification. As a result, one limitation of this review is the inability to further classify these papers. In order to keep the review consistent and accurate, and due to time constraints and inexperience in the field, the author has chosen not to categorize these papers.

Table 4 provides a list of the top eight most frequently used techniques for solving the TFP, including references to the papers that applied them. Additionally, the Genetic Algorithm, which appears in 93 articles (roughly 23% of all eligible papers), is further divided into articles about the Non-dominated Sorting Genetic Algorithm II (NSGA-II) or novel modifications like the Enhanced Genetic Grouping Algorithm [28], Improved Adaptive Genetic Algorithm (IAGA) [35], and GA-enabled Insert Virtual Members (IVMGA) algorithm [38]. For additionally details on the most used techniques within each (sub)category, the reader can refer to Figure 2. Notably, the top eight algorithms shown in Table 4 are used in more than half (53.6%) of all reviewed articles.

3.2 Most Used Optimization Techniques

3.2.1 Genetic Algorithm

The Genetic Algorithm (GA) is a well-known metaheuristic used to generate quality solutions to various search and optimization problems [23]. Inspired by the natural selection and genetics, the algorithm begins by generating an initial population of solution, also called chromosomes. Each chromosome is assigned a fitness value based on how effectively it solves the problem. The higher the value, the higher the chance for it to be selected [23]. After a fitness value is associated with each chromosome, the algorithm selects parent chromosomes to create offspring. This is followed by the crossover operation, where genes from parent chromosomes are recombined to produce new solutions. Finally, the mutation operation alters random genes in chromosomes to maintain diversity and explore the solution space [23]. According to the result of this systematic literature review, the Genetic Algorithm and its variations are the most used optimization techniques in the field of team formation. Its robustness to change makes it suitable for dynamically changing teams [25]. Its ability to explore the research space over time without getting stuck in a local search makes it ideal for adaptive team formation

Table 4. Grouping of articles based on their optimization technique

№	Optimization technique or algorithm	Total	References
1	Genetic algorithm (GA)	58	[14 – 18, 20 – 22, 24, 27, 31 – 33, 36, 37, 41 - 44, 46, 48 – 53, 55, 57 – 59, 61, 64, 66, 68, 69, 71, 72, 76, 77, 79 – 81, 83, 85, 89, 90, 93 - 106]
1a	Variations of GA	21	[19, 23, 28, 35, 38, 40, 42, 45, 47, 54, 56, 63, 65, 70, 73, 75, 78, 86, 87, 88, 92]
1b	NSGA-II	14	[25, 26, 29, 30, 34, 39, 42, 60, 62, 67, 74, 82, 84, 91]
2	Greedy-based algorithms	36	[105, 152 – 187]
3	Integer Linear Programming (ILP)	32	[83, 107 – 124, 126 - 133, 205 - 209]
4	Clustering algorithms	18	[148, 188 - 204]
5	Particle Swarm Optimization algorithm (PSO)	13	[1 – 13]
6	K-means clustering algorithm	9	[140 - 148]
7	Simulated Annealing	9	[22, 134 – 139, 150, 151]
8	Dynamic programming	7	[179, 210 - 215]

problems [25, 35]. Moreover, with control over mutation and crossover, the GA effectively forms both homogeneous and especially heterogeneous groups [52].

3.2.2 Greedy Algorithm

Greedy algorithms are the second most frequently used optimization technique, taking around 9% of the share. These algorithms build the solution each iteration, making the most beneficial choice at each step without considering the global problem. Furthermore, they exhibit a lower computational complexity since the current solution is focused only on the local optimum. Due to their simplicity and lower computational cost, greedy algorithms are often preferred for problems involving large datasets [222].

3.2.3 Integer Linear Programming (ILP)

According to the results of this review, ILP ranks third among the most used optimization techniques, with a 1% difference in shares compared to Greedy algorithms. ILP is a type of mathematical programming used to find the best solution given some constrains. All variables must be integers, and the objective function linear. Although ILP can accommodate various objectives and is suitable for complex TFPs, it is an exact approach which aims to find the best solution, making it computationally expensive [220].

3.3 On Research Question 2

The last research question (RQ2) focuses on identifying the application domains where the techniques from RQ1 are mostly applied. This review identified six primary application domains: General, Education, Healthcare, Sport, Software Development, and Game teams. As expected, most papers use optimizations for general team formation no matter the domain. The education field follows, comprising a significant 30.6% of all papers. This domain includes teams in higher education, pre-higher education, various learning contexts, and any kind of teams formed for educational purposes. After Education, Software Development and Sport and the next most frequently occurring domains with shares of 3.2% and 2.5%, respectively. Figure 4 below illustrates the distribution of papers per context. The following results are not surprising, as effectively forming educational teams promotes collaboration and knowledge sharing. Successful groups formed in an educational context are of crucial importance to the society.

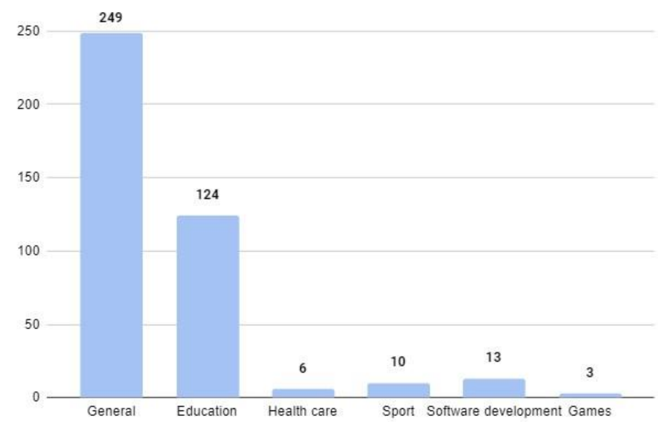

Figure 4. Distribution of papers per application domain

3.4 Reviewing Some Relevant Papers in the Field

Table 5 provides information from some highly relevant papers on the top three most frequently used optimization techniques – Genetic Algorithm, Greedy algorithm and ILP. This table aims to offer a comprehensive understanding of the field by presenting examples and comparing different approaches.

One key finding related to the Genetic Algorithm is that all three selected papers apply it within the educational context, reinforcing the results of RQ2 that education is the most frequently addressed *specific* application domain. Interestingly, although all three articles apply the GA, they modify different aspects of it to achieve different objectives. For instance, [23] modifies the mutation function, [15] alters the crossover function, while [19] introduces an additional penalty function, which is not a standard component of the GA. These modifications allow the GA to target different objectives or group types.

Furthermore, the greedy algorithms proposed in these papers select one expert at each iteration. They build the team iteratively based on the most beneficial choice at each step, without considering the global problem. In both cases, the objective is

Table 5. A comprehensive review of some highly relevant papers for the top three most frequently used algorithms

Title and reference	Short description of the algorithm	Team type & Experiment	Main findings (Strengths and Weaknesses)
Genetic Algorithm			
An improved Genetic approach for composing optimal collaborative learning groups [23]	The paper proposes an Improved GA by implementing a second mutation operation and elitist strategy. The elitist strategy ensures that the best chromosomes always propagate to the next generation. On the other side, the second mutation ensures higher diversity of the population.	Team type: Heterogeneous, homogeneous, mixed and balanced Groups Experiment: Empirical study and Simulation	The result from the empirical study indicate that the algorithm outperforms other methods such as random selection or self-selection, in terms of group and individual grades as well as student satisfaction. The proposed method is stable and meets all group requirements. Moreover, the simulation is run 10 times across 8 databases, successfully finding solution for each database within a reasonable time frame. However, the computational complexity increases with the problem size, limiting its scalability to no more than 180 students.
A genetic algorithm approach for group formation in collaborative learning considering multiple student characteristics [15]	The article proposes a versatile algorithm that can work with an unlimited number of characteristics of various types (e.g., demographic, cognitive). It employs a modified crossover operation with multiple random crossover points.	Team type: Inter-homogeneous and intra-heterogeneous groups Experiment: Empirical study	The results of the study suggest that the algorithm outperforms other generic approaches in terms of average grades of both collaborative activities and individual exams. The results indicate that the algorithm effectively creates heterogeneous groups which can collaborate successfully. However, it does not outperform other exhaustive approaches when the number of characteristics or students is small.
An optimized group formation scheme to promote collaborative problem-based learning [19]	The algorithm proposed in this study accounts for the heterogeneity of students' knowledge and learning roles, and the homogeneity of their social interactions. It incorporates a penalty function that considers imbalances in the fitness function.	Team type: Heterogeneous Groups Experiment: Empirical study and quasi-experimental research	The result of the study demonstrates that the algorithm effectively forms collaborative groups based on students' knowledge level, learning roles, and existing social interactions. Additionally, while the algorithm outperforms random group formation, there is no significant difference compared to a self-selection approach. The experiment was conducted for a short period and therefore, the algorithm's effectiveness may not extend to long-term collaborative groups.
ILP			
Synergistic team composition: A computational approach to foster diversity in teams [108]	The ILP algorithm is effective for forming small synergistic teams, with the objective of creating teams that are diverse in gender and personality while covering all required skills.	Team type: Heterogeneous and balanced Teams Experiment: Simulation	For small instances of the problem, it is computationally efficient and can satisfy all constraints. However, one limitation is that this ILP algorithm does not scale well for larger instances of the problem, such as teams with more than three people.
Group Optimization to Maximize Peer Assessment Accuracy Using Item Response Theory [115]	The algorithm utilizes team formation based on Item Response Theory to enhance the accuracy of peer assessment. Additionally, it incorporates external raters to further improve the accuracy of the results. The algorithm considers five constraints and aims at maximizing the lower bound of the Fisher information for each learner.	Team type: Depends on the objective Experiment: Simulation	Without the external rater selection model, the algorithm cannot increase the peer assessment accuracy and fails to meet its objectives. However, introducing the model significantly enhances assessment accuracy. The experiment is run ten times with varying number of external raters, demonstrating that the accuracy improves as more raters are added.

Greedy algorithm			
T-shaped grouping: Expert finding models to agile software teams retrieval [155]	The algorithm selects the best candidate at the *i*-th iteration who possesses the *i*-th required skill. It is designed for T-shaped experts, who are experts in one required skill and have a general knowledge in other necessary skills. The algorithm proposes two models – one based on the StackOverflow profiles of the candidates (XEBM), and one based on their skill sets (RDM). These models are particularly suitable for forming agile teams.	Team type: Depends on the objective Experiment: Simulation	Both greedy algorithms were tested against three other baseline algorithms. The results indicate that the proposed models outperform the baseline methods. Although the XEBM performs significantly worse than the RDM model, it still runs better than the baseline algorithms. In contrast, RDM algorithm surpasses in over 78% of the cases the comparison algorithms.
Profit maximizing Cluster Hires [153]	The article proposes two greedy algorithms that select individuals one at a time while aiming to satisfy the budget constraint, maximize the profit, and achieve the objective. Both proposed algorithms allow adjustments to how many times an expert.	Team type: Depends on the objective Experiment: Simulation	The algorithms were tested with data from two large datasets, each iteration under varying budget constraints. Both algorithms outperform competitors with a $200 budget constraint, where the maximum is $1000. However, beyond a certain threshold of budget constraints and profit, the algorithms become

creating one team. This approach is the standard for greedy algorithms, which focus on local optima and are therefore more suitable for single-team formation problems. In contract, Genetic Algorithms, as population-based metaheuristics, are ideal for problems involving the formation of multiple teams. This is why the authors of [15, 19, 23] went for GAs rather than greedy-based approaches multiple-team formation problems.

4 LIMITATIONS AND FUTURE DIRECTIONS

Out of the 405 papers that passed the initial eligibility criteria, 81 did not specify the names or classification of their algorithms. As a result, one limitation of this review is the inability to further classify these papers. To maintain consistency and accuracy, and due to time constraints and limited experience in the field, the author chose not to categorize these papers. This resulted in 20% of all reviewed articles being unclassified, which might have an influence on some of the reported statistics.

There are several future directions that could extend the scope of this study. First, another literature review can be conducted focusing on the attributes used in the specified optimization techniques. While reading the papers, the author observed various attributes such as skill set, preferences, personality traits, Belbin roles, experience, past collaborations, workload, salary, past performance, demographics, academic grades, location, rank, level of expertise, and education level. This is a small example of all possible attributes that can be used to form teams. It would be worth identifying which attributes are mostly frequently used in different techniques or application domains. This could help professionals select the most appropriate algorithm for their project or task based one the application domain and attributes at hand.

Another direction could involve extending the taxonomy from Figure 2 to include a broader range of algorithms such as Bee Colony Optimization (BCO), Ant Colony Optimization (ACO), Firefly Algorithm, Sine-cosine Algorithm, Artificial Neural Networks, Hill Climbing Algorithm, Local Search algorithm, Hungarian algorithm, Branch and bound algorithm, Tabu Search, and many others observed during this study.

A third, more interesting future direction would explore how Artificial Intelligence (AI) and Machine Learning (ML) are used in the field of TFP and what optimization techniques are proposed. As AI has gained more popularity in recent years, it could play a crucial role in team formation in the near future.

Finaly, another study could be done focusing exclusively on TFP in higher education. As the results showed, around 30% of the papers focused on algorithms used to form learning teams, highlighting the importance and relevance of this application domain.

5 CONCLUSION

The focus of this research is the Team Formation Problem (TFP), which is critically important for our society. The TFP is a complex optimization problem, which aims at forming effective groups while considering various factors. The aim of this paper was to conduct a Systematic Literature Review (SLR) to identify the most frequently used optimization techniques and classify them based on their application domain.

In summary, a taxonomy table was provided in Figure 2, demonstrating how the most used optimization techniques in team formation can be classified. Three major categories were identified: Exact, Approximation and Hybrid algorithms, each divided into subcategories. For each subcategory, examples are provided, along with the total number of papers found.

Furthermore, a comparison between different (sub)categories explains why certain algorithms are preferred in specific situations. The top eight most used optimization techniques were identified. The main takeaway of this review is that the Genetic Algorithm has been used in roughly 23% of all reviewed articles, making it the most frequently used technique overall. It is followed by Greedy-based algorithms (9%) and Integer Linear Programming (ILP) approaches (8%). Another important finding is that the most common application domains are General (60.5%) and Education (30.6%) with other domains (Sport, Healthcare, Software development, Game teams) barely constituting 8.9%.

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