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REVIEW ARTICLE

# Competency and collaboration based project team selection: A systematic and methodological literature review

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## Abstract

Size, diversity, competence and cooperation ability of members affect the performance of a project team and thus the success of the project. This article aims to critically review the quantitative and scientific characteristics of the literature on the project team selection problem and to identify the gaps in considered attributes and selection methods for further studies. This review differs from other review studies on project team selection in terms of scope, time horizon, selection criteria and inclusion of bibliometric analyses. 45 publications about the project team selection are selected to review within more than 15,000 ones in June 2024. A five-stage systematic method— including scanning related keywords in databases, setting time period, skimming titles, skimming abstracts with introduction and conclusion parts of the studies and sample selection ensuring uniform representation— is used to identify these studies. Then, the bibliometric data of these publications are analyzed before scientific analyses of the selected publications. It is detected that there is an increasing trend in the number of studies conducted in this field as well as the number of citations to them. It is also observed that mathematical optimization methods are used for small datasets and few constraints, whereas multicriteria decision making, data mining/machine learning and (meta)-heuristic methods are preferred as complexity increases and nonlinearity emerges. In conclusion, there is a need for a comprehensive team selection model considering technical and soft skill requirements with salary and communication costs together. Complexity, accuracy and precision analyses should also be performed to ensure the performance of the proposed model.

## 1. Introduction

Project is defined as a group of interconnected or interrelated activities that must be carried out together in a certain period to achieve a certain purpose and to create innovation [1]. The success of a project is related to the effective and efficient management of its three main elements: time, cost and scope [2, 3]. In this direction, effective management of limited resources–including infrastructure, machinery-equipment, materials and human resources–stands out as a way to reduce costs and increase project efficiency.

A project that is completed on time and within the planned budget, where the expected outputs are achieved and the project team completes the

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process with satisfaction is considered a successful project. All these success criteria are directly related to the performance of the project team. The performance of a project team is directly related to its size, as well as the diversity, competence and collaboration ability of its members.

A project can involve a single person or thousands of people and can be carried out by a single organization or with the joint initiative and cooperation of more than one organization. The correct selection of a project team has vital importance in achieving a project's goals and completing it successfully [3, 4].

Assigning people who provide the necessary competencies does not ensure efficiency and desired quality. To address these issues, people assigned to a team should focus on a common goal and work collaboratively with adequate communication. A good team should not only collect but also integrate the knowledge, competency and skills of its members with a synergy.

The purpose of this article is to review previous scientific studies on the problem of project team selection, to examine the quantitative characteristics of the literature in this field with a critical review of related studies and to identify the current situation and gaps in the literature in this field. By examining the current situation of the literature on this subject with a critical review, future research directions to address existing problems can be proposed. With this article the following research questions could be answered:

- In the literature, how frequently has the project team selection problem been studied?
- How qualified are the studies in the literature on the project team selection?
- In the literature, which methods have been used for project team selection problems?
- In the literature, which attributes have been considered to select a project team?

There are limited literature review studies on project team selection. Costa et al. [5] reviewed 51 studies on software project team selection between 2001 and 2018. They analyzed the objective, method and attributes used in the studies selected via the snowballing procedure. Vishnubhotla et al. [6] reviewed 16 studies published between 2001 and 2016 in terms of attributes considered to form an agile software team and Cunha et al. [7] extended this study to the period 2001-2022 considering 18 studies. Zainala et al. [8] also reviewed the literature with the snowballing method to identify attributes that are vital for agile software project teams for the period of 2007-2019 considering 40 studies. Our study differs from all these in terms of the scope, time horizon, selection criteria and inclusion of the bibliometric analyses.

In the following sections of the article, first, the methodology of the literature review followed for this article is summarized. It includes the method of identifying studies on project team selection and how to select the publications to be examined in detail. Second, analyses regarding the bibliometric properties of the publications to be examined within the scope of this article are be shared. In the following section, the methods applied for project team selection with the parameters used and the results of related studies in the literature are reviewed. In the last section, the reviewed findings are discussed in terms of applied methods, considered attributes, etc. The article concludes with gaps in the literature and suggestions for future studies on this subject to solve unsolved problems.

## 2. Review Methodology

A systematic 5-stage method was applied to scan the studies on project team selection in the literature and to select those which will be reviewed in detail. These stages are summarized in Fig. 1. The search study was done in June 2024.

At the first stage, the keywords in Table 2 were scanned in the titles, abstracts and keywords of the English and Turkish publications listed in the databases given in Table 1. Staffing was not included in the keyword list since it is mostly used in scheduling studies and this makes eliminating the irrelevant studies difficult. As a result of the scanning, more than 15,000 publications containing relevant keywords were found.

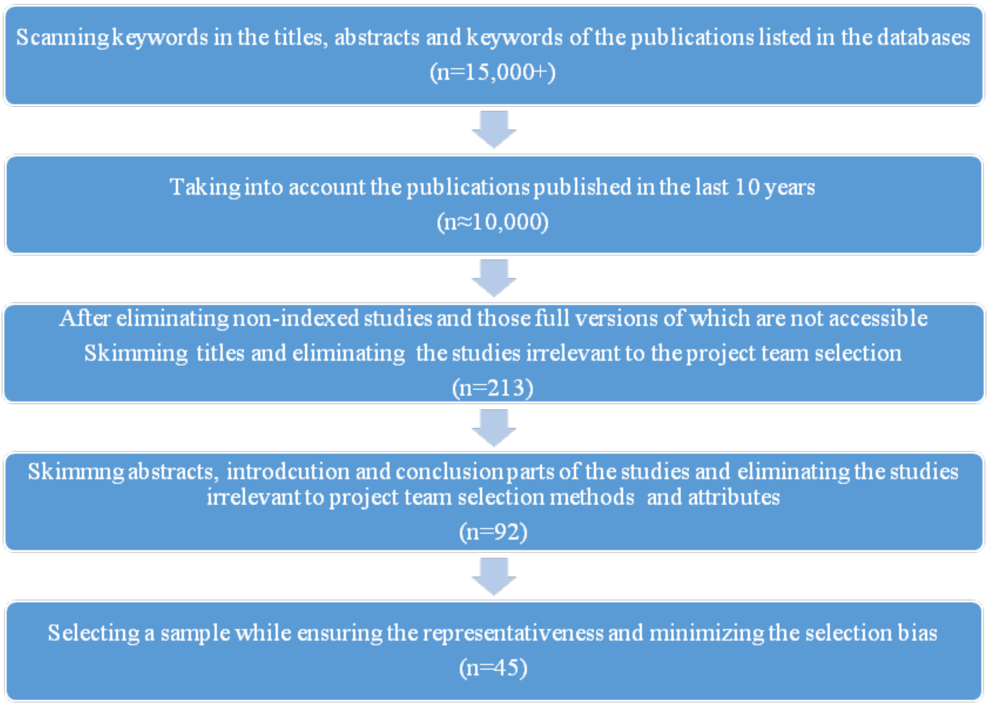


Fig. 1. Representation of the review methodology

Table 1. Databases used for the literature review

| Database | Url |
|---|---|
| Web of Science | https://www.webofscience.com/wos/woscc/basic-search |
| Scopus | https://www.scopus.com/search/form.uri#basic |
| Science Direct | https://www.sciencedirect.com/search |
| IEEE | https://ieeexplore.ieee.org/search/advanced |
| Springer Link | https://link.springer.com/advanced-search |

Table 2. Number of publications including scanned keywords

| Keywords | Number of Publications | | |
|---|---|---|---|
| | All | Last 10 Years | Last 5 Years |
| project team selection | 3850 | 2040 | 1035 |
| project team formation | 2400 | 1780 | 780 |
| project team building | 7450 | 4450 | 2450 |
| project team composition | 1450 | 1090 | 565 |

Approximately 10,000 of the publications listed in stage 1 were published within the last 10 years while 5,000 of them were published within the last 5 years. At the second stage, publications older than 10 years were eliminated and those published between 2014 and 2023 were chosen.

At the third stage, after exclusion of the non-indexed studies and those full versions of which are not accessible, the titles of the publications were skimmed to eliminate the ones not directly relevant to the project team selection. 213 publications were selected for further skimming.

At the fourth stage, the abstract, introduction and conclusion parts of the 213 publications selected in the previous stage were read for deeper skimming. Then, 92 publications decided to be directly related to the review scope were chosen as the universe.

As the final selection stage, a sample was chosen from the universe. The selected sample was provided to represent the distribution of the universe in terms of quality, publication year and publication type. The h-index values and Q- factors of the journals, number of citations, average h-indexes of the authors, etc. were considered as quality factors. 45 studies were selected within the 92 studies to allow for a more in-depth review. To preserve the representativeness of the sample and minimize selection bias, a stratified sampling method was employed, with publications drawn in equal proportions from strata defined by publication year, quality level, and sector. The unselected 47 studies have similar features in terms of quality, publication time, sectoral distribution etc. Thus, omitting these studies does not negatively affect how well the article reflects the status of the project team selection issue in the literature.

In conclusion, 45 publications listed in Table 5 were selected for deep analysis within the scope of this article. However, other studies are also cited in various sections of this article.

## 3. Bibliometric Analyses

To reveal the current status and development of the literature on the project team selection problem, bibliometric analyses of the 45 publications selected to review in this article were performed.

Among these 45 publications, 31 are peer-reviewed and indexed journal articles, while 14 are proceedings presented at various national/international congresses/conferences. The distribution of these papers concerning their publication year is shown in Fig. 2. While the number of papers on project team selection increased until 2019, a sudden and serious decrease was observed in 2020. Although statistical testing on the reasons for this decline in 2020 is beyond the scope of this study, it might be due to the COVID-19 pandemic, which has resulted in deceleration of various areas globally. In fact, the number of publications started to increase again after 2020.

Articles comprising 31 of the 45 publications were from 27 different peer-reviewed and indexed journals published in 10 different countries. The countries of these journals can be seen in Table 3. On the other hand, conference proceedings were presented at 14 different congresses/conferences, which occurred in 12 different countries. This information is listed in Table 4. Moreover, the distribution of journal articles and conference proceedings with respect to publishers is given in Fig. 3. Nearly all of the conference proceedings were obtained from IEEE. Similarly, IEEE is seen as one of the main publishers of the journals with Springer and Elsevier.

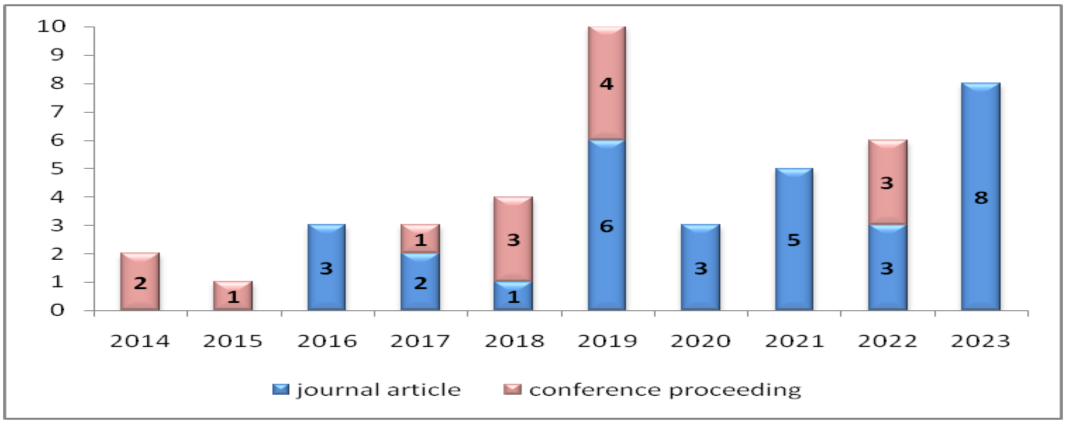


Fig. 2. Publication type and year distribution of the literature on project team selection

Table 3. Countries in which journals of articles were published

| | | | | |
|---|---|---|---|---|
| Austria | Brazil | Germany | International | Netherland |
| 1 | 1 | 1 | 1 | 4 |
| Switzerland | Türkiye | Ukraine | UK | USA |
| 4 | 1 | 1 | 13 | 4 |

Table 4. Countries in which conference proceedings were presented

| | | | | | |
|---|---|---|---|---|---|
| Bahrain | Dubai | Greece | Indonesia | New Zealand | Spain |
| 1 | 1 | 1 | 2 | 1 | 2 |
| Sweden | Panama | Taiwan | Thailand | Türkiye | Ukraine |
| 1 | 1 | 1 | 1 | 1 | 1 |

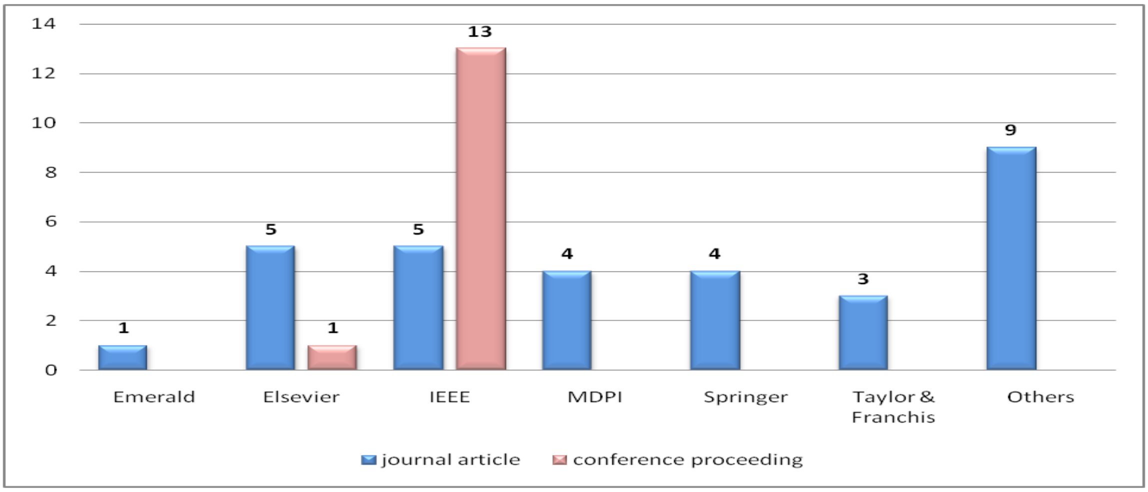


Fig. 3. Distribution of the studies related to project team selection according to their publishers

There are 144 different authors of the 45 publications selected for review. Only 8 of these researchers are authors of more than one publication. Moreover, the majority of the publications have two, three, or four authors (Fig. 4). While there are only 2 single-authored articles, the publication with the highest number of authors is an article with 9 authors. For conference proceedings, on the other hand, the maximum number of authors is 5. This situation indicates that studies on the project team selection problem are also carried out collaboratively with a team. Considering the project nature of the publications reviewed here, the formation of the teams involved in writing these publications can be considered as an example of the project team selection problem.

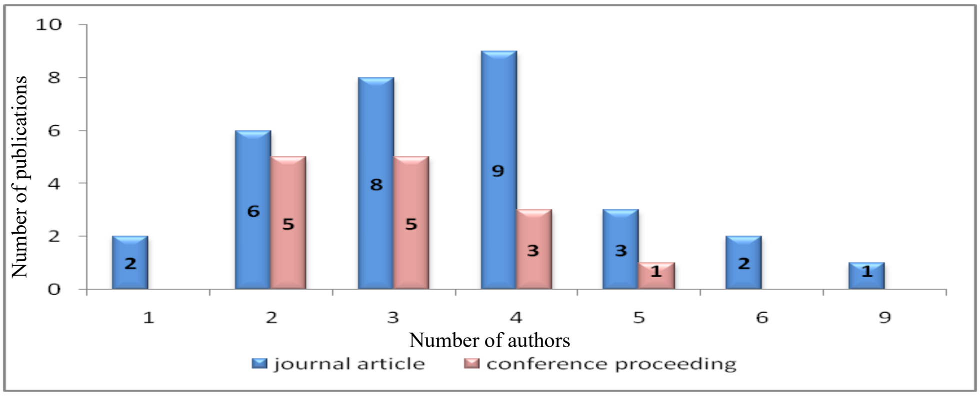


Fig. 4. Distribution of publications with respect to the number of authors and publication type

To analyze the expertise and competence of the authors producing selected publications, their h-index, which sheds light on the productivity of these researchers and the impact of their publications, is used. The h-index of these 144 researchers ranged from 0-34 and the average h-index was 7.88. Indeed, the majority of h-indexes are under 10, even under 5. Additionally, authors with no cited publication or only one cited publication constitute approximately 25% of all authors (Fig. 5). The average author's h-index value for each publication is also examined. It differs from 1 to 18, but is mostly in the range of 4-7, as shown in Fig. 6. When this situation is compared with the individual h-indexes of authors given in Fig. 5, it is inferred that highly productive and experienced researchers collaborate with those being new in the area with fewer publications and citations.

Fig. 7 shows that approximately 40% of the articles have been cited more than 5, whereas 20% of them have been cited more than 10. Nearly all proceedings, on the other hand, have been cited fewer than 5. Moreover, 11 of the 45 selected publications remain uncited. However, most of them are new ones published after 2020, as shown in Fig. 8. In addition, Fig. 8 shows that, in general, the number of citations to the publications produced in recent years is less than 5. Considering future studies which will refer to past ones, especially the recent ones, it is expected that the number of citations to the recent studies will increase over time.

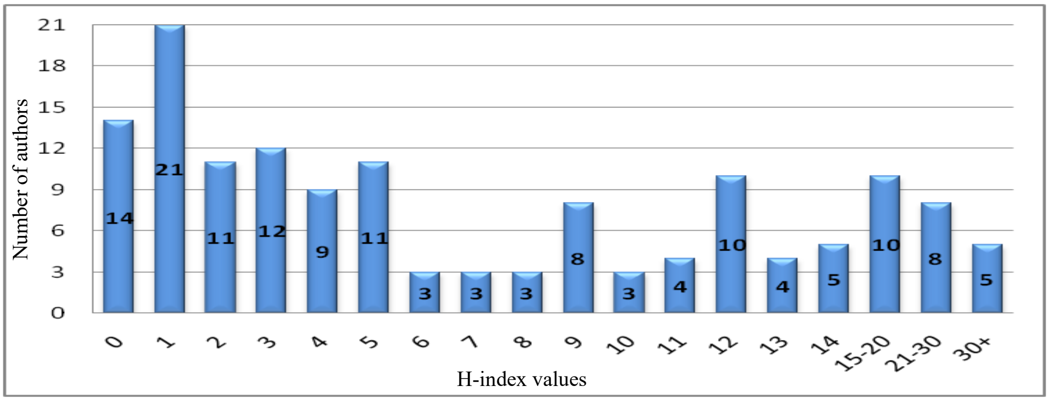


Fig. 5. Distribution of authors with respect to their h-index

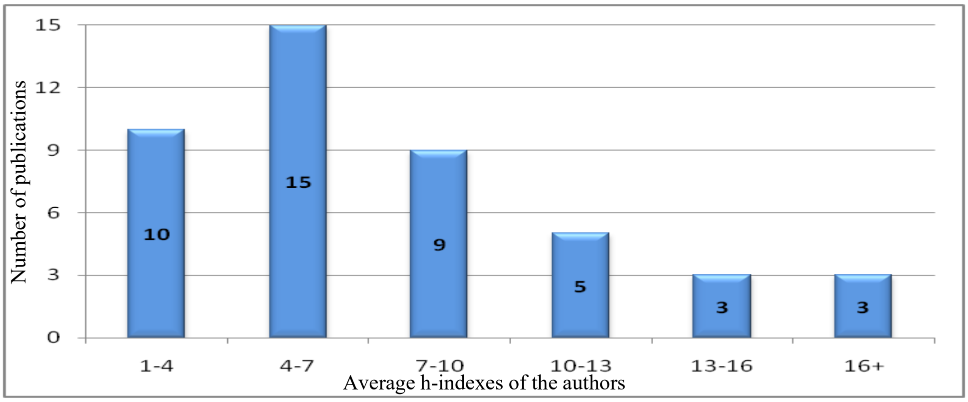


Fig. 6. Distribution of publications with respect to the average h-index of their authors

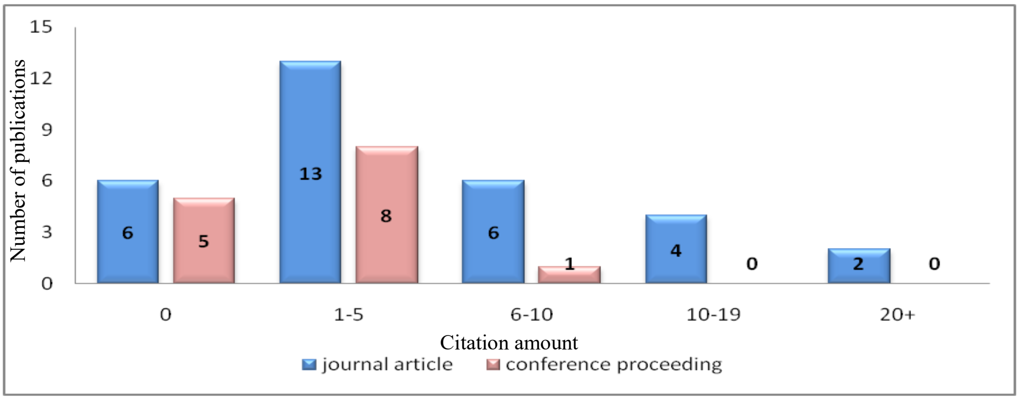


Fig. 7. Citations for the literature on project team selection with respect to publication type

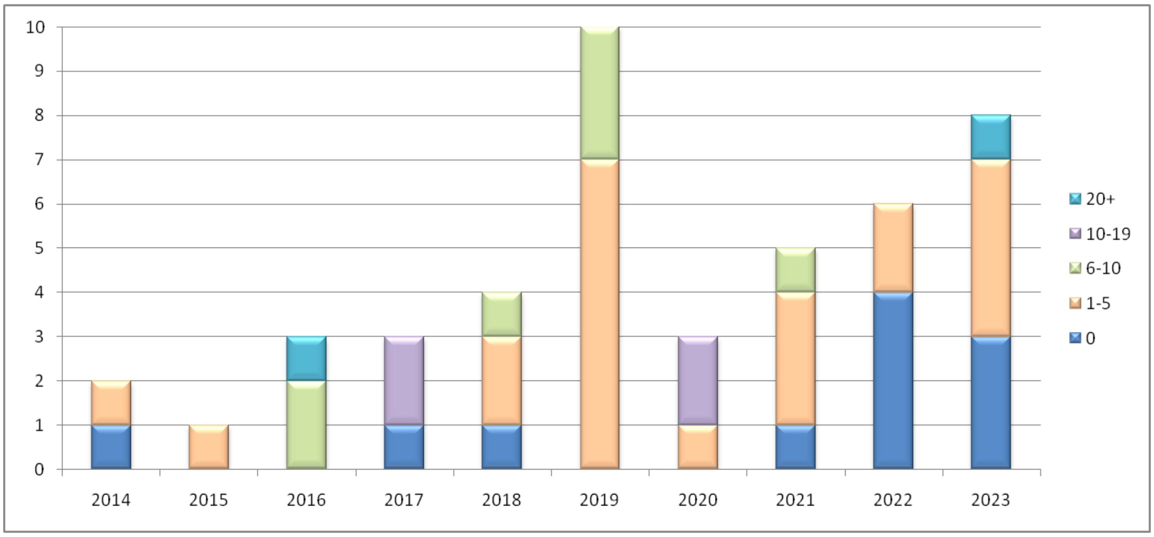


Fig. 8. Citations to the literature on project team selection with respect to years

The last bibliometric analysis concerns the quality of the journals in which selected articles were published. In this context, the Q-factors and h-indexes of these journals are examined. Fig. 9 indicates that more than half of the selected articles were published in Q1 journals, whereas more than 20% of them were published in Q2 journals. If the h-indexes of the journals are inspected, it is observed that the h-indexes are under 100 for the majority of the journals although there are articles published in journals with h-indexes of approximately 250 (Fig. 10).

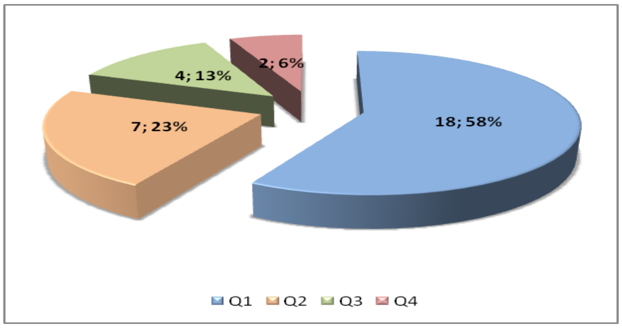


Fig. 9. Q-factor distribution of journals in which articles were published

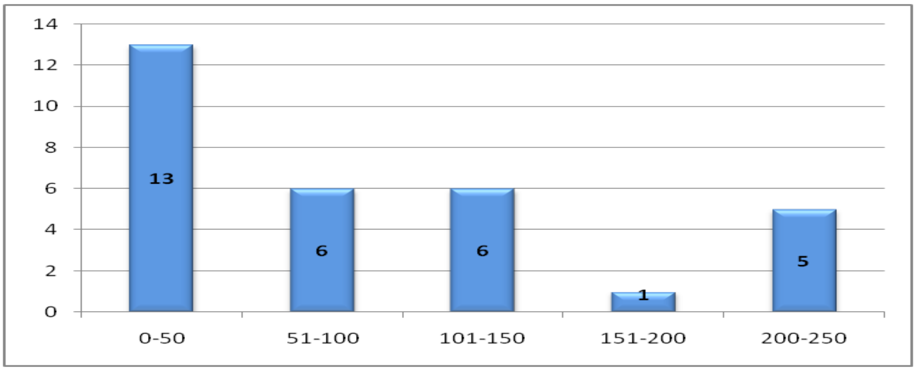


Fig. 10. Distribution of journals on which articles were published with respect to h-index

As a result of the bibliometric analysis on 31 articles and 14 proceedings selected for analysis, the following issues have been reached:

- Researchers with different competencies and productivity levels work together or separately on the project team selection problem.
- Despite the temporary decline in 2020, probably due to the pandemic, the number of studies conducted in this field and the number of citations to the studies have an increasing trend.
- These works have been published in different countries on almost all continents of the world.
- Most of the articles resulting from the studies were published in high-level referred and indexed journals belonging to different publishing houses.

## 4. Literature on the Project Team Selection Problem

There are many studies in the literature with the purpose of creating a project team that objectively considers technical skills and/or soft skills. The first analytical approach to build multifunctional project teams based on the customer requirements was suggested by Zakarian&Kusiak [9]. They organized the attributes taking into account for team formation with Quality Function Deployment (QFD) planning matrix and ranked candidates with Analytical Hierarchy Process (AHP) approach.

Only 45 of the studies related to project team selection were analyzed within the scope of this article. The authors, years, types and aims of the selected publications are presented with their methods and parameters in Table 5.

In the selected studies, the project team selection problem has been addressed for a wide range of areas, from public projects to product development and from construction projects to R&D projects. However, studies on software projects stands out the most in the selected studies. Software projects are followed by the establishment of student teams for graduation/term paper projects. Indeed, there are other examples of creating student project teams in many other studies that are not included in the scope of the analysis [4, 53-56].

In the selection of the project team, to find the right people meeting the needs of the project, the technical and social skills of the team member candidates, as well as their experience, education level, knowledge, expertise and competencies, were taken into consideration. Since they are the basic components of project management, time and budget constraints were also considered. In this context, the candidates' workload and the wages they would receive were the parameters used in the selection decision. In addition, in a limited number of studies, candidates' communication skills, past collaborations, recognition and social networks as well as their demographic characteristics and personalities were also taken into account in team selection. In a few studies, intro–team similarities and differences are also among the parameters affecting team selection decisions.

Table 5. Selected studies in the literature on project team selection

| Author(s) | Year | Type | Aim | Method | Parameters |
|---|---|---|---|---|---|
| Anes et al. [10] | 2023 | Article | To select project teams considering performance and competences with the aim of controlling costs by eliminating uncertainties in schedules and time-extending errors | PERT<br>Monte Carlo Simulation | Performance<br>Experience<br>Competencies<br>Communication skills |
| Jin [11] | 2023 | Article | To select the optimal team members in a virtual environment for smart port development projects | MCDM<br>-DEMATEL<br>-TOPSIS | Expert quality<br>Salary<br>Interdisciplinary knowledge<br>Experience<br>Interpersonal ability<br>Communication capability<br>Cross-cultural adaptability |
| La Torre et al. [12] | 2023 | Article | To form an optimal team favoring artificial intelligence in decision making by minimizing cost and maximizing human-machine trust | Goal programming | Cost (salary)<br>Technology acceptance<br>Source credibility<br>Self efficacy |
| Lai et al. [13] | 2023 | Article | To form large number of project teams by considering similarities within and between teams and by providing skill matching with tasks and communication in teams | Data Mining: A heterogeneous information network embedding method | Competencies<br>Expertise field<br>Language level<br>Certifications<br>Technical skills<br>Experience<br>Demographic information (nationality, gender, age)<br>Educational background<br>Interpersonal interaction background<br>Project requirements |
| Ribeiro et al. [14] | 2023 | Article | To establish a team having members matching with project requirements and aligning best with each other | A meta-heuristic algorithm based on SOHCO (SOft skill, Hard skill and COMPany Fit) | Teams size<br>Project requirements<br>Experience<br>Trainings<br>Technical skills<br>Quality<br>Productivity<br>Soft skills<br>Company fitness |

Table 5. Cont'd

| | | | | | |
|---|---|---|---|---|---|
| Rostami & Shakery [15] | 2023 | Article | To develop model to find best experts for an agile project team considering expertise level | Neural network<br>Integer linear programming | Level of expertise<br>Required knowledge |
| Silva et al. [16] | 2023 | Article | To understand the relevance of soft skills in the selection agile project teams | Document (e-mails reports) analysis<br>Interview and questionnaire to collect data<br>Data analysis<br>Benchmarking | Soft skills |
| Vasiljevic & Lavbic [17] | 2023 | Article | To allocate students to projects teams based on their personality | XGBoost<br>Simulated annealing | Personality traits<br>Satisfaction |
| Assavakamhaenghan et al. [18] | 2022 | Article | To develop an algorithm on recommending software teams and evaluating their effectiveness | Random Forest<br>Max Logit | Historical collaboration<br>Expertise<br>Co-project frequency competency<br>Teammate interaction diversity<br>Project description<br>Technical skills<br>Role experience (being a part of similar project i.e. Project familiarity) |
| Costa et al. [19] | 2022 | Article | To form assertive teams for multiple project with high rate of similarity between them | Structured Task Model to creating developers' profiles<br>Genetic Algorithm | Project requirements<br>Knowledge<br>Software skills |
| Talmor [20] | 2022 | Article | To create thousands of three-member teams with diverse and conflicting interests for a nationwide public sector project | Integer Linear Programming | Project requirements<br>Candidates features<br>Cost |
| Tanbour et al. [21] | 2022 | Conference Proceedings | To suggest the most suitable skilled software development professionals to projects tasks | Random Forest | Salary<br>Availability/workload<br>Software skills |
| Teslyuk et al. [22] | 2022 | Conference Proceedings | To recommend a scrum team for software development projects | Integer Linear Programming<br>MCDM<br>-AHP | Productivity<br>Competencies<br>Salary<br>Roles in the team |
| Yuhana et al. [23] | 2022 | Conference Proceedings | To develop a classification model for the composition of the software development team | Decision Tree<br>Questionnaire to collect data | Team role<br>Gender<br>Social skills<br>Personality<br>Team performance |

Table 5. Cont'd

| | | | | | |
|---|---|---|---|---|---|
| D'Aniello et al. [24] | 2021 | Article | To propose a hybrid approach for the allocation of human resources on projects specifically designed for knowledge-intensive small and medium enterprises | An intelligent system using knowledge driven top-down and bottom-up approaches together | Knowledge<br>Skills<br>Attitudes<br>Cost<br>Project requirements<br>Candidates' preferences<br>Duration |
| Dotsenko et al. [25] | 2021 | Article | To develop a method on the formation of a functionally adaptive project team under given constraints | A meta-heuristic model named as Logical Combinatorial Algorithm | Competencies<br>Level of commitment<br>Project requirements<br>Team size<br>Cost |
| Kassim et al. [26] | 2021 | Article | To propose a framework of a decision-making system by outlining the combinations of factors to form a collaborative team | MCDM<br>Fuzzy Logic<br>Genetic Algorithm | Performance<br>Competencies<br>Technical skills<br>Knowledge<br>Experience<br>Reliance<br>Leadership skill |
| Kononenko & Sushko [27] | 2021 | Article | To create an adaptive project team that can work effectively with increased uncertainty and inability to plan team activities with a given degree of accuracy | MCDM<br>Fuzzy sets | Competencies<br>Project requirements |
| Tuarob et al. [28] | 2021 | Article | To suggest project teams satisfying role requirements, technical skills and teamwork compatibility | Max Logit<br>Random Forest<br>Natural Language Processing | Collaboration history<br>Task similarity<br>Competencies<br>Diversity<br>Experience<br>Success rate<br>Skills |
| Chiang & Lin [29] | 2020 | Article | To develop a model on human resource allocation for a project team | Integer Linear Programming | Salary<br>Skills<br>Duration<br>Communication capability |

Table 5. Cont'd

| | | | | | |
|---|---|---|---|---|---|
| Hajarolasvadi & Shahhosseini [30] | 2020 | Article | To provide a new tool considering qualified collaboration and individual competencies for team selection | A two-stage heuristic model based on uniqueness of competencies and social fitness in a team | Competencies<br>Personalities<br>Interpersonal relationship (sociogram) |
| Yun et al. [31] | 2020 | Article | To analyze relationship between features of top-management team members and performance of mega-projects in terms of timing, quality, cost, safety and innovation | Regression Analysis | Age<br>Gender<br>Experience<br>Educational background<br>Cost<br>Quality<br>Innovation level<br>Duration<br>Safety |
| Ashenagar & Hamzeh [32] | 2019 | Article | To select the most appropriate members for the projects providing required skills with minimum cost | A meta heuristic algorithm based on communication cost<br>Social Network Graphs | Expertise<br>Connection between experts<br>Salaries<br>Communication cost |
| Çavdur et al. [33] | 2019 | Article | To form student-project teams considering student preferences for graduation projects | Two-Stage Goal Programming | Preferences of students and instructors<br>Qualifications of students (language level, GPA, software skills)<br>Team size<br>Workload of instructors |
| Çavdur et al. [34] | 2019 | Article | To develop integrated solution approach for the problem of forming balanced and homogenous student-project teams | Questionnaire to collect data<br>MCDM<br>-AHP<br>Two-Stage Goal Programming | Preferences of students and instructors<br>Qualifications of students (language level, GPA, software skills)<br>Team size<br>Workload of instructors |
| Jin et al. [35] | 2019 | Article | To select the most competent and cooperative teams | Genetic Algorithm | Age<br>Gender<br>Experience<br>Educational background<br>Motivation<br>Reputation<br>Expertise<br>Competence<br>Interpersonal relationship/interaction with others |

Table 5. Cont'd

| | | | | | |
|---|---|---|---|---|---|
| Kalayathankal et al. [3] | 2019 | Article | To develop a model for the selection of project teams considering qualitative parameters | MCDM<br>Fuzzy Set<br>Soft Set | Communication skill<br>Problem solving skill<br>Technical skills<br>Decision making skill |
| Coelho et al. [36] | 2019 | Conference Proceedings | To allocate members to a software development project team | MCDM<br>Genetic Algorithm | Affinity<br>Productivity<br>Experience<br>Cost |
| Ivan et al. [37] | 2019 | Conference Proceedings | To generate a shortlist of suitable candidates compatible with working in an agile project team | Data Mining:<br>-Random Forest<br>-K-nearest Neighbor Algorithm | Experience<br>Technical skills<br>Educational background<br>Earnings<br>Salar<br>Success rate<br>Results on technical tests |
| Machado & Stefanidis [38] | 2019 | Conference Proceedings | To form teams with similar quality for multi-disciplinary projects | A Heuristic Model based on team- project fitness | Skills<br>Project requirements |
| Nand & Sharma [39] | 2019 | Conference Proceedings | To form student project teams balanced in terms of skills and which gives effective outcomes | Meta-heuristic model based on Firefly Algorithm | Presentation skills<br>Software skills |
| Su et al. [40] | 2018 | Article | To select member for a collaborative new product development team | MCDM<br>-AHP<br>Genetic Algorithm | Performance<br>Individual knowledge<br>Experience<br>Publications<br>Implicit knowledge<br>Previous collaborations<br>Communication skills<br>Similarities and differences |
| Akbar et al. [41] | 2018 | Conference Proceedings | To form student project teams | Data Mining:<br>K-Means Algorithm | Preferences |
| Dzvonyar et al. [42] | 2018 | Conference Proceedings | To compose project teams of students for software engineering courses | Linear Programming with Simplex Algorithm | Language level<br>Technical skills<br>Gender<br>Age<br>Motivation<br>Project requirements |

Table 5. Cont'd

| | | | | | |
|---|---|---|---|---|---|
| Fitria & Nugraha [43] | 2018 | Conference Proceedings | To form a team having interdependency in terms of skill level | A meta-heuristic model based on artificial bee colony method | Hard skills<br>Quiz grade<br>Soft skills<br>Salary |
| Fathian et al. [44] | 2017 | Article | To form optimal and reliable team of experts | Linear Programming | Skills<br>Collaboration network<br>Reliability |
| Basiri et al. [45] | 2017 | Article | To find a collaborative team which covers required skills and minimizes the communication cost among team members | BRADO (BRAin Drain Optimization): A meta-heuristic swarm-based algorithm | Skills<br>Social network<br>Communication cost |
| Okur & Nasibov [46] | 2017 | Conference Proceedings | To assign most suitable people to project teams by providing quality based homogeneity | 2 heuristics based on similarity within vs between teams<br>Fuzzy Logic to form relationship matrices | Competencies (within and between teams) |
| Ghasemian et al. [47] | 2016 | Article | To predict scientific collaboration success of scholars based on their previous collaborations | Hypergraph: for representing the collaboration relations<br>Data mining for clustering scholars:<br>-Naive Bays<br>-Artificial Neural Networks<br>-Random Forest | Expertise level<br>H-index, g-index, average citation<br>Familiarity (jaccard similarity)<br>Centrality |
| Pitchai et al. [48] | 2016 | Article | To develop project team formation model for large-scaled organizations | MCDM<br>Fuzzy Logic<br>Genetic Algorithm | Team size<br>Required skills<br>Availability/workload |
| Hsu et al. [49] | 2016 | Article | To compare different project team member selection orientations(homogenous-heterogeneous-interdependence) for a small design firm | Simulation: Agent-Based Modeling | Educational background<br>Salary<br>Experience<br>Expertise<br>Licenses<br>Interaction with team<br>Interaction with environment<br>Availability/workload<br>Previous collaborations<br>Scope<br>Budget<br>Duration |
| Gerogiannis et al. [50] | 2015 | Conference Proceedings | To select suitable human resources for an R&D project of a SME | MCDM<br>Fuzzy model | Project requirements<br>Software skills<br>Competencies |

Table 5. Cont'd

| | | | | | |
|---|---|---|---|---|---|
| Yang et al. [51] | 2014 | Conference Proceedings | To develop a new clustering method for cooperative project team building | Clustering Algorithms:<br>-k-means<br>-agglomerative hierarchical | Number of clusters<br>Dissimilarities<br>Preferences<br>Team sizes |
| Watthananon & Yoosuka [52] | 2014 | Conference Proceedings | To recruit team members by matching individual competency with organizational expectation and expectable outcomes from each project | Data Mining:<br>-Information Gain for feature selection<br>-Support Vector Machine | Analytical thinking<br>Conceptual thinking<br>Team work capability and cooperation<br>Leadership<br>Self confidence<br>Competency |

To solve the project team selection problem, Multi-Criteria Decision Making (MCDM) and Machine Learning/Data Mining methods have been mostly used in the literature. Linear programming methods, which are not efficient due to the complexity of problems with many constraints and variables, are also frequently used methods, especially for small-sized student-project team formation problems where complexity is low. Notably, few simulation studies exist in the literature, where meta-heuristic methods such as Genetic Algorithm, Simulated Annealing, Firefly, Artificial Bee Colony, Logical Combinatorial and Swarm-based Algorithms are also preferred. There are wide variety of MCDM methods used for project team selection in the literature, such as Analytical Hierarchy/Network Process, Fuzzy Methods, TOPSIS, DEMATEL, Data Envelopment and PROMETHEE. Supervised methods such as Regression, Support Vector Machine, K-Nearest Neighbor, Decision Trees, Random Forest, Naive-Bayes, Artificial Neural Networks, XGBoost and unsupervised methods consisting of clustering and association analysis and reinforcement methods are also used in the literature for project team selection as machine learning/data mining methods.

Linear programming methods are generally used for student-project team selection problems in the literature. Çavdur et al. [33, 34] aimed to increase diversity within the team, reduce imbalances between teams, and establish fair project teams with equal conditions, in two different studies they conducted, on the problem of creating a project team for students and appointing an advisor. The two-stage goal programming method was used in these studies. In the first stage, students were assigned to project teams. In the second stage, faculty members were appointed as consultants to designated teams. The first study investigated the assumption that the criteria used for goal programming are of equal importance [33]. In this study, the effects of making small changes in the criteria weights and having different importance of the criteria on the results were also observed. In the second study, which is a continuation of the previous study, the weights of the criteria in question were determined. It was weighted with the Analytical Hierarchy Process (AHP) method in line with the opinions received from each student and faculty member through a survey [34]. When the results are compared with real-life data, the proposed model gives successful results in a reasonable time.

La Torre et al. [12] also applied goal programming to form a team, members of which are eager to use technology. They did not consider competencies or technical skills but attitudes. Although the proposed model was tested on three different cases and the teams formed by the model were shared, there is no information about verification and validation analyses.

There exist some other studies that use linear programming methods for project team selection. Chiang and Lin [29] applied the integer linear programming method to find the right team to achieve the objective function of maximizing team efficiency in situations with and without a budget constraint. Similarly, Talmor [20] applied the integer linear programming method to establish 3-person teams for public projects with maximum diversity and minimum incompatibility with project requirements.

Teslyuk et al. [22] also wanted to use integer linear programming to form a team for a software development project. However, since the established model is non-linear, one of the variables was kept constant. The model was solved repeatedly by changing the value of the variable remaining constant each time. The alternative results were sorted via AHP method and the best one was selected. Since team synergy will be disrupted if a person leaves the team with good communication, Fathian et al. [44] attempted to establish a project team with an integer linear programming model that uses cooperation and competence needs as constraints and minimizes the possibility of leaving the team. Unlike other studies using the Linear Programming method, in this study, team collaboration and continuity along with competencies and costs were taken into account. Dzvonyar et al. [42] developed the simplex algorithm-based Team Allocator for Software

Engineering (TEASE), which forms a student-project team for software engineering courses as a linear assignment problem. The studies of Bağlarbaşı Mutlu [55] and Rodoplu [4] are also examples of student-project team formation with integer goal programming, which are not included in the analyses conducted here.

When class size increases, small linear programming methods do not yield effective results due to the increase in time and space complexity. For these cases, data mining/machine learning methods become an alternative way to solve the team selection problem. Akbar et al. [41] attempted to solve the problem of forming a student-project team for high-volume classes via the clustering method. In this study, students' subject preferences were grouped with the clustering approach and students were matched with projects being compatible with their interests. The k-means algorithm was used during the study. Although there is no explanation for selecting the k-means algorithm, Yang et al. [51] studied the performance of this algorithm. They compared the performance of k-means and agglomerative hierarchical clustering algorithms for cooperative team formation. In addition, the effect of adding complete must-link constraints was also inspected. This study shows not only the time and space simplicity of the k-means algorithm but also the efficiency provided by complete must-link constraints.

Unlike the study of Akbar et al. [41], studies exist in the literature using unsupervised classification methods for student-project team selection such as those of Wei et al. [53] and Alberola et al. [56], which are not included in the scope of this article.

Watthananon & Yoosuka [52] graded each candidate in terms of their competency, familiarity and personal relationships and classified them into teams according to the appropriateness of their features in accordance with organizational expectations. To select the best method of classification, Naïve Bayes, Support Vector Machine and Decision Tree were compared and the middle one was chosen with the best performance. Tanbour et al. [21] also made use of supervised learning methods to build a team for a software development project with a database including information of 600 experts. After testing and comparing the performance of logistic regression, Decision Tree and Random Forest methods, the last one was chosen with the highest accuracy level. The study of Ghasemian et al. [47] is also an example in which supervised learning methods (Naive Bayes, Multilayer Perception (MLP) and Random Forest) were used for team formation based on the familiarity and expertise level of the candidates. Similarly, Ivan et al. [37] developed a data mining-based model to choose the best team. After pre-processing of data, the success rate of each candidate was predicted via different predictive learning methods. The prediction obtained with the Random Forest method was used due to its best accuracy. Then, the k-nearest neighbor algorithm was used to form a collaborative and effective team. Although it is not included in the scope of this article Naseer et al. [57] also selected a suitable software project team by using the decision tree method.

As another supervised learning methodology example differing in classification methods, Yun et al. [31] used the regression analysis method to analyze the relationships between the demographic characteristics of top management teams (i.e., age, gender, managerial level, senior management experience, and educational background) and mega project performance in terms of schedule, cost, quality, safety, and technological innovation. A sample of 42 mega projects and 208 senior management team members was used for analysis. According to the analysis results, the demographic characteristics of the top management team members affect their decision-making preferences and thus project performance. Additionally, experience has a direct relationship with project performance in terms of technological innovation performance and educational background in terms of cost.

There are also studies using classification and regression methods together. Assavakamhaenghan et al. [18] scored the chance of prospective teams to complete the project successfully by using machine learning algorithms. After testing different supervised algorithms, the Random Forest was chosen with the best performance. The estimation of the scores is followed by a variant of Max-Logit to detect the top K teams having maximum performance. This study is important due to the use of both technical and soft skills. Similarly, Tuarob et al. [28] recommended a model for software team selection including Random Forest to rank teams and Max-Logit to select the best. Unlike Assavakamhaenghan et al. [18], they used Latent Dirichlet Allocation as natural language processing to detect collaboration and communication between candidates.

Rostami and Shakery [15] also developed a multi-step model including both machine learning and linear programming methods for agile project team formation with high coverage, strong communication and cost effectiveness.The best possible candidates were selected via a heuristic based state-of-the-art method and their knowledge level was detected from their posts on Stackoverflow. Approximately 2 million posts of 85,000 users were used. The related knowledge level of the selected candidate was subsequently estimated with the help of a neural network by using the detected knowledge level. Lastly, by using related knowledge level data, the best team was detected via linear integer programming. Finally a model with approximately 10% higher performance than the similar ones was obtained.

Easy access to business and mental power in every corner of the world provided by digital platforms and the remote working style that has become widespread, especially during the Covid-19 pandemic, have made it possible to work with crowdsourcing teams. Especially for global companies, active in wide geographic areas and multi-disciplinary projects, crowdsourcing not only saves time and costs but also provides effective results by reaching the right person in the right location. For crowdsourcing team selection, Lai et al. [13] developed a model based on a pair-wise random walk, which mines members' suitability to tasks and their communication with each other. Using project requirements and limited information about candidates obtained from their resumes, a network was constructed based on a heterogeneous information network embedding method. To select the best team, 5 different similarity measure algorithms were developed. The similarity values used by algorithms were calculated based on time zone, cultural background, experience and skill similarities. The efficiency of these algorithms was compared in terms of symmetry, accuracy, uniformity and comparability. Then, the best one was chosen.

MCDM methods could also be chosen to solve complex team selection problems. Gerogiannis et al. [50] solved the team selection problem for an R&D project of a SME with a group-based fuzzy MCDM approach. They used aggregated linguistic evaluation of each manager about not only the required skills and their importance but also the fitness of candidates to these skills.

Jin [11] conducted a survey to evaluate MCDM methods in terms of ease of use, performance, self-efficacy and usefulness. Although TOPSIS was chosen as the best method according to survey results, it was combined with FMEA and DEMATEL. The team was chosen from the candidates satisfying project requirements about skill, available time and etc. By considering Risk Priority Number and uncertainties calculated with the suggested FMEA-DEMATEL-combined TOPSIS method, the best team was selected.

For many cases MCDM methods are combined with Genetic Algorithm, which is a meta-heuristic method. Su et al. [40] used the MCDM approach to select a team for a product development project due to the NP-hard nature of the problem. The aim is to maximize both competence and collaboration of the whole team by providing constraints on within-team similarity in terms of competency and knowledge. The AHP was used to determine the importance of each competency and knowledge and the best team allocation was chosen with the help of the Genetic Algorithm which is fast and efficient.

Beside the studies combining MCDM methods with Genetic Algorithm, there are many studies using only Genetic Algorithm for MCDM process.

Jin et al. [35] used Genetic Algorithm to create a team with high individual ability and good inter-individual relationships to maximize team performance. To rate the competencies and interpersonal relationship levels of the candidates to be included in the team, the opinions of existing employees who knew the candidates were used. The lack of an objective criterion to evaluate the candidates and the approach with which each team member will positively affect the teamwork are the weaknesses of the study. The study of Costa et al. [19] on building successful teams to conduct multiple projects in large-scale organization is another example of MCDM studies with Genetic Algorithm. The model assigns suitable teams to given projects based on the skills and performance of the candidates obtained from performance data of their past projects. The suggested algorithm was tested with a dataset including 12 projects with 1063 tasks and 52 candidates. The analyses yield acceptable results with 85% precision and 75% acceptance. Similarly, Coelho et al. [36] assigned members for a software development project considering multiple criteria like affinity, experience and cost using Genetic Algorithm.

Genetic Algorithm could also be used with fuzzy methods to solve MCDM problems. Kassim et al. [26] selected the optimal project team using Genetic Algorithm with fuzzy logic. Since there are uncertain factors such as experience and leadership among the criteria that could be taken into consideration in team selection, the criteria to be used were determined by the fuzzy logic method. Then, a Unified Theory of Acceptance and Use of Technology (UTAUT) survey was applied to company employees to evaluate the proposed model. The model was evaluated in terms of Performance Expectancy (PE), Effort Expectancy (EE), Social Impact (SI) and Facilitating Conditions (FC), and employees' willingness to use the proposed model was measured. The results showed that employees are willing to use the proposed model and will use it if it is useful and mandatory. In the model developed in the study, interpersonal interactions and the diversity of the project team were not taken into account. The team selection model for large-scale organizations proposed by Pitchai et al. [48] also includes fuzzy logic to evaluate candidates and Genetic Algorithm to select the best team.

Unlike the last two studies, Kononenko and Sushko [27] only used fuzzy methods to establish a team in an uncertain working environment where the activities of team members cannot be planned with any certainty. They aimed to benefit from maximum competencies at the highest level. Similarly, Kalayathankal et al. [3] weighted qualitative parameters with a fuzzy approach and combined both fuzzy and soft set theories with set models to solve project team selection problem.

Complex projects with multi-tasks requiring different competencies often demand multidisciplinary teams having required skills and attribute diversity to maximize output. However, forming such a team can be problematic in terms of balancing the quality of teams assigned to different sub-tasks and the workload of team members. To solve this problem, Machado and Stefanidis [38] built a heuristic model to form a team by minimizing differences between teams and providing teams with similar qualities. The model is based on the fitness value of each candidate to each sub-task in terms of competencies. A fitness value matrix with dimensions kxp (k is the number of candidates and p is the number of sub-tasks) is formed. Then, the highest fitness value for each sub-task is found and the corresponding candidate is assigned to that sub-task. The assigned candidate is removed from the pool and the process is repeated until all sub-tasks have a team with the required competencies. As another example for the multi-disciplinary project team selection, Rahmanniyay et al. [58] developed a heuristic based on partitioning the complex problem into clusters, solving each one separately and finally aggregating solutions of the clusters.

Hajarolasvadi & Shahhosseini [30] developed a tool that provides team selection with a two-stage heuristic model, taking into account intra-collaboration and individual competencies together. In the first stage of the heuristic method, a pool of people with the required competencies is created, and heterogeneous teams are formed from this pool, where one person complements the other in terms of competence. In the second stage, sociograms are drawn for each of the candidate teams created in the first stage and the homogeneity of the teams is evaluated in terms of similar personality traits and common values. Finally, the teams are ranked and the best team in terms of heterogeneous competence and homogeneous personality is selected.

Ribeiro et al. [14] proposed a team formation heuristics based on fitness of candidates not only to the project requirements but also to the project team. Correlation matrices are used to determine these fitness values. Each relation is weighted by the leader according to its importance for the project. It aims to provide integrity and cohesion by reaching a desired, but not maximum, fitness value which prevents putting dominant individuals together. This algorithm gives similar and consistent solutions with several MCDM methods like TOPSIS.

Okur & Nasibov [46] developed a heuristic considering homogeneity between teams in terms of quality. According to suggested heuristic, candidates are ordered in descending order according to their quality and each candidate is assigned to a team fitting the best. If there is not such a team a new team is constructed. This algorithm is reported as having sufficient flexibility and precision.

Dotsenko et al. [25] built a team selection model based on formal transformations of candidates. The model aims to form a team which can perform sustainably during crisis periods such as Covid-19. This is achieved by a meta-heuristic algorithm, Logical Combinational. The candidates operating each function are grouped and their features are identified. Groups of candidates are enumerated constructively. Then, the best one having the required features is selected.

Basiri et al. [45], considered both collaboration among team members and the required skills while developing a meta-heuristic swarm-based algorithm to form a team. The candidate with the lowest communication cost is named as brain individual, the position of an ordinary individual is adjusted based on the force of attraction and repulsion of its neighbors. The brain individual is changed when it has a neighbor having lower cost. The algorithm balances diversification and intensification while enabling an unhappy member to migrate other teams.

Ashenagar & Hamzeh [32] developed a meta-heuristic algorithm based on forming the most cohesive subgroups for each task of a project. The total distance of each expert to others is calculated via social network graphs. Then, this is used as the communication cost. In addition, each expert is weighted for each task in terms of the suitability of their skills, expertise and knowledge to the requirements. The most prior expert is chosen as central one and subgroups are formed from experts having the required skills, considering communication cost minimization. This algorithm was preferred due to its lower time complexity and success in approximating the optimal solution.

Nand & Sharma [39] approach the student project team selection problems differently. They suggested a meta-heuristic model based on the Firefly Algorithm to minimize skill-level differences between different teams. The performance of the Firefly Algorithm was compared with that of Particle Swarm Optimization (PSO) and Invasive Weed Optimization (IWO) and the suggested heuristics were reported as having better results.

D'Aniello et al. [24] developed an intelligent team formation system for knowledge-intensive SMEs. The system combines all knowledge-driven, top-down leader-selected and bottom-up consensus-based team formation approaches to balance their disadvantages while maximizing possible strengths. The proposed system selects the best candidate as the project team leader considering the skills, expertise and competence of candidates with their personality and attitudes. Then, the team leader proposes alternative teams with a top-down approach. The final team is decided with a consensus of employees according to their preferences.

Anes et al. [10] stated that in agile organizations, the performance and competencies of people should be taken into consideration during the selection of the project team to provide cost control by reducing uncertainty in the project execution period. They estimated the task durations according to the performance of the team with the PERT method and simulated the deviations that may occur in the performance of the team for various reasons with the Monte Carlo method. Although team performance has a dynamic structure due to the learning curve and continuous improvement, it was considered static in this study.

The social skills of team members, except internal and inter-team communication skills, were not taken into consideration by Anes et al. [10]. However, Silva et al. [16] revealed the importance of greater consideration of soft skills than of technical ones for project team selection in agile project management. In selecting the project team for the pilot application in a company that adopted an agile approach to project management, only the performance and technical skills of the employees from the previous year were taken into account, without considering their social skills. The failure observed in the first 6 months of the pilot project resulted in the abandonment of agile project management which reveals the importance of social skills. Similarly, a simulation study using an agent-based modelling method was conducted by Hsu et al. [49] to explore differences in the performance of ability-based teams and communication/collaboration-based ones. As a result, higher performance was obtained from the second one for both homogeneously and heterogeneously distributed team.

Similarly, Vasiljevic & Lavbic [17] considered five different personality traits (openness, conscientiousness, extraversion, agreeableness, and neuroticism) to develop an algorithm for team formation with data from 31 teams of 157 students. The model aimed to maximize the satisfaction of members while technical skills and demographic features are ignored. XGBoost was used to predict team satisfaction and it achieves 74% accuracy and 69% precision. An algorithm based on the simulated annealing method was also used to detect personality traits increasing satisfaction.

As a combination of these two opposite aspects, Yuhana et al. [23] claimed that hard skills are necessary criteria to form a good team, but are not sufficient to be best without being balanced with soft skills. Thus, they classified software developers to form an effective team via different supervised learning methods by considering both hard and soft skills. As a result of the analysis, the decision tree method was chosen as the developer classification method with higher accuracy and lower complexity.

All the selected studies were analyzed in terms of their applied methods, attributes and limitations, as well as their similarities and differences. A detailed discussion of the analyses is given in the next section.

## 5. Discussion

The project team selection problem can be seen across all sectors and areas. Studies selected for inspection from the literature also represent different sectors and areas but focus mostly on software project teams and student-project team selection. The agile approach in project management also increases the importance of team selection for software projects.

Mostly, Python has been used for the implementation of the proposed models. However, for the optimization models, LINGO and GAMS have been used with Python [12, 44]. In addition, there are examples in which C, C# and Java are used for execution.

Studies in the literature include multiple attributes as selection criteria. While the number of attributes used in a study varies from 1 to 12, mostly 3 or 4 features of the candidates are considered to form a project team as shown in Fig. 11. The more features considered to form teams, the more effective and efficient is the team with synergy. Thus, studies considering more features to form a team are required.

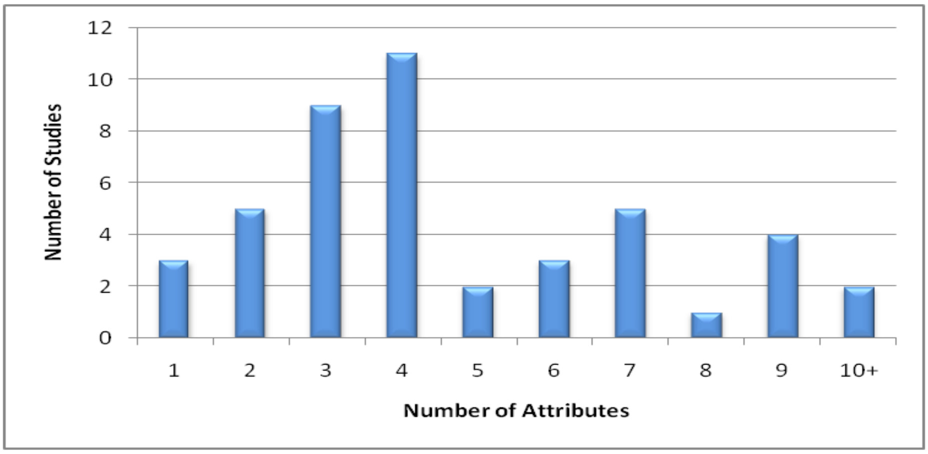


Fig. 11. Distribution of studies with respect to the number of considered attributes

Fig. 12 reveals that the most commonly used feature is expertise/knowledge level/education, followed by technical skills such as language skills, presentation skills and software skills [19, 21, 27, 58]. The cost of the team is also considered as expected, which is represented by the salary. On the other hand, the soft skills and personality of the candidates are taken into account far less than the technical ones. The synergy of a team, which can be measured by similarities, interrelationships and previous collaboration, has also been ignored in many studies. This represents a significant gap in the literature.

The problem can be defined as a linear model and can be solved efficiently with few parameters and a small candidate pool when only a few parameters are considered. However, this problem is much more complex in real-life. Thus, the usage rate of linear programming methods has also decreased over the years as the complexity of the problem increases and MCDM, machine learning and meta-heuristics methods are commonly used for the selection of project teams in the literature.

It is inspected from Fig. 13 that in the reviewed studies MCDM was increasingly used until 2019.

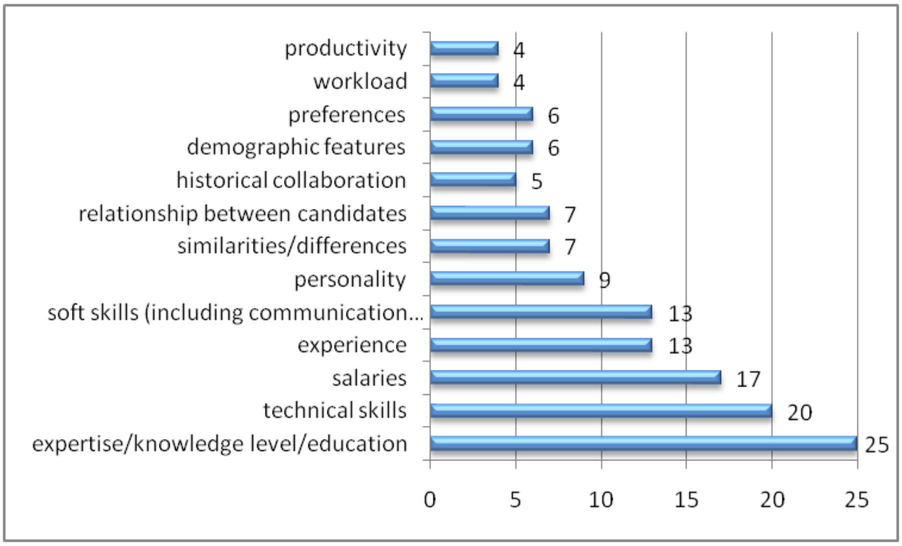


Fig. 12. Number of selected studies using each attribute

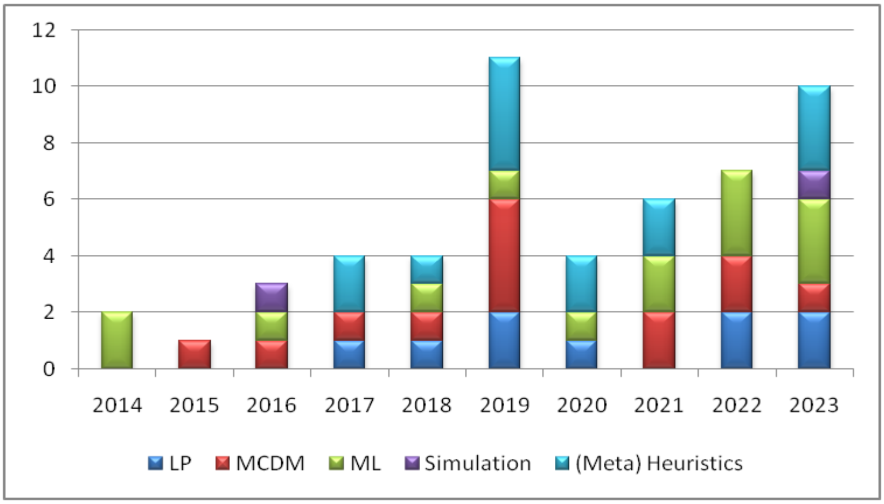


Fig. 13. Distributions of studies with respect to years in terms of the applied methods

Then, its usage rate has decreased while machine learning methods have been used more in recent years. The most commonly used methods in the reviewed studies are Genetic Algorithm and Fuzzy Methods while Random Forest is the most used machine learning method due to their high accuracy and precision. For example, Ivan et al. [37] used Random Forest with the accuracy rate of 66% while Vasiljevic & Lavbic [17] used XGBoost with 74% accuracy and 69% precision. In addition, Ghasemian et al. [47] also used Random Forest with 67% precision.

Several limitations are observed in the literature. First, although space and time complexity due to the nonlinear structure of the problem are mentioned in most studies, detailed complexity analysis through calculations is rare [19, 32, 35, 46, 51]. Second, not only the number of considered parameters but also the number of teams is limited by the small size of the candidate pool especially for the studies in which linear programming methods are used. Costa et al. [19] studied with 28 candidates and 12 projects to test the proposed Genetic Algorithm Model. Similarly, Yuhana et al. [23] developed a Decision Tree model to form a project team by using the information of 57 students. Third, the efficiency and effectiveness of the proposed methods with the performance comparison in terms of accuracy and precision are discussed in a few studies [17, 18, 28, 37, 46, 47, 52]. Finally, although it could be possible to address complexity without compromising optimality if linear programming methods merge with other non-optimal methods, the lack of studies using multiple methods together is observed in the literature.

As a conclusion to the scientific analyses of the literature, it can be inferred that the solution method used for the team selection problem changes with the space and time complexity of the problem as well as the aim of the study. The problem complexity is determined by factors such as multi-objectiveness, the size of the candidate pool and the number and types of parameters to be considered.

## 6. Conclusion

This article reviews the selected studies addressing the project team selection problem, which is crucial for the success of a project with the bibliometric analyses. It is concluded from the bibliometric analyses that researchers with different competencies work together or separately on the project team problem. There is an upward trend in the number of studies conducted in this field and the number of citations to them. On the other hand, it is inferred from the content review of the studies that although there are many studies on project team selection, they generally propose models for a specific project type especially for software projects. In addition, some of them work with either quantitative or qualitative parameters. There is a need for a comprehensive team selection model considering both the technical and soft skill requirements with the salary and communication costs together. Moreover, the prospective model should ensure accuracy and precision while challenging simultaneously with space and time complexity. The model should also be adaptable to different project types with minor modifications and should be efficient for a large candidate pool.

This review study has several limitations. As a further study, one can review the literature over a broader time frame. In addition, member selection studies can be reviewed not only for project teams but also for all types of teams such as sport, operation and education teams. Keywords could be searched in other databases like Google Scholar and additional keywords related to team formation like staffing and team assembly could be included to the study.

## Declaration

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### Author Contributions

M. K. Gürbüz: Conceptualization, Methodology, Formal analysis, Investigation, Data Curation, Writing - Original Draft, Visualization. T. Çetinyokuş: Conceptualization, Methodology, Writing - Review & Editing, Supervision.

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### Data Availability Statement

The data presented in this study are available on request from the corresponding author.

### Ethics Committee Permission

Not applicable.

### Conflict of Interests

The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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