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Optimizing Team Staffing: A Review of Computational Approaches to Team Formation

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14. ABSTRACT

Despite the increasing reliance of both military and civilian organizations on team-based work structures, individual staffing approaches remain the norm. However, this approach fails to consider the complex interactions among individuals in a team and the importance of those interactions to optimal team member assignment. The present review summarizes recent computational methods of team-level staffing approaches, identifies promising areas for further research, and discusses potential applications. Two questions drive the present investigation: (1) What are the common decision types, algorithmic approaches, and optimization constraints in the team formation literature? (2) How can theoretical contributions from psychology advance computational approaches to team formation to make them both psychologically relevant and applicable to real world problems? A final set of 35 peer-reviewed articles were examined resulting in annotations and a literature review that considers the current state of research and areas warranting future investigations and collaborations.

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OPTIMIZING TEAM STAFFING: A REVIEW OF COMPUTATIONAL APPROACHES TO TEAM FORMATION

EXECUTIVE SUMMARY

Research Requirement:

The U.S. Army has recently emphasized the strategic importance of small units of Soldiers, and in doing so, highlighted the importance of understanding how those units can best be formed. This review summarizes recent computational approaches to the problem of team formation and identifies promising areas for further research and potential applications.

Procedure:

This annotated bibliography offers a multi-disciplinary review of the current computational approaches to the team formation problem. We organize the review around two questions: (1) What are the common decision types, computational approaches, and optimization constraints in the literature? (2) How can theoretical contributions from psychology advance computational methods of team formation to make them both psychologically relevant and applicable to real world problems?

Findings:

We find first that computational approaches to team formation fall broadly into three decision type categories: team member replacement, multiple team formation, and single team formation. Within each of those categories, decisions to join a team can either be exogenous (i.e., membership is decided by an external advisor) or endogenous (i.e., the individuals themselves decide whether or not to join the team) to the team. Computational approaches to each of those decision types tend to vary, with approaches including general algorithmic models and network-based architectures. While our aim is not to review the details of those solutions per se, we do find differential potential for certain computational approaches to be implemented at a scale useful for team staffing decisions in organizations such as the Army. We find that theoretical advances from the organizational and psychological sciences can be used to inform how the inputs and constraints included in these models can be used to optimize team composition.

Utilization and Dissemination of Findings:

This work amounts to a summary and overview of current computational and theoretical approaches to team formation. Internal to the Army, the findings presented in this review will inform ongoing efforts to understand the foundations of optimal team composition. Beyond that conceptual contribution, this work also has the potential to aid in the development of practical tools to support the assignment of Soldiers to teams, and to support the ad hoc generation of those teams themselves. External to the Army, this work synthesizes team composition literature from several disciplines. While the problem of team formation has been well studied within the computer sciences and within the psychological sciences, those streams of research have remained largely distinct. Our work highlights the contributions psychological research on this problem can make to the development of algorithmic tools within the computer sciences.

OPTIMIZING TEAM STAFFING: A REVIEW OF COMPUTATIONAL APPROACHES TO TEAM FORMATION

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Introduction

In organizations across industries and the world, teams are at the center of the stage. Consisting of three or more individuals, those teams work together to achieve a common goal, perhaps even surpassing the individual potential of their members. As leaders continue to take advantage of team structures to maximize output and enable efficiency, the challenge of composing high-performing teams has come to the fore.

Traditionally, decision-makers tasked with assembling teams have relied on approaches such as staffing heuristics, cluster hiring approaches, or simply "intuition" to create teams, but the results are not necessarily optimal. Consider, for example, the case of the U.S Army which recruits tens of thousands of Soldiers each year. Traditionally, new candidates work with a recruiter at the time of enlistment to choose a military occupation specialty (MOS) based on the needs of the Army and their scores on the ASVAB (Armed Services Vocational Aptitude Battery; i.e., aptitude, previous training). These new recruits then complete basic training in addition to any MOS specific technical training before they are given their first duty assignment within the Army at large. Once assigned to a unit, the final team placement falls to First Sergeants who often rely solely on heuristics and intuition to make these early and important decisions (Thompson & Schnaak, 2018). Despite the message from the Chief of Staff of the Army, General McConville, that "Army leaders have a sacred obligation to build cohesive teams" (Initial Message to the Army Team, 2019, p. 1), the practicality or guidance of how such a "cohesive" team should be built remains unclear.

While team cohesion is considered as a critical aspect for team success (Acton et al., 2020; Grossman et al., 2021), researchers within organizational psychology have advocated for the importance of optimizing team composition along many other dimensions as well. For instance, team composition is linked to optimal robustness, performance, and effectiveness, among others (Bell et al., 2018). Although many of those team-level outcomes can be improved through team-building and training exercises (e.g., Salas et al., 2008), initial staffing decisions critically impact the trajectory of teams at every level. Recent theories leverage the similarity, diversity, and complementarity of potential team members (e.g., Zaccaro & DiRosa, 2012; Driskell et al., 2017) and demonstrate that the mix of attributes within a team is an important predictor of group-level outcomes (Bell et al., 2018). While it is well established that a variety of individual characteristics matters to team outcomes, prescriptive guidelines for how to optimally mix characteristics are less well established. Beyond that gap in the literature, figuring out how to apply those theories remains complex. The dynamic and fluid nature of teams, combined with the sheer number of potential members and teams needed, yields a decision landscape that is vast.

At the same time, research within the field of organizational psychology was detailing the features of a team's composition that produced optimal teams, a separate literature developed: this one focused on team formation within the computational sciences. This largely independent literature aimed to develop algorithms to solve the problem of assigning people efficiently and effectively to teams. Broadly concentrated in the computer sciences, researchers formalized the problem of creating a team as one where there exists a pool of candidates, a set of constraints (e.g., team size), and an objective function (e.g., member diversity; Andrejczuk et al., 2019; Bahargam et al., 2019). The algorithmic task is to select a group of individuals from the pool that satisfies the constraints and optimizes the objective function. That process of selection is deceptively simple, and its complexity gave rise to a wide range of algorithmic and theoretical approaches.

The first aim of this review is to consider a taxonomy of those varied approaches to team formation algorithms. We will focus specifically on enumerating the common team types, computational approaches, and optimization constraints. The second aim of this review is to situate the computational work with respect to the team composition insights developed in the psychological sciences. To this end, we will highlight ways in which theory from psychology can advance computational methods of team formation with the aim to propose ways to be more psychologically relevant as well as to be applicable to team decisions facing leaders in the real world.

The remainder of this paper is organized as follows. After an explanation of the methods used to assemble our corpus, we focus on specifying three key categories of team staffing problem types: team member replacement, multiple team formation, and single team formation. Within each type, we discuss the current key algorithmic approaches. We conclude the review by discussing how theoretical advances in organizational psychology can advance the existing algorithmic approaches to team formation. Specifically, our discussion will focus on how models of team composition (e.g., structure, diversity of personalities, team member roles) and team performance can inform the constraints specified in the computational literature.

Methods

Taking an integrative approach, we carried out a multi-disciplinary literature review to identify relevant empirical papers focused on team composition and staffing (Cronin & George, 2020). Online databases (PsychINFO, Academic Source Complete, Business Search Complete, DTIC, and Google Scholar) were searched for peer-reviewed articles containing the following keywords: team composition, team staffing, and team formation. We retained and reviewed articles that indicated the use of new or existing computational tools or algorithms of team composition, team formation, or team-based selection. From our initial set of articles, we applied a set of exclusion criteria. Articles were excluded if they were non-English. Articles related to software program management, multi-agent systems (MAS), or AI/robotic teams were reviewed but later removed if the intent of the article was singularly on scheduling concerns or task allocation for a pre-existing team. We also excluded articles if the teams being formed featured exclusively AI agents to focus our attention on approaches that factored in human components/factors (e.g., personality, network).

This procedure yielded a final set of 35 peer-reviewed sources of which eight were drawn from the psychological or management literature. The remainder of the articles were sourced primarily from the engineering, software development, and computer sciences fields. Each of these papers was coded to identify the type of team formation decision, key constraints considered, the algorithmic approach, and the utility of the methods developed and was further annotated in Appendix A. Relevant review articles were also retained and annotated in Appendix B. To account for gray literature (e.g., conference proceedings, white papers, proposals) that are unindexed yet often the source of novel engineering and computer science research (Borrego et al., 2014), we also tracked prevalent references in each to identify additional articles for inclusion that were missed in our initial search resulting in a total of 43 algorithmic approaches that were retained and coded (see Appendix C).

A Typology of Team Staffing Decisions

The general problem facing those making team staffing decisions is to decide how to construct a team given a pool of candidate team members. The complexities of that decision, however, can vary widely depending on the type of team being created. That is, the procedure to create a single team will be different from the one used to create multiple teams. In turn, these two will also differ from the procedure to replace a team member on an existing team. These differences will present when the teams are created manually and will be magnified when teams are created algorithmically.

We use the type of team staffing decision as the first way to distinguish among computational approaches and categorize each paper in our bibliography into three primary categories: team member replacement, multiple team formation, and single team formation (see Table 1). In doing so, we can tease apart different computational tools that would be appropriate for each of those distinct staffing tasks.

Table 1

Each category of staffing decision type with description and example

Decision Type	Decision Description	Example
Team member replacement	*Exogenous:* Assigning an individual to an existing team	*Replacing a member who got promoted and left the squad*
	Endogenous: Deciding which existing team to join	*Ranking individual preferences for open positions*
Single team formation	*Exogenous:* Assigning individuals to one new team	*Forming a team for a specific mission*
	Endogenous: Deciding to join a new ad hoc team	*Volunteering to join a temporary team to complete an exercise*
Multiple team formation	*Exogenous:* Assigning individuals to multiple new teams	*Restructuring several teams after a reorganization or deployment*
	Endogenous: Self-organization of individuals into multiple teams	*Reorganization in the field in response to rapidly changing personnel or environmental circumstances*

Within each category, we consider additional ways to categorize the literature. For instance, some models assume staffing decisions are exogenous to team members (i.e., an external agent decides team membership), and others consider that decision endogenous (i.e., individuals decide whether or not to join a team). Specifically, in the context of the Army, models of staffing that represent the decision as exogenous may be more useful or easily applicable than models that are interested in the endogenous decision.

Team Member Replacement

Our first staffing problem domain is that of team member replacement. We categorize approaches into those in which the decision to join a team is exogenous and those in which the decision is endogenous. Exogenous decisions are made externally; that is, the problem setting is figuring out, given an open slot in an existing team and a set of constraints, which of a pool of possible candidates would be the best fit. In the case of endogenous team member replacement decisions, the problem facing the agent could instead be which team they should join, or how they should act now that they have joined an unfamiliar team.

Exogenous Replacement

The literature that looks at member replacement as an exogenous decision offers direct insights into ways automated systems could inform team staffing decisions. Here, we review research that demonstrates three broad approaches: graph-based (Li et al., 2015), neural-based (Sapienza et al., 2019), and general approximation algorithms (Malinowski et al., 2008).

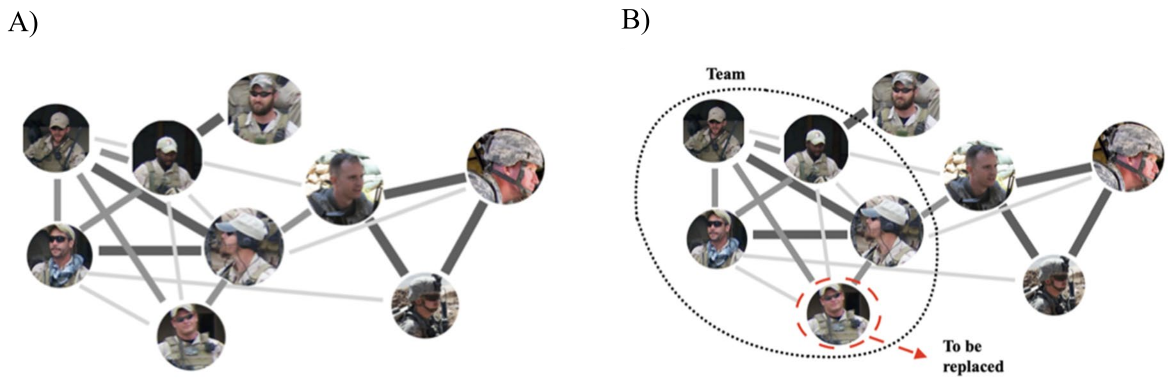
Graph-based, or network-based, approaches begin with a community of individuals who belong to a social network. The structure of that network captures how they relate to other people and what skills they themselves hold. To borrow an example from Li et al., (2015), a social network could consist of all current movie actors ("nodes" in the network) who have different connections ("edges") with other actors based on the previous films and genres they have acted in. Within such a setting, the problem of member replacement would be to find the best replacement actor given a vacancy in an existing cast.

Relationships can be captured by a social network in more general settings and communities as well. For instance, within the Army, instead of nodes representing current actors, they could represent each Soldier within a certain division. The connections among Soldiers would be revealed by edges with other nodes (Soldiers) based on more fine-grained group memberships. For instance, members of an airborne division will have connections with each other based on what previous team, squad, and platoon they served in. The task of replacing a Soldier within a specific team would simply be to find the most suitable Soldier (e.g., one with a similar background) given the current vacancy.

Li and colleagues place two constraints at the core of their network-based approach: the replacement candidate should match the team and vacancies in terms of skills held, and they should have a social network similar to that of the departing team member. Optimizing both constraints would ensure that the new member would have the skills needed and the social connections necessary to join the team with minimal disruptions. Within the context of acting, skills and connections may be derived from acting histories, while within the context of the Army, skills could be represented by a Soldier's knowledge, skills, behaviors, and preferences (KSB-Ps) and social connections made from previous service history. Methodologically, Li and colleagues model the team as a labeled graph (where each individual is uniquely represented by a node in the network) and then use graph kernels as a way to compute similarity in skill and social connectivity (illustrated in Figure 1). Intuitively a graph kernel is a function that computes the similarity between pairs of graphs; it is an approach also leveraged in other network-based approaches in this review. Using kernel functions is, however, computationally intensive so the authors propose fast heuristic-based methods to reduce the time needed to reach a solution.

Figure 1.

Social Network of Army Soldiers



Note. A depiction of an Army social network (panel A) where individual Soldiers[1] are nodes and the strength of connection between Soldiers is represented by edges. In this example, darker and thicker edges could represent a tighter social connection, whereas thinner and lighter lines depict weaker connections. If two Soldiers have no immediate ties to one another, there is no edge between them. In panel B the problem of team member replacement in the event of a member departure is depicted.

More recent work has focused instead on neural architectures to solve for team replacement. In one notable example, the authors work with teamwork data from a large online multiplayer game (“Dota 2”) to capture the influence players have on their teammates (Sapienza et al., 2019). Using that influence network, they build a recommendation system which predicts, for any given player, new teammates that will help them improve their personal performance. The backbone of the system is a specialized instance of an autoencoder, a type of unsupervised learning neural network architecture that both learns the structure in a data set and can generate new data according to that structure. While promising in their accuracy and scalability, current neural architectures offered in the literature suffer similarly as graph-based approaches: existing methods have not been translated into systems for large scale general use.

Our final categorical approach to exogenous team member replacement is through the use of general approximation algorithms. Malinowski, Weitzel, and Keim (2008), for instance, use a probabilistic latent semantic analysis (PLSA) technique to build a trust-based recommendation

[1] Soldier images taken from the following images: “Keeping Watch” (photo by Spc Kristina Gupton; Flickr, The U.S. Army); “Medal of Honor: Staff Sgt. Robert J. Miller” (Flickr, The U.S. Army); “Sicily Drop Zone” (photo by Sgt. Michael J. MacLeod; Flickr; The U.S. Army)

system. They propose that existing systems designed to support team staffing neglect key relational aspects that impact potential team fit so they introduce trust among team members as a central variable. The PLSA model they build is similar to recommendation systems used to suggest books a customer might enjoy, or songs they should listen to: if employee A trusts employee B, and employee B trusts C, then the model infers that A should trust employee C as well. Using ratings of trust among current team members as well as similarities in job preferences, the authors derive a subset of a pool of candidates who have maximum predicted trust with the existing team members. To be applicable in real world contexts their approach should be validated using data that might be accessible in real human resource settings. That is, the trust-relational network data needed to generate recommendations based on relationships must be sufficiently dense; if it is too sparse, as was the case in Malinowski et al.'s experimental data, the model will fail to recommend.

As the Army continues to modernize and move towards informed placement strategies, its changing approaches to talent management are reflected in recent initiatives. Efforts to develop and employ a service-wide matchmaking service highlight the potential to use rich personnel data to find best fits for Soldiers. Just as Malinowski et al. (2008) aims to develop a system to support staffing decision makers, researchers within the Army have proposed to leverage Soldier KSB-Ps and non-professional resume data collected on the Army's AIM2 website to make team staffing recommendations (Thompson & Schaak, 2018; MacGregor & Tomberlin, 2017).

Endogenous Replacement

In general, the literature belonging to the category of endogenous team member replacement decisions considers the decisions facing an "ad hoc" agent. Models reflect either how the agent decides to join a new team or how the agent, newly assigned to an existing team, learns to assimilate or lead their new team.

One example of an algorithmic approach to the first problem (that of deciding to join a team) is offered by Chen et al. (2015). Chen proposes a Bayesian reinforcement learning framework to capture the tradeoffs free agents make when deciding to join new teams or partnerships. They find that a set of key environmental properties – the turnover rate of individuals through teams, and the rate at which novel tasks are introduced – directly impact how agents are able to balance rewards from successfully completing tasks and short-term knowledge gain. For example, when the introduction rate of new tasks to the environment was high, the demand for a large variety of skills increased and individual workers learned fewer new skills. Their work has implications for the relevance of Bayesian learning frameworks for modeling how one might decide to join one team over another. It also highlights the importance of environmental properties in endogenous staffing decisions. Teams within the Army see differential amounts of turnover and task novelty. The results of Chen's work suggest that understanding the ways in which environmental features influence perceptions of potential squad members, as well as the extent to which certain squad and team structures encourage the acquisition of new skills, will be important to capture in models of Army staffing.

If the problem facing the agent is to instead figure out how to act once they have joined that new team, a learning algorithm approach might be applicable. For instance, Barrett et al.

(2013) and Agmon et al. (2014) consider the case in which a new member learns how to fit into the existing team. In the case of the work by Barrett and colleagues, that new member is given a transfer learning mechanism for learning the behaviors and types of possible agents. Agmon et al., (2014) follow a similar approach but focus specifically on the case where the new team member must lead the team. Again, the task facing the new leader is to learn about their team so that they may lead them to the best possible outcomes (i.e., optimize joint action utility).

Summary

The problem of choosing an individual to join an existing team is of particular relevance to an organization such as the Army. Given the rates of both planned and unplanned personnel turnover, an architecture that can optimally fill a vacant position is valuable. Current exogenous computational approaches to this problem offer exciting and varied solutions that take into consideration not only skill fit but also interpersonal features. Optimizing such interpersonal fit of a new team member is particularly important for adding an individual while minimizing disruption to team processes. Choosing a replacement who has close social connections with current team members or high potential for collaboration may be an effective way to quickly build shared mental models or shared experiences that can help a team adapt readily to changes in membership (Bell et al., 2018; Mathieu et al., 2000). Such work has direct implications for helping squads achieve readiness in the face of personnel changes.

Research on endogenous team member replacement also sheds light on team development. The work regarding how agents learn about their environment and about each other has relevance for the development of a team once it has formed. Learning about fellow teammates, their "types", and their expected behaviors, can help each team member to learn how to act. Mechanisms that introduce transparency into team culture can therefore help to facilitate team member integration. Adding transparency to team learning also has the potential to facilitate leader development.

The general computational problem of solving for optimal team member replacement is, however, computationally intense, especially in the context of network-based extractions. Li et al. (2015) approximate that for a candidate pool of one million individuals, standard graph kernel computations would take approximately 1.7 hours to find one replacement member for a team of ten.[2] While the "fast algorithms" they develop significantly reduce that computational time, it remains the case that the pressure on usable systems to be efficient is significant. Alternative methods of representing both interpersonal data (i.e., social connections) and personal information (i.e., skills) such as the neural network approaches in Sapienza et al. (2019) may prove more computationally feasible. To that end, future work should extend the basic research discussed in this section to tools for practical use, with the primary focus on scalability.

[2] Note that the authors do not specify the processor underlying this estimate. We offer it here as a compelling illustration of the computational intractability of current graph kernel approaches and of the research need for developing algorithms that can be realistically applied to practical settings.

Single Team Formation

Approaches, both exogenous and endogenous, to single team formation are dominated by the development of network-based approaches to team extraction. Many of the following papers focus on extracting a team of experts from a pool of candidates and consider how team hierarchy and robustness impact that extraction.

Exogenous Formation

In an early demonstration of a network-based approach to team formation, Lappas et al. (2009) aim to extract a team from a social network using capabilities and social connections as constraints. Constraining team membership by skill coverage is a common constraint that we have seen previously in this review and we will see again. However, just as a viable team must have the necessary skills, Lappas and colleagues require them to also have members who can effectively collaborate. One novel advance of this work was to operationalize potential for collaboration by communication cost, represented by the social network structure. As in Li et al., (2015; exogenous team member replacement; see also Figure 1), a social network graph consists of nodes which represent individuals and edges among nodes which could represent social structure such as distance between two individuals in an organization, or whether or not Soldiers have previously belonged to the same squad or served on the same installation. For example, if two Soldiers served alongside one another in the same small unit (e.g., within a squad or platoon), the weight of the edge would be greater than it would be if they were more distantly connected by a shared brigade or deployment region. Using these embedded representations of social connection, Lappas et al. propose different ways to leverage those connections to extract a subset of individuals that have low communication cost (e.g., similarity of service record) and necessary skills.

Dorn and Dustdar (2010) also focus on extracting an expert team from a network but offer a solution that introduces two more realistic constraints. The network they work on is built from an online forum community where the authors derive skills from the topics each user posts about. Their first constraint targets the skill requirements of Lappas's team extraction; however, while Lappas set skill requirements at a threshold below which no expert would be considered for inclusion, Dorn and Dustdar permit a tradeoff between social compatibility and skill. Second, they require every individual in the final team to be connected to one another. This requirement contrasts with the approach of Lappas to focus only on the strongest tie.

Kargar and An (2011) further build on the network-based approach to team formation and make two primary contributions: they introduce new ways to define communication cost and they address the distinct problem of finding a team of experts that has a leader. The communication cost functions they propose are sensitive to the relationships among individuals with the same expertise and consider communication cost specifically between individuals and the leader of the team. To find the leader and corresponding team of experts, Kargar introduces a brute-force exact polynomial algorithm that was novel, but minimally scalable. In 2012 Kargar and colleagues approached the problem of forming teams which have a coverage of skills, minimal communication cost, and minimal personnel cost. They introduce a cost function that is simply a linear combination of communication and personnel cost and offer an approximation algorithm to extract the team from the social network graph. Their subsequent paper in 2013 is largely an extension of that work.

Teams that have a formal hierarchy are commonly overlooked in the algorithmic approaches discussed in this review. The work by Kargar and An (2011) is a notable exception in its specific consideration of team leaders. Teng et al. (2014) build off that work and consider the case in which there isn't a singular leader guiding a team but rather a hierarchy of leaders coordinating with each other as well as with their teammates. Intuitively, each leader only has the capacity to communicate with a finite number of individuals so one of Teng's key constraints in hierarchy formation is what they term "communication load".

The above work marks an advance in algorithmic approaches incorporating social aspects beyond skills held by an individual. While each has a different way of embedding and optimizing social compatibility, each recognizes that a team requires more than just members who have the right skills to be successful. The next set of papers considers a different aspect of building a team: robustness.

One way of being robust is for a team to have a skill distribution such that one or more members can be lost and the team still has the skills necessary to complete a task. In an Army setting, robustness in this sense might reflect the need of a squad to complete their task even in the event of losing a Soldier. Okimoto et al. (2015) define the Task-Oriented Robust Team Formation (TORTF) problem as multi-objective constraint optimization problem: the goal is to find a team of individuals that is both robust to the loss of one or more agents and that minimizes cost of assembling the team. In this case, an individuals' cost increases with the number of skills they possess. Crawford et al. (2016) build on Okimoto's work by proposing a set of approximation algorithms that are more scalable than the exact algorithms proposed by Okimoto. The approaches they propose to solve the TORTF problem scale to large problems and efficiently trade off robustness and cost of a team.

Endogenous Formation

In our example of endogenous single team formation, Anagnostopoulos et al. (2017) formalize a problem they term team formation with outsourcing (TFO). In this setting, tasks arrive at a marketplace where there is a dynamic team of workers ready to complete it. The problem Anagnostopoulos solves is to figure out the optimal algorithm for hiring new workers to that team, firing existing workers, and outsourcing tasks the team cannot complete. Each worker has a set of skills and sets their fees (hiring fee, outsourcing fee, and salary) which represent the sole source of cost in the algorithm. A variety of algorithms are proposed including one where the minimum cost set of individuals is found that covers the required skills, and one where workers are never hired, only outsourced. While this paper explicitly does not consider any parameters other than skill coverage and cost (in terms of wages), it represents a novel contribution to team formation in an online, ad hoc, setting. Several papers in the endogenous multiple team formation section (e.g., Rockicki et al., 2015) return to the problem of team formation in online crowdsourcing settings.

Summary

The primary contributions of literature within this category revolve around their incorporation of interpersonal relationships (in terms of communication) and their development of network-based methods for team formation. The effort to create interconnected teams is one step towards adopting a psychologically sensitive approach to team formation. In considering communication and social connections when forming a team, a decision maker is able to assemble individuals that may more quickly achieve team cohesion, build common ground, and construct shared mental models than teams with higher social start-up costs. The advantage given to teams with minimal communication costs may help to reduce the time it takes to bring the team to readiness, a metric important to the development and sustainment of Army units (McCrystal et al., 2015).

Many of the incremental advances reviewed in this section are aimed at developing algorithms that have greater efficiency and scalability. Given the computational costs of leveraging social network information to derive optimal teams, and the promise of those methods to be useful to practitioners, future work should continue to build systems that can handle multiple objectives at scales relevant to user expectations.

Multiple Team Formation

Here we categorize current exogenous and endogenous algorithmic approaches to multiple team formation by the features they consider and by their algorithmic approach. In this section we begin to see rigorous consideration of other, social, factors that impact teamwork, beyond simply skills held by team members. While communication cost was a significant focus in single team formation, here we discuss inclusion of personality traits and considerations for how personality interacts with team tasks.

Exogenous Formation

The literature devoted to exogenous approaches of multiple team formation can be organized into two broad categories. The first contains research aimed at incorporating the personality of potential members, whereas the second can be described as a methodological category of network-based approaches.

Similar to the research discussed previously that was novel for the consideration of teammate communication and coordination potential (e.g., Lappas et al., 2009), research that includes psychological and more general personnel factors represents an important step within the computational sciences towards including psychological predictors of team success. In one example of a person-centered approach, Stylianou and Andreou (2012) propose a multi-objective algorithm for balancing team member skills and personality traits. Using the five-factor model of personality (Barrick & Mount, 1991) in combination with career handbooks, the authors derive links between different professions and desired personality characteristics. They include these synergies along with skill requirements, team size preferences, and scheduling constraints in a variety of genetic algorithm approaches. Broadly, a genetic algorithm is modeled after natural selection wherein genomes are evaluated according to a fitness function and those with higher fitness scores pass on part of their genome to the next generation. The details of how fitness is assessed reflect dimensions of optimization such as personality trait fit and team size. Incorporating some methods from a previous study (Gerasimou et al., 2012; see below), the authors ultimately develop a tool reviewed later in this article, IntelliSPM.

Farhangian et al. (2015a) endeavor to similarly balance individual skill, personality, and task specifications in their team formation. They employ personality types from the Myers-Briggs Type Indicator[3] (MBTI; Myers et al., 1998) and team role expectations from Belbin Team Roles (Belbin 2012) in an effort to capture the relationship between the creativity and social interaction of a task to individual personalities. Unlike other articles in this review, Farhangian uses an Agent Based Model (ABM) setting to model the effect of task dynamics on team formations. As tasks come online, managers must select the best team for the task even if that requires some team members to be reallocated from existing teams. The ABM captures that rescheduling cost and the authors explore team formation rules that either minimize under- or over-competency of team members. This approach is uniquely useful for investigating the dynamics of task allocation and dynamic environments in general and promising extensions could aim to develop user-interface tools with ABMs as the foundation formation algorithm.

Both the above papers seek to inform staffing by linking personality traits with roles within a team. Stylianou and Andreou (2012) derive those links using career handbooks while Farhangian et al. (2015a) hypothesize certain connections between traits required for a role and personality profiles. The structure of jobs within the Army offers a potential data source for incorporating features of a team role into staffing decisions. One recently developed measure, the Adaptive Vocational Interest Diagnostic (AVID), aims to help Soldiers identify a MOS that matches their interests and is likely to yield high job satisfaction (Nye et al., 2019). Personality characteristics derived from the Soldier Tailored Adaptive Personality Assessment System (TAPAS; Drasgow et al., 2012) are currently used to identify appropriate and potential MOS so it could be the case that methods following those of Stylianou and Andreou, and Farhangian and colleagues could leverage both AVID and TAPAS responses to assign Soldiers to teams and positions fitting with their preferences and motivations.

In a series of three papers from 2016, 2018, and 2019, Andrejczuk and colleagues propose personality-based algorithms of team formation. Andrejczuk et al. (2016b) use personality traits from the MBTI (Myers et al., 1998) to partition individuals into heterogeneous teams balanced on personality and gender with the aim to increase general performance. They develop algorithms for small and large team settings and compare their results with manually assembled teams, ultimately finding their algorithmic teams to be superior. Andrejczuk et al. (2018b) extend that approach by developing an algorithm, SynTeam, to solve what they dub the Synergistic Team Composition Problem (STCP). Their method efficiently partitions individuals into balanced teams that will exhibit relatively equal performance based on their gender distribution, personalities, and competencies. Finally, Andrejczuk et al. (2019) offer a direct extension of Farhangian et al. (2015; see above). They aim not to form a single heterogeneous team, but rather to assign individuals into "psychologically balanced," competent, and gender-balanced teams. As was the case with Farhangian's approach, personnel data from Soldier

[3] We note that although the Myers-Briggs Type Indicator is commonly used as a personality assessment, psychologists and personality researchers recommend using psychometrically validated scales such as such as the Big Five trait inventory (John & Srivastava, 1999; John et al., 2008). See the section on "Integrating insights from psychological sciences" for a discussion.

TAPAS scores could be leveraged within an Army application. We review this paper in the section on tools, as it ultimately resulted in a web-based application for student team formation.

Another example of a personality-based multiple team formation approach is that introduced by Gilal et al. (2018). As above, they use the MBTI to capture team member personality traits and include that feature in team composition. The larger aim of this paper is to identify the appropriate classification technique from a set of varied options: logistic regression, decision tree, and rough sets theory. In forming the teams, they consider team role (member or leader), personality, and gender, as well as a dichotomous team performance variable using data collected from undergraduate students. They find that each of the three classification techniques produced different solutions, with the logistic regression method failing to meet the accuracy benchmark. One important takeaway from this work is that different algorithmic approaches can produce wildly different solutions which may or may not be inferior to other potential algorithms.

Our second category of exogenous approaches to multiple team formation consists of research that employs a network-based approach. The first research in this category is that of Anagnostopoulos et al. (2012) who consider a setting in which individuals have (binary) skills and are related to others in a social network. The author's goal is to figure out how to form a team in response to dynamically introduced tasks such that all required skills are covered, communication cost is minimized, and the workload of each individual is balanced. They borrow the communication cost definitions from Lappas et al. (2009; see above section) but make the more realistic assumption that people need not be directly related to have potentially good coordination — they could be connected by second or third level relation. This more relaxed characterization of social connections may be more appropriate when deriving social networks to capture Soldier relations.

Rangapuram et al. (2013) similarly build off Lappas et al.'s early work. Their goal is to provide a more realistic and flexible setting for the formation of teams where the team may have a leader, restricted size, and preference for easy communication. One way in which their approach offers increased nuance is that constraints can be put on the number of team members who have a certain skill of a certain level; that is, preference can be given not only to those who have a certain skill, but to those who have the highest (or lowest) competence. They also broaden their sense of distance to include both social distance (i.e., collaboration potential) and geographical distance. The constraints considered by Rangapuram and colleagues are of particular relevance to team formation tasks facing those in the Army. A constraint missing most often in the computational literature is team formation with a leader; in the present paper a team leader is chosen a priori and the team of subordinates are chosen to have minimal distance to that leader.

Additional nuance is offered by Gutiérrez et al. (2016) in their formalization of the "Multiple Team Formation Problem" (MTFP). An explicit extension of a single team formation problem, MTFP aims to allocate individuals to multiple projects where they may only partially dedicate their time. The authors use a small and generic network to depict social aspects of the problem; their sociometric matrix captures how each team member perceives and is perceived by other members. The algorithmic approach Gutiérrez offers for the MTFP has ready analogies to real-life mission settings and their inclusion of a sociometric matrix is a promising way to include social components of team building.

Outside of a network setting, a recent paper by Bahargam et al. (2019) aims to develop a team formation scheme that explicitly considers the collaboration potential of a team by minimizing "faultline potential." Team faultlines, which are described as dividing lines that split a group into relatively homogenous subgroups based on attribute differences (e.g., age), have been noted for their effect on team cohesion and performance but have proven difficult to measure in a way that could be leveraged for team formation. Bahargam proposes an algorithmic approach that minimizes "conflict triangles" that exist based on surface level characteristics (e.g., race or gender). Given the well-documented benefits of team diversity on performance (Horwitz, & Horwitz, 2007), the algorithms developed could be best used to partition a large population into groups that value diversity but minimize faultlines.

Although Bahargam and colleagues used surface-level characteristics to model faultlines, psychological research of teams suggests that surface-level features are only of particular importance during the early stages of a team. Deep-level attributes (e.g., personalities, teamwork preferences, values) are more likely to continue to interact and influence team processes and effectiveness over time (Bell et al., 2018). Future applications of Bahargam's type of triangle minimization approach may be particularly useful for forming teams to prevent team conflict. For example, this method could leverage research on conflicting personalities that could be especially harmful for the effectiveness of certain types of teams (i.e., teams on long term missions).

The final paper in this section is one that forms the foundation for both a tool discussed at the end of this review, and a personality-based approach mentioned earlier in this section. Gerasimou et al. (2012) propose a particle swarm optimization (PSO) approach to aim in team formation and project assignment. This computational approach is biologically inspired (as are genetic algorithms) and seeks an optimal solution to a problem by starting with a set of random solutions (called particles) which are moved around in solution space according to simple rules (an analogy from nature may be bees searching for pollen). Gerasimou demonstrates the strength of such an approach in this article and builds on the PSO method in later work (e.g., Stylianou & Andreou, 2012; Stylianou, Gerasimou, & Andreou, 2012).

Endogenous Formation

Of the literature on endogenous multiple team formation, some work focuses on discovering general principles that guide self-organization into teams, leveraging naturalistic data sets and crowdsourcing tasks to examine how individuals may naturally sort themselves into teams given their preferences and constraints. Other work aims to algorithmically compose teams by prioritizing agents, or to look at team formation through a lens of learning and inference.

In one large-scale study of self-organized teams, Wax et al. (2017) used data from a massively multiplayer online role-playing game (MMORPG; Dragon Nest) to evaluate how teams form and what predicts their success. They find evidence for three primary mechanisms of formation: homophily (i.e., similarity of players, specifically in terms of level and "guild" membership), familiarity, and geographical proximity. In general, they find that surface-level homophily in terms of player level positively predicted team performance; that is, teams with differing player levels performed worse than teams with players of equal status. The authors contribute that particular finding in part to the structure of Dragon Nest; homologous teams engage in more appropriate quests. In the context of the game Computer Go, Marcolino et al. (2013) find that heterogeneity of a team is preferred to a homogeneous team. They model a player team where each member agent votes each round for what action they think should be taken. Within their context they find that a diverse team outperforms a team composed of copies of the strongest agent – a finding that reflects the value of opinion diversity.

Rockicki, Zerr, and Siersdorfer (2015) are also interested in self-organization of teams but particularly with the aim of using team structures to increase individual performance via competition. They take the context of online crowdsourcing work (e.g., Amazon's Mechanical Turk) where tasks are usually completed by individuals who are monetarily incentivized to complete high quality work. In an empirical study they allow individuals to complete tasks (e.g., image classification) individually, as part of an assigned group, or as part of a self-organized group and find that compared to individual competitions, team scenarios yielded the highest quality work. Within the self-organized team formation condition, they observed that the primary strategy was for individuals to join one of the top-performing groups (as broadcast on a leaderboard). A secondary strategy was for low-performing teams to combine forces in a pattern they termed "competitive merging".

If the aim of crowdsourced self-organized groups (or coalitions) is to work together to complete complex tasks instead of working together to complete more of the same task, the demands on organization change. Peleterio et al. (2015) present a model for building and maintaining coalitions and they focus on two decision mechanisms. First, their mechanism allows a coalition leader to decide if they should keep their current coalition and then how they should assemble a team based on skill and reputation. Second, the participating individuals can decide to remain part of a coalition or join another. Central to both mechanisms are calculations of agent skills, agent collaboration potential (i.e., "synergies" based on past interactions), and reputation of both extant coalitions and individuals. In an empirical evaluation, Peleterio showed that this decision framework supports high quality teams that produce high quality work. In a similar vein, Farhangian et al. (2015b) propose an auction-based framework in which task requesters and contributors decide how to manage teams. Requestors receive bids from contributors and decide who to put on a team based on familiarity, past success, and personality fit. The inclusion of personality in this auction scheme is a novel contribution and reflects the psychological literature that suggests personality characteristics have a large role to play in team performance (e.g., Driskell, et al., 1987; Barrick et al., 1998; Bell, 2007).

Spradling and colleagues (2013) focus still on the case where different team members complete different tasks but are interested in the combination of player preferences for their own role and for team composition. They term this situation a Roles and Teams Hedonic Game and propose algorithms that partition teams according to both preferences on individual roles and preferences for team roles to fill. In this way, individuals can automatically be matched with others who agree roles X, Y, and Z are needed and are interested in uniquely playing one of those roles. The authors offer a heuristic optimizer to solve the formation problem.

Finally, Liemhetcharat et al. (2014) and Chalkiadakis et al. (2010) focus on approximating learning algorithms to reflect how individuals update their information about potential teammates and use that information in coalition formation decisions. Liemhetcharat (2014) explores this by having pairs of teammates interact in “learning instances" during which they can learn about the task through experience or, more interestingly, how to coordinate better with their teammate. The team formation goal is then to choose the optimal team after all training has concluded. In a similar vein, Chalkiadakis et al. (2014) propose a Bayesian model-based reinforcement learning framework which allows individuals to update their beliefs about the types of people with whom they are interacting. As they refine their beliefs, the agents must decide whether or not to form new teams (explore) or rely on partners they know (exploit). This work is novel for the way in which it combines dynamic group formation with individual-type uncertainty and their core algorithm is shown to be robust and computationally feasible.

Summary

Several themes emerge from the literature on multiple team formation. First, we reviewed several papers that were novel in their inclusion of personality as a team formation constraint. In some cases, the algorithmic approaches considered personality traits as the second half of a multi-objective approach for optimizing team composition (with the first half being skill oriented; Stylianou & Andreou, 2012; Andrejczuk et al., 2016). While those papers differed in what they viewed as an optimal distribution of personality traits, they form the algorithmic foundation of an approach to select team-relevant traits and determine optimal distribution of those traits among teams.

In others, personality was included in a more nuanced consideration of how individuals fit into teams but also into team roles (e.g., Farhangian et al., 2015). Later, in the section on “Integrating insights from psychological science” we discuss the opportunity for Soldier personnel data to be leveraged in order to fit an individual to an optimal role. Outside the realm of personality, papers in the above section also offered new algorithms to extract multiple teams from a network of individuals (e.g., Rangapuram et al., 2013) where other team features such as leader/follower dynamics and team communication were considered.

The reviewed research on endogenous multiple team formation offered more general insights into how teams might dynamically self-assemble (or dynamically re-assemble) depending on needed skills and synergies of potential team members (e.g., Peleterio et al. 2015). While not directly relevant to forming multiple teams in an Army setting, Liemhetcharat et al. (2014) and Chalkiadakis et al.’s (2010) research on learning algorithms could be used to better understand how various trait combinations in a team impact how readily members can learn about each other. In particular, Liemhetcharat highlighted the importance of opportunities to learn about tasks and about the behaviors of teammates. The more a set of team members knows about a given environment and about the collaboration behaviors of other members, the more optimal they become.

Tools for Automated Team Formation

The landscape of potential algorithmic approaches to solve team formation problems is, as the previous sections demonstrate, vast. Arguably, the majority of efforts within those fields of research have gone to presenting proof of concept solutions, and not solutions which are meant to be implemented by practitioners. A small emerging literature aims to fill that gap by providing algorithms that incorporate constraints important to their target audiences and programs that are built in systems that can be customized and implemented by individual users.

One set of tools currently available leverages an input program called Comprehensive Assessment for Team-Member Effectiveness (CATME; Ohland et al., 2012) which is a survey-based peer evaluation tool. In one part of the survey students are able to provide feedback on how well their teams are working together. The other part of the survey is integrated with a team assembly framework called Team-Maker (Layton et al. 2010). Central to the usability of Team-Maker is that it allows instructors to decide which of a set of criteria are important when forming a team. For instance, they could prioritize Grade-Point Average (GPA) distribution in groups such that teams either have students of similar or dissimilar GPAs. They could also decide that allocation according to that GPA rule was more important – or should receive greater weight – than allocation according to gender. While this tool was developed for academic classrooms, it does have the flexibility for users to define their own rules, creating an opportunity for specialized users to include preferences for KSB-Ps, performance evaluations, or previous experience.

The selection of a best set of groups is found in Team-Maker with a hill-climbing algorithm, an optimization technique that finds local maxima by making incremental changes to its solution from a random initial starting point (in this case, random allocation of students to groups). The algorithm begins with a random allocation of students to groups and then swaps two students at a time, recomputing the group fit scores each time. One drawback to CATME's Team-Maker is that it does not allow for the manual shuffling of team members. As such, a unit leader, armed with tacit knowledge about positive or negative social dynamics between two Soldiers, would not be able to switch them within the system.

In 2011 Dimiduk and Dimiduk introduced a new program, GroupEng, that targeted two particular flaws of Team-Maker. First, GroupEng introduces privacy improvements by keeping data inputted by students and teachers local, unlike Team-Maker which stores it externally. It also addresses a weakness of the group value determination in Team-Maker which allows for teams to be weaker on average than other groups if they have satisfied certain rules. As a result, Team-Maker could lead to large deviations in group strength even when instructors indicated a preference for equally strong groups. While there may be situations in which such large deviations are useful or do not significantly impact team outcomes (e.g., when assembling a sub team from a larger unit), such a violation could be hazardous for partitioning Soldiers into equally resilient teams deploying under high-risk conditions.

Hertz et al. (2019) offer yet another algorithm to solve the Team-Maker problem, gruepr. Their set-up is essentially the same as before, with an instructor gathering information on participating students, indicating desired scoring rules, and then preferred weighting of those rules. This time, Hertz and colleagues solve the assignment problem using a genetic algorithm. Here, genomes are arrays of student IDs representing potential group membership which are evaluated according to a group compatibility score. Those with higher fitness scores pass on part of their genome to the next generation and as evolution within the model proceeds, random mutations occur (students are randomly swapped between teams) and over generations, the optimal distribution of students to teams emerges. The authors demonstrate dominance of gruepr's team allocation over both random and instructor-selected assignments.

So far, all of the above tools nicely incorporate basic information about participants, such as their schedules or GPAs, but none have incorporated any additional personnel factors. Andrejczuk et al. (2019) propose a tool that fills that gap by considering personality traits of potential team members. Their tool, EduTeam, is based on their SynTeam algorithm, a heuristic algorithm based on local search. As in Stylianou et al. (2012; see below), Andrejczuk aims to sort students into teams that are balanced in size, skills, personality, and gender. Their approach is to randomly compose teams of the given size as an initial solution and then iteratively select two teams at random and shuffle members. To evaluate proficiency of a team solution they calculate a score that depends both on competency of the team (balance and coverage of skills needed to complete a task) and congeniality of a team. Congeniality in their sense is based on a set of heuristics surrounding the personality types defined by MBTI (e.g., a team is more congenial if it has a balance of sensing-intuition and thinking-feeling types). While the authors employ Myers-Briggs type, Army specific metrics such as TAPAS scores could be used equivalently to capture primary personality factors (derived in this case from the Big Five) and additional factors such as team orientation. Overall, the SynTeam algorithm is shown to be efficient at large numbers of students and partitions, making it a promising tool for team segmentation in the real world.

The procedure for all the tools discussed so far is to provide instructors with flexibility in creating rule sets and preferences, but then lock them into the algorithmic groupings. Thio and colleagues (2018) offer a tool, Teammatic, with a "mixed initiative approach" that directly addresses that inflexibility. Similar to others, their tool begins by having instructors upload information about their students (e.g., their schedules, topic interest, gender) and then creating constraints to govern team formation. Allocation proceeds according to a greedy algorithm that maximizes a score function that reflects the instructor's constraints. Importantly, after the teams have been generated, instructors can move students to different groups. To support these swaps, Teammatic suggests potential exchanges that will still yield groups scoring high on the specified criteria. A tool such as Teammatic may be particularly useful in a military setting where leaders and decision makers are likely armed with implicit knowledge about potential team compositions. With the system's swap suggestion tool, that leader could combine algorithmic insights with their tacit knowledge to enact informed changes.

Outside of a classroom setting, Stylianou et al. (2012) offer a tool aimed at software project managers. As before, their tool takes as input information about potential team members but this time that information includes both personal traits of team members (five-factor model of personality) and project features (e.g., duration of task, skill level needed). Their tool has two primary functionalities: first, using a multi-objective genetic algorithm, individuals are assigned to teams according to skill and personality fit. The objective function of this step minimizes the number of individuals assigned to a task, maximizes the personality fit of individuals to the nature of the task, and maximizes skill fit. The second functionality of their tool takes a set of team assignments as given and outputs a schedule of tasks that will yield the shortest possible project duration. In this step, the user has the option of using a genetic algorithm or a single-objective particle swarm optimization algorithm depending on their preference. While this particular tool is geared towards project management, its explicit consideration of how a certain personality trait aligns with a specific task is novel and an important reflection of psychological constraints. It may be a promising tool to use for specific duration missions where team functionality is tightly linked to the nature and duration of team tasks.

The final tool we consider here is one that addresses the so far unaddressed issue of team member replacement (Zhou et al., 2018). In that work, the authors build a network-based recommendation system with the specific aim of being transparent to the user. Their tool, EXTRA, uses a random walk graph kernel approach to choose minimally disruptive candidates to replace current team members. Using a graphical interface, the decision maker can then explore the foundations of that recommendation by learning, for instance, what the social connections are between the candidate and current team and how the candidate's skills compare to those held by other members. This tool is unique in its focus on member replacement and in its interactive design.

Summary

The tools reviewed here represent the major advances in the last decade of development. Many of these tools are used actively by large communities (e.g., CATME and Team-Maker in education settings) and have evolved to be adaptable and user-friendly by building flexibility in the types of constraints to consider during team formation. Some tools offered on the market go beyond skills and schedules to include personality traits when assembling final teams (Stylianou et al., 2012; Andrejczuk et al., 2019).

The landscape of tools is ripe for methods that include other social factors, such as team communication and coordination costs which could be represented by past collaboration between service members. A paper mentioned earlier in this review, by Sapienza et al. (2019), used a neural architecture for building a recommender system which could be a scalable way to include both skill and collaboration in team formation. Rad et al. (2021) propose an open source toolkit using such an approach and employ an efficient variational Bayes neural architecture. As the field of automated tools advances, there is opportunity to introduce new computational tools (such as those network-based approaches) to user systems. In doing so, additional staffing problems such as team member replacement decisions could be included in automated decision tools.

Integrating Insights from Psychological Sciences

Recent years have seen significant advances within the computer sciences on the computationally difficult problem of team formation and composition. One overarching theme of this review is that the landscape of approaches to forming teams is extensive. Some computational tools are common to all decision types (e.g., genetic algorithms, graph kernels). Other tools, such as network- or graph-based approaches, have been employed for single and multiple team formation but have not been leveraged for team replacement systems or user-friendly tools (see Appendix C for a summary of algorithmic approaches and tools). Papers in the review also vary in the extent to which individuals are privy to, or involved in, the architectures that assign them to teams (a distinction aligned with the exogenous/endogenous categorization), and the extent to which they are characterized solely in terms of their skills.

Organizational science is not particularly well positioned to inform variation arising from algorithmic approaches. To date, the limited attempts by organizational psychologists to create decisional tools have fallen short. For instance, although Donsbach et al. (2009) developed a staffing tool that considered both staffing decisions (e.g., creating a new team vs. filling an opening to an existing team) and individual team role propensities (i.e., individual experience and personality), its practicality was limited to staffing one team at a time, while also restricting the input to no more than 50 candidates and 12 open positions. Organizational psychologists are, however, well positioned to leverage their theories of team composition to inform, or create, decision tools for automated staffing that are psychologically sensitive. Below, we consider three main areas that psychology has identified as important for composing teams. For each, we highlight current algorithmic approaches that either address that area or are potentially adaptable and relevant.

Skills, Individual Attributes, and Team Role Propensity

A common way to optimize assignment of individuals to teams is by considering the skills held. An optimal team by this metric has full or redundant (Okimoto et al., 2015) coverage of skills required to complete a given task. However, an individual's ability to contribute to either a team or individual task is far wider than simply their skill level and includes attributes such as their cognitive ability, personality, and gender (Barrick et al., 1998; Devine & Philips, 2001; Van Vianen & De Dreu, 2001; Fisher et al., 2012; Lykourentzou et al., 2016). In the case of personality, one of the challenges facing work within the computational sciences is measurement based. The measures employed by the papers reviewed here (e.g., MBTI) have been replaced in modern research in favor of more scientifically derived scales (Pittenger, 2005). At their core, algorithmic approaches that included personality in their team-fit calculations represent an important step towards psychological sensitivity. However, to reflect modern theories of personality and teams, architectures must be built around more robust models of personality (e.g., Big Five traits; Barrick & Mount, 1991). Army settings are particularly well positioned to leverage algorithmic approaches to personality-sensitive team formation. While academic instructors may lack more detailed aptitude or personality data on their students, Soldiers each have ASVAB and TAPAS scores and a wealth of other personnel data that can immediately be incorporated.

Efforts to formalize the specific relationship between personality and team roles also suffer from a lack of rigorous tools. For instance, Stylianou and Andreou (2012) sought to optimize the fit between personality and occupation, as derived from a career handbook while Farhangian et al. (2015) offered an ABM framework that represented the dependency between personality traits and role tendencies based on MBTI types and Belbin role descriptions (Belbin, 1993). Both of these papers offer a framework for considering how team members may be more or less suited to complete a particular part of a task or occupy a particular team role. Research from psychology suggests that indeed, the characteristics of an individual motivate and enable them to occupy some roles more effectively than others. For example, Mathieu et al. (2015) create a taxonomy measure, Team Role Experience and Orientation, that defines the behaviors associated with different team roles found in the literature (e.g., a "Challenger" pushes a team to explore all possible solutions to a problem; interested readers may refer to Appendix A for a full list of- team roles). Future computational work should continue to include person-role matching considerations and incorporate motivation of an individual to complete a task as part of the fit optimization.

Beyond person-role fit, certain distributions of personality traits are critical to group effectiveness. While algorithmic architectures such as that developed by Andrejczuk et al. (2016) partition individuals into heterogeneous teams balanced on personality, it may be the case that only certain characteristics are important to balance on. For instance, Halfhill et al. (2005) find that relationship-oriented personality traits such as agreeableness predicted team performance beyond task-oriented traits such as achievement motivation. That said, Bell (2007) notes that particularly in the case of agreeableness, minimum agreeableness is more important than average agreeableness when composing a team; all it takes is one disagreeable member to disrupt the balance of an otherwise agreeable team. Moreover, findings from across civilian teams may no longer stand when tested against an Army population. The relationships among personality characteristics and Army-relevant team outcomes need to be both understood and incorporated to create teams that may perform optimally. For example, although high group extraversion is typically predictive of high team performance, it may be detrimental to teams operating in austere or isolated environments (Palinkas et al., 2000).

Personality is one way to represent compatibility of team members but there are other factors that impact interpersonal relations that subsequently impact team performance. Many papers here formalized “communication cost” as a way to capture potential for effective collaboration among team members. Sometimes that cost was represented by histories of collaboration (e.g., Lappas et al. (2009) used co-authorship in a database of articles), and other times, closeness in a social network (e.g., Rangapuram et al., 2015). Communication cost could be additionally represented by a wealth of other data sources, such as service history or geographical histories (e.g., deployment locations, or posts on which a Soldier has lived).

Among psychologists there is generally a consensus that interpersonal cooperation and communication are important for optimizing teamwork (Sheng et al., 2010). Indeed, interpersonal cooperation itself is required to collaboratively problem solve and resolve conflict (Korsgaard et al., 2005). Network-based approaches offer a natural and promising architecture for representing relationships that could facilitate such cooperation but for practitioners, aside from the high computational costs of current network algorithms, deriving the relevant social network would require appropriate data on individual members. Malinowski et al. (2004) for instance, propose that data on colleague trust perceptions could be derived from company-wide surveys.

Team Hierarchies

The overwhelming majority of computational approaches to team formation reviewed here imply that teams are entirely egalitarian and do not consider team hierarchy in the formation decision. Of the exceptions (Agmon et al., 2014; Kargar and An., 2011; Rangapuram et al., 2013; Gilal et al., 2018), the team leader is usually taken as given; that is, a team is formed around a pre-designated leader. There is therefore a lack of computational approaches in which, given a pool of candidates, a team is extracted with consideration of who in that team will assume the position of a leader.

In a context such as team formation in the Army, it may be the case that leaders are indeed prespecified, and the goal would be to select the optimal group of subordinates for that leader. Alternatively, it may be the case that a leader needs to be recruited to lead an already formed team. In the first case, there is some preliminary algorithmic work that formalizes the optimal relationship between a leader and a subordinate as one that minimizes the communication cost between them (Kargar et al., 2011). Current algorithmic approaches don't speak to the second situation in which, given a team, a leader is chosen (this decision problem would likely fall in the category of exogenous team member replacement). Insights from organizational psychology could inform the characteristics desired in a leader given the features and goals of the team (Carter et al., 2019).

Task Type

In the organizational science literature, task type is considered to impact team performance both in terms of the tasks completed by team members (e.g., negotiation vs. advising; Wildman et al., 2012) and in terms of tasks completed by the team as a whole. This latter type of team-task interaction reflects task context and captures the impact of complexity, environmental uncertainty, and interdependencies of subtasks. Generally, different tasks require different types of teams (see Hollenbeck et al. (2012) and Lee et al. (2015) for a description of team type conceptualization, also Steiner (1972)). Research suggests, for instance, that as tasks become more complex and as environments become more uncertain, the demand of teams to be more cohesive also increases (Andrejczuk et al., 2018).

The impact of task types can also be seen in the team formation decisions across the Army; leaders show differences in the attributes desired for strategy, negotiation, and crisis response teams (Baltos & Mitsopoulou, 2007). Baltos and Mitsopoulou (2007) also note that the extent to which personal relationships and collaboration potential matter for team formation decisions changes with the external team context, with interpersonal relationships less a factor when the team is entering a crisis response situation. Within the current review, Farhangian et al. (2015b) represents one of the few algorithmic staffing papers to consider task type in formation decisions, though their design is limited to two types of tasks -- structured tasks and open-ended, "cognitive" tasks. There is, therefore, a significant opportunity to develop team formation algorithms that consider the nature of the tasks the team is being designed to complete.

Conclusion

Over the course of this annotated bibliography we have provided a multi-disciplinary review of current and emerging computational approaches to team formation. We adopted a taxonomy which categorized those approaches into decision type and exogeneity/endogeneity of decision makers in an effort to highlight the relevance of computational systems to real-life team formation problems. We concluded with consideration of areas that organizational science has identified as important for composing teams.

One goal of this review is to offer researchers from psychology an overview of the last decade of computational literature on team formation. In doing so, we are able to highlight the areas we see as particularly ready for interdisciplinary research. It is likely that the disconnect between the organizational and the computational literatures has several sources. For instance, it may arise from structural differences in the field, where prestigious computer science publishing outlets include peer-reviewed conference proceedings as well as the traditional peer-reviewed journals, leading to potential advances going overlooked by researchers in other fields unfamiliar with those norms. Additionally, as is often the case in multi-disciplinary work, computer scientists are unfamiliar with the experimental work of psychologists, and psychologists are in turn unfamiliar with computer scientists' architectures and mathematical methods, rendering each side inaccessible to the other. This review aims to be accessible to both.

From a practitioner's standpoint, we hope this review provides insight into the current ready-to-use tools for team formation and into the possibility of adapting more basic research to decision systems that are psychologically sensitive and user friendly. Part of the challenge facing developers of these tools is algorithmic; a useful tool must have low computational costs and be scalable to the extent that the user needs to create a large number of teams from a large pool of candidates. But there is also a user challenge present. It may be that in order for an algorithmic approach to be adopted by a human user, that user must feel like they have control over the outcomes – Gómez-Zará et al. (2020) discuss this need in terms of a high- or low-participation team assembly architecture. There is therefore a need for automated tools that are transparent in their process and allow for human intervention. One example that we have seen in this review is EXTRA by Zhou et al. (2018) which is novel both for its use of network-based team formation algorithms and for its level of user engagement, allowing users to explore the decisions outputted by the algorithm through visual displays. In doing so, the authors offer a decision tool that begins to draw the curtain back from the algorithmic "black box" by increasing user understanding of how the automated processes unfolded, thus potentially increasing user trust in the outcomes (Balfe et al., 2018). Future efforts to develop high-participation systems should continue to make the algorithmic process transparent and amenable to human decision-maker refinements.

As researchers from both the computer and the organizational sciences continue to explore the problem of team formation, there is great opportunity for them to engage in deeply interdisciplinary work. This review detailed the primary algorithmic approaches to solving three different types of team staffing problems and offered insight into how psychological research on team composition could inform those approaches. While solutions to team formation abound, the gap between basic science proof-of-concept research and user-focused tools is large. Closing that divide will require the development of algorithmic approaches that scale, optimize psychologically relevant constraints in an adaptable way, and offer transparency as to their assignment process.

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Appendix A: Annotated Bibliography of Selected Papers

Team Member Replacement

Agmon, N., Barrett, S., & Stone, P. (2014, May). Modeling uncertainty in leading ad hoc teams. *In Proceedings of the 2014 International Conference on Autonomous Agents and Multi-Agent Systems* (pp. 397-404).

These authors focus on modeling how new team members learn how to assimilate into an existing or newly formed team. According to the problem, ad hoc teamwork exists when a team of agents needs to cooperate without being able to communicate a priori and each agent must decide on the next action based on the actual (recursive) teammate behavior. Here the authors consider that there are only two types of agents: a best response agent who chooses their action based on the current state of the world assuming that their teammates will continue to behave as they have in the past, and an ad-hoc agent, or one that has a better awareness of the full team and the possible actions they may take. Using this knowledge, ad hoc agents (i.e., new leaders) must try to influence the collective selection of actions in the team to reach a joint optimal solution. Computationally the problem becomes how to lead the team to the optimal steady cycle (osc; cyclic set of joint actions) with minimal cost.

Agmon introduces the Reducing Expected Action Costs for Teamwork (REACT) algorithm to select the best action that the ad hoc team leader should take at times of a point of no return to the osc, employing an indirect planning method driven only by the most informed agent to solve a set of problems. When a decision needs to be made, the algorithm will calculate the possible consequences of each choice of action given the uncertainty of expected behaviors and provide the most risk aversive decision to maximize the team’s utility. Thus, the proposed algorithm is formed with the assumption that the ad hoc agent will have an idea of their teammates' types and subsequent behavior, albeit with some uncertainty. The algorithm will then analyze the cost/impact of misidentifying their teammate’s types on the optimal solution. Empirical results show that using REACT to reason about uncertainty outperforms making incorrect assumptions of your teammates, suggesting the potential savings of such an approach to be quite large.

Li, L., Tong, H., Cao, N., Ehrlich, K., Lin, Y. R., & Buchler, N. (2015, May). Replacing the irreplaceable: Fast algorithms for team member recommendation. In *Proceedings of the 24th International Conference on World Wide Web* (pp. 636-646).

Li and colleagues focus on the problem of team member replacement within the setting of a social network: given a vacancy within an existing team, how can you find the best replacement candidate? They place two constraints at the center of their approach: first, the replacement should match the existing team in terms of skills held and should have similar skills to that member which they will be replacing. Second, they should have a social network similar to that of the existing team members. This second constraint, termed *structure matching*, follows the literature suggesting that there will be less disruption within the team if the replacement is someone who has similar relationships with current team members, either because there is a history of collaboration or overlap in peripheral colleagues. The authors formalize the problem of team member replacement by modeling the team as a labeled graph and using graph kernels as a way to represent the skill and structure match requirements. They offer a variety of fast approximation algorithms and for each, apply them to real world data sets to show that they are both effective (accurate) and efficient (scalable). Take, as an example, the case in which Matt Damon is no longer available to film *Saving Private Ryan*. The top replacement as generated by their algorithm is Samuel L Jackson who has participated in movies of similar keyword categories (i.e., Jackson has the action and drama movie skills) and who has collaborated with other actors starring in *Saving Private Ryan*.

The methods and conceptual approaches outlined in this paper represent an important contribution to the smaller literature of team member replacement. Formalizing the problem within the setting of a social network enables the authors to include important social considerations and go beyond simple skill matching.

Malinowski, J., Weitzel, T., & Keim, T. (2008). Decision support for team staffing: An automated relational recommendation approach. *Decision Support Systems, 45*(3), 429-447.

This article is an example of how an algorithm used to estimate team compatibility can be integrated into computer-based human resource practice. Here, the authors present a decision support system which recommends candidates from a wider pool that will best match future team members in terms of interpersonal compatibility, thereby enhancing pre-selection results. In considering this interpersonal dimension, their model goes beyond previous work that largely focuses on skills and abilities (i.e., the fit between person and job) not between person and team. That is, they argue that a decision support system used for building teams should consider more than just whether the CV and the job match but also the relational attributes of its members.

The foundation of their recommender system is a computational model aimed at predicting trust relations between previously unknown individuals, taking into account both social and human capital of candidates. Authors discuss the merits of the two prominent filter techniques used for recommender systems: 1) Content-based models that use information about objects already rated (these models may filter out features such as category name, title, or author) and 2) collaborative methods that that try to identify users with similar tastes or attributes. Applying a combination or hybrid of the two, a probabilistic latent aspect (PLSA) model using the Expectation Maximization (EM) algorithm is used to predict collaborative trust, direct trust, and similarity-based trust before taking an average of all available trust paths among the three. The recommender system was tested on 21 University students after they were asked to rate their preference for 100 job profiles and to rate their relationships with the other students in the seminar with promising results for producing desired team member matches.

One aspect that they do not mention is how the user should go about collecting a survey of interpersonal relationships that exist among team members. Rather they suggest that some parts of the data required for such an approach could be derived from personal profiles already stored electronically in HR information systems (e.g., past projects/team assignments or performance evaluations). Taken together, this piece is one of the few published articles that explicitly outlines how human resources can improve team-based assignments through the consideration of the relational aspects that assess person-team fit in addition to person-job fit.

Sapienza, A., Goyal, P., & Ferrara, E. (2019). Deep neural networks for optimal team composition. *Frontiers in Big Data*, *2*, 14.

Sapienza and colleagues focus specifically on the role of cooperation in team composition. They have two broad conceptual goals: to specify the influence teammates have on each other in the short and long term, and to design a framework to recommend teammates that would improve individual performance. For each of these goals, they demonstrate that the improvements can be predicted with a deep learning architecture.

To their first goal, the authors construct a network that encodes information about how individuals perform when they work together with others. To construct that network, they turn to large online multiplayer games (in their case, "Dota 2") where teams of players have to cooperate to achieve a shared goal and performance is reflected in ratings. Interested readers can turn to the paper to learn more about that co-play network but its main interest to us is in how it is subsequently used in a recommendation system. To build the recommendation service the authors formalize a "teammate autoencoder" which is a specialized instance of a traditional autoencoder. Put simply, an autoencoder is a neural network that learns how to compress data and then reconstruct it in such a way that the noise in that data is minimized. The innovation in the present paper is to modify the traditional structure to accommodate the co-play network designed in the goal above. Doing so allows the authors to predict new teammates for a given player that will be beneficial to them and improve their individual performance. In a series of evaluation studies, they demonstrate that their method far outperforms recommendation models currently in use in the literature.

In this paper Sapienza demonstrates the ability of deep neural networks to represent how individual players influence those with whom they collaborate and then how to use that network of influence to predict future synergies among individuals. While future work needs to be done to implement these techniques at scale, this is a promising application of deep learning techniques to the problem of team member replacement.

Single Team Formation

Anagnostopoulos, A., Castillo, C., Fazzone, A., Leonardi, S., & Terzi, E. (2018, July). Algorithms for hiring and outsourcing in the online labor market. In *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining* (pp. 1109-1118). London, United Kingdom.

These authors introduce and propose a model for the team formation for outsourcing (TFO) problem, which they describe as a middle ground between crowdsourcing and team formation. In the model, tasks arrive online (i.e., unknown to the team a priori) to a core team of hired workers. However, in this scenario the team is dynamic as new team members can be hired and existing team members can be fired. It is also possible to outsource some parts of an incoming task to a non-team member to complete. Thus, the problem becomes one of finding an online cost-minimizing algorithm that can be used to balance the costs and salaries associated with the hiring, firing, and outsourcing of members to complete a task. Unlike other solutions to the team formation problem, this situation does not focus on optimizing the communication cost as there is no assumption of a network among individual workers. Their algorithmic design takes an online primal-dual approach to allow for an algorithm that can account for both the outsourcing and the hiring cost of all workers. The premise of this is to create a sequence of integer programs to model the online problem by incrementally introducing variables and constraints before considering their duals and linear relaxations (essentially embedding a set-cover problem in an online algorithm). The authors design several algorithms, namely LumpSum and TFO, that are shown to have logarithmic competitive approximation ratio. Experimental results further suggest that the primal-dual technique can effectively take into account multiple sources of cost, leading to cost saving practices in the context of online labor markets.

Kargar, M., & An, A. (2011, October). Discovering top-k teams of experts with/without a leader in social networks. In *Proceedings of the 20th ACM International Conference on Information and Knowledge Management* (pp. 985-994).

Kargar and An build on the problem of extracting teams from a social network as introduced in Lappas et al. (2009). Their aim is twofold: to introduce two new ways to define communication cost, and to introduce the problem of finding a group of experts with a leader. The communication cost functions they propose specifically address key weaknesses in the stability and relevance of the cost functions proposed by Lappas. The first new cost function, "sum of distances", considers communication cost between pairs of individuals within a team that have the same expertise. "Leader Distance" on the other hand, considers the communication cost between a leader and each team member. Both functions readily capture the intuition that it is desirable to have experts on a team who can easily collaborate and communicate with each other, and that it is important for a leader to be able to do the same with her team members. The authors proceed to propose algorithms for each communication measure (an approximation algorithm for minimizing "sum of distances" and an exact polynomial algorithm for minimizing "leader distance") and demonstrate effectiveness in producing either one or a collection of top teams with or without a leader. Empirical evaluations using both a dataset of academic papers (DBLP) and a dataset of movies and actors (IMDb) show that Kargar and An's algorithms produce teams with lower communication costs (as they define them) than the algorithms and cost functions used by Lappas et al. (2009). In later work, Kargar and An (2017) expand their approach to include personnel cost as well as communication cost.

This work is a significant extension of previous efforts to create teams within a network setting. The communication structures developed address realistic obstacles facing individuals newly assembled into a team. Furthermore, it is the first to offer a method for forming a team with a designated leader who is both skilled and closely connected to their team members.

Kargar, M., An, A., & Zihayat, M. (2012, September). Efficient bi-objective team formation in social networks. In *Joint European Conference on Machine Learning and Knowledge Discovery in Databases* (pp. 483-498). Springer, Berlin, Heidelberg.

In addition to finding a team of experts from a social network with low communication cost, these authors extend the team formation research to consider the personnel cost. That is, they introduce a bi-objective cost function for team formation that is able to effectively balance the overall combined communication and personnel cost across a team of qualified agents. Here the social network is modeled as a graph in which nodes represent experts and two nodes have an edge between them if they worked with each other in the past. As in their previous work (Kargar

& An, 2011), the authors use the “sum of distance” cost function to consider communication cost. They then introduce a personnel cost function that increases the cost of each expert as a multiple of the number of skills that they will be responsible for. To solve the bi-criteria optimization problem the two objectives are combined into one with a tradeoff parameter that considers the weighted sum of the two functions. The same 2-approximation algorithm (2011) is used to find a team of experts that minimizes the combined cost. Three heuristic algorithms (iterative replacement (ItReplace) and two variations of a minimal cost contribution (MCC/MCC Rare)) are also proposed to help find the best team of experts. Using pre-existing data from IMDb and DBLP, results indicate that the four proposed algorithms are both effective and efficient at finding a team in a social network, performing the task much faster than doing so using the exact or random method.

While the current approach requires that experts (agents) have the necessary competencies to perform a task, the proposed algorithms do not require any specific motivations. That is, a major limitation of this approach is that the communication cost function does not consider the expert's motivation to work in a team or with potential members of a team, regardless of their proximity in a social network.

Lappas, T., Liu, K., & Terzi, E. (2009, June). Finding a team of experts in social networks. In *Proceedings of the 15th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining* (pp. 467-476).

The authors offer a novel approach to the classic team formation problem by solving the problem in the context of social networks. This paper serves as a foundation for later work mentioned in this annotated bibliography, namely that of Kargar & An (2011, 2017) and Gutiérrez (2016).

Lappas et al. define the problem of team formation as one where a subset of experts is extracted from a larger network according to two constraints: how closely the experts’ skills meet the requirements of the task and how effectively the group can work together. In the case of the first constraint, that of skills, each individual is first defined by a particular set of abilities. A potential group of individuals is only viable if at least one individual in that group has a skill required by the task at hand. The specification of the communication constraint relies on individuals being organized into an undirected and weighted graph (network) where the weights between individuals represent the communication cost between them. Just as a viable group must have individuals with the necessary skills, it should also consist of individuals who can effectively collaborate; that is, ones with low communication costs. The authors propose two ways to define communication costs among team members and specify two possible algorithms for solving each. Each proposed algorithm is evaluated using a collaboration graph extracted from a dataset of academic publications and is assessed on the communication cost, cardinality (size) of the team, and connectivity of the generated team. They find that their proposed algorithms are able to form task-oriented teams that have low communication costs, although the teams varied in their size according to the underlying algorithm.

Their specification of the team formation problem allows for a more nuanced incorporation of attributes important to team composition. For instance, while they assume that skills are binary (individuals either have a skill or not) and that tasks either require a skill or not, their approach could be generalized to specify graded skills in both cases. The authors also note that by minimizing communication cost they are implicitly solving for small teams. Their method could, however, be extended to be a "bi-objective" optimization problem meaning that both an optimal communication cost and an optimal team size could be considered in team formation.

Okimoto, T., Schwind, N., Clement, M., Ribeiro, T., Inoue, K., & Marquis, P. (2015, May). How to Form a Task-Oriented Robust Team. In *AAMAS* (pp. 395-403).

Okimoto et al. (2015) present a more realistic model of the team formation problem to consider that there may be circumstances in which one or more (*k*) team members may be unable to complete their task (e.g., dangerous conditions; failed technology). Using a binary approach in which an agent either does or does not have a skill-set, the authors define the problem as identifying a team that is both cost efficient and *k*-robust such that the overall goal (or task) can be completed in the event of member loss. They offer two algorithmic approaches using a branch and bound technique. The first, Algorithm for Robust Teams (ART), is intended to identify a singular team that is both cost-efficient and *k*-robust. If said team can be found, the second, Algorithm for Optimal Robust Team (AORT) aims to find the best solution to the bi-objective constraint, presenting all possible solutions of the trade-off between team cost and team robustness.

Each algorithm is evaluated using a number of small benchmarks on a small problem set. Authors find that identifying an optimum robust team is no more computationally advanced than is that of identifying an optimum efficient team. However, to be robust, the skill distribution amongst team members must be such that every skill required to complete a task/set of tasks is covered by at least k+1 of its members. In terms of team staffing, the utility of this approach may be better suited to teams in which it is critical that there are members with redundant skill sets as the cost of each team member is likely to rise in accordance with the number of skills that they bring to the team. For more advanced guidance on the task-oriented robust team formation problem, we direct interested readers to Crawford et. al., (2016) who introduce and evaluate a handful of approximation algorithms and an evolutionary computational approach that is scalable to larger problem sets and complexities.

Teng, Y. C., Wang, J. Z., & Huang, J. L. (2014, May). Team formation with the communication load constraint in social networks. In *Pacific-Asia Conference on Knowledge Discovery and Data Mining* (pp. 125-136). Springer, Cham.

In addition to finding a team of experts to cover all of the skills required at minimum communication cost, these authors consider the team formation problem for occasions in which a single leader is unable to manage the needs of a larger team or project. That is, there are some instances in which experts are further divided into different groups based on their skills and the tasks required of a project. In this scenario, multiple leaders are organized into a hierarchical structure in which their communication load is limited to a certain number of leaders or team members at the next lowest level. This constraint is referred to as the communication load parameter.

The authors present a two-phase framework. During the first phase, all teams that are qualified are identified based on the methods for identifying a group of experts with a leader first developed by Kargar and An (2011). For the second phase, they developed a naive algorithm called Brute-Force to find the team and hierarchy with the minimal communication cost (the degree-constrained minimum spanning tree) by enumerating all the eligible teams and hierarchies. Due to the time-consuming nature of this method, they presented two additional algorithms to cut down on the number of teams that need to be considered during the hierarchy establishment phase of the process. The Opt algorithm uses the lower bounds of the communication cost to prune some of the qualified teams in the first phase. However, the execution time for this computation still suffers when used in large social networks. The Approx algorithm instead provides a more scalable solution that finds nearly-optimal teams by applying a 2-opt change approximation for the hierarchy establishment of each qualified team as opposed to the enumeration method used in the first two approaches. Experimental results suggested that when a nearly-optimal solution is acceptable, Approx is much more efficient for identifying a solution to the team formation problem when considering multiple leaders in a hierarchy with only a small increase in the communication cost.

Multiple Team Formation

Anagnostopoulos, A., Becchetti, L., Castillo, C., Gionis, A., & Leonardi, S. (2012, April). Online team formation in social networks. In *Proceedings of the 21st International Conference on World Wide Web* (pp. 839-848).

Anagnostopoulos et al., (2012) expand the team formation problem to consider how to form teams online (via a networked community) such that coordination cost is minimized while also ensuring that there is a fair allocation of the overall workload among experts with a diverse set of skills. Using the diameter and Steiner tree communication cost measures proposed by Lapps et al. (2009), authors present algorithms that are shown to approximate the optimal solution in an online case. Unlike previous offline models, their model does not assume that team members need to be directly connected to be socially compatible. Instead, coordination and communication costs can be reduced by limiting the team diameter such that parameters can be bound to the longest shortest path[4] among team members (e.g., the distance between team members could be set to not exceed second or third connection). Once the communication cost is bound, the online algorithms can be used to solve the bi-objective social task assignment problem to minimize the maximum load for team members. In doing so, the proposed algorithms must also keep track of the tasks (or teams) individuals in the network are already assigned to. Although the authors use Internet Movie Database (IMDb) and Bibsonomy as their source of experts and gauge of social compatibility, they suggest that the team diameter function can model other network preferences such as past interactions, geographical proximity, compatibility in collaborating, or distance in a company's hierarchy. Moreover, while balancing task allocation is the primary objective of the proposed algorithms, this is the first work to specifically acknowledge the problem of team formation to meet the demands of an incoming stream of tasks in an online setting.

[4] In graph theory, the longest shortest path is one way to describe the diameter of a graph. In network analysis it can be thought of as the fewest number of steps required for the most distantly linked pair of teammates within a group to connect with each other.

Andrejczuk, E., Bistaffa, F., Blum, C., Rodríguez-Aguilar, J. A., & Sierra, C. (2019). Synergistic team composition: A computational approach to foster diversity in teams. *Knowledge-Based Systems*, *182*, 104799.

These authors propose a model to predict team performance given a complex task and based on the individual attributes of the members in the team. Extending Wilde's post-Jungian theory for team composition, the current model assumes that different types of tasks require different personalities such that teams with multiple personalities will benefit through the diverse approach each member will contribute to different tasks. They introduce the Synergistic Team Composition Problem (STCP) as one whose goal is to partition a group of agents into a set of heterogeneous teams balanced (i.e., both congenial and proficient) across team member competencies (non-binary), personality, and gender.

Two algorithms are proposed as a solution. The STCPSolver is an optimal algorithm that is effective for smaller instances of the problem while the SynTeam is an approximate (heuristic) algorithm that can provide high quality, though not necessarily optimum solutions. STCPSolver generates all possible teams of a given size and computes the best synergistic value for each team before generating an integer linear programming (ILP) encoding of the problem. For larger problems, SynTeam instead randomly composes teams of the given size as an initial solution and then iteratively selects two teams at random and shuffles members, generating the synergistic value of all partitions. The algorithm stops after a given number of non-improving iterations occur. The two algorithms are validated using empirical data obtained from analyzing student performance in multiple University classrooms. The benefits of SynTeam with respect to STCP are found to grow as the number of students and the size of the partitioned teams increase. Due to the promising results, authors developed a web application, EduTeam (http://eduteams.iiia.csic.es), which is publicly available for teachers who wish to use the SynTeam algorithm to partition their classroom into synergistic teams.

As a whole, STCP identified a new type of constrained coalition formation problem which requires a balanced coalition structure in terms of both coalitional values and coalition sizes. Although STCP is introduced and tested in the domain of student team composition, the authors suggest that the two algorithms may offer guidance for any institution in need of automatic team composition.

Bahargam, S., Golshan, B., Lappas, T., & Terzi, E. (2019). A team-formation algorithm for faultline minimization. *Expert Systems with Applications, 119*, 441-455.

Bahargam and colleagues are the first to introduce faultlines to the team formation literature. The authors define the faultline-partitioning problem as the problem of partitioning a set of workers into teams of equal size such that the total faultline potential across teams is minimalized. Team faultlines, which are described as hypothetical dividing lines that split a group into relatively homogenous subgroups based on attribute differences (e.g., age, sex, race), have been well-documented for their effect on team cohesion and performance. However, most measures available for measuring faultlines utilize clustering algorithms that require pre-existing teams, rendering them with little applicability to automated team formation. To handle the advanced computational efficiency of identifying faultline-minimizing teams, a measure must be easy to compute for a given team in polynomial time (linear computation efficiency) and be easy to update in constant time should a person join or leave the team (constant updates efficiency). To solve this problem, the proposed algorithm (FaultlineSplitter)[1] works to minimize the potential “conflict triangles" that exist based on surface-level characteristics such as gender and nationality. For example, the authors describe that there are three possible triangle types for a given attribute: (+,+,+), (-,-,-), or (-,-,+) based on the signs of their edges. Team faultlines can only appear in the presence of (-,-,+) triangles. That is, bad triangles, where one individual is dissimilar from the other two, serve as a proxy for faultlines as they measure the extent that similar groups of people can oppose those that are different from them.

The algorithm starts with a random partitioning of the population into the set number of groups and then iteratively reassigns individuals to teams until the faultline potential of the obtained partitions does not improve across iterations (similar to the k-means algorithm). This is achieved through the execution of two functions. The AssignCosts routine returns the cost of assigning each individual to every team in which cost can be thought of as the number of conflict triangles an individual will incur if they are placed on each team. The ReassignTeam routine then uses these costs to produce new assignments of individuals to teams, treating the partitioning as a *b*-matching problem that can be solved using the Hungarian algorithm (a commonly used combinatorial optimization algorithm). The performance of the FaultlineSplitter algorithm was evaluated against real and synthetic data and was found to perform better than Greedy or Clustering algorithms, improving as population size increases.

While team-builders may eliminate faultlines by creating highly homogenous teams, this approach goes against the well-documented benefits of team diversity. Instead, the algorithmic framework described in this paper offers guidance for an automated tool that can be engineered to partition a large population into numerous low-faultline teams without over-penalizing diversity.

The Python implementation is available online: https://github.com/sanazb/Faultline.

Gerasimou, S., Stylianou, C., & Andreou, A. S. (2012, June). An Investigation of Optimal Project Scheduling and Team Staffing in Software Development using Particle Swarm Optimization. In *ICEIS (2)* (pp. 168-171).

According to this paper, one of the main reasons for software project failures and delays is the inability of project managers to estimate the time needed for software development and to adequately assign team members to meet the task and time demands of a given project. To address this problem, authors suggest a swarm intelligence approach to automate the decision process to meet two goals: 1) to optimize the sequence of task executions to minimize the time needed to complete the tasks and 2) to form skillful and productive teams that best utilize developer skills and experience. Their approach accounts for both constraints (i.e., violation of task dependencies; skill coverage; conflicting work schedule) and fitness of the solution as evaluated by the duration of the project and the experience of the assigned team members. Using a combination of Constriction and Binary-PSO variations, the authors tested the algorithm against a total of 7 projects of varying size and complexity. Results suggest that the PSO algorithm generated feasible solutions in all cases, however as the size and complexity of the projects increase, the generation of optimal solutions begins to wane as difficulties arise in the evolution of the algorithm. For example, despite satisfying all constraints, "needless" gaps in schedules were observed.

This article provided an initial attempt to determine whether particle swarm optimization could represent a viable approach for producing acceptable team-based solutions in the context of software project management. As a result of the promising findings, these authors have continued to build on research capitalizing on the use of genetic algorithms to improve development team formation. For example, within the same year they expanded the above approach to provide solutions to a multi-objective problem to account for social factors (Stylianou & Andreou, 2012) and even to create a tool to help project managers allocate project teams (Stylianou et al., 2012).

Gilal, A. R., Jaafar, J., Capretz, L. F., Omar, M., Basri, S., & Aziz, I. A. (2018). Finding an effective classification technique to develop a software team composition model. *Journal of Software: Evolution and Process*, *30*(1), e1920.

Recognizing poor team composition as a common cause of project failure, these authors aim to identify an effective classification technique to develop a model for more effective composition of software development teams. One reason for this is that team composition across software teams has traditionally focused on the technical skills of team members without considering the role that non-technical (soft) skills have on team effectiveness. After reviewing some common data mining techniques, these authors describe how to use predictive data mining techniques to discover relationships from historical (pre-existing) data. Using three classification techniques for team formation (logistic regression, decision tree, and rough sets theory (RST)) they developed a model of software team development that predicts team performance using personality type (MBTI), gender, and team role (team leader, analyst, designer, programmer, and tester). They evaluated the three classification techniques using data collected from undergraduate student teams of four programmers and one team leader. Results suggest that the two heuristic algorithms of RST (Johnson Algorithm and Genetic Algorithm) provided the highest prediction accuracy for measuring the performance of the model followed by the decision tree algorithm. Logistic regression failed to meet the obtained prediction accuracy benchmark. In turn, each technique returned different results after implementation.

Taken as a whole, this paper provides an example of how to develop and validate a team composition model. Results suggest that using only one technique may result in biased outcomes. Instead, model development techniques should be chosen carefully as different approaches can cause different results. Moreover, the model validated by this research suggests that both personality and gender play an important role in team composition and across role assignments.

Gutiérrez, J. H., Astudillo, C. A., Ballesteros-Pérez, P., Mora-Melià, D., & Candia-Véjar, A. (2016). The multiple team formation problem using sociometry. *Computers & Operations Research, 75*, 150-162.

Although healthy team member relationships are associated with heightened team productivity, the social aspect this involves is difficult to measure and as a result has often been neglected in models of team composition. These authors propose the Multiple Team Formation

Problem (MTFP) as a mathematical programming model for maximizing the efficiency of the positive interpersonal relationships among people who share a multidisciplinary work cell. This optimization model consists of a quadratic objective function, linear constraints, and integer variables. The sociometric matrix is argued to serve as a useful proxy for understanding the problem because it provides a quantitative vision of how each potential group member perceives and is perceived by his/her peers within their group. Within this matrix, the predisposition of each individual for working with another individual is labeled -1, 0, and +1 indicating their affinity as negative, neutral, or positive. Three algorithms are then proposed as a solution to the optimization of multiple team formation: a Constraint Programming approach (CP) provided by a commercial solver, a Local Search heuristic (LS) and a Variable Neighborhood Search metaheuristic (VNS). The performance of the algorithms are evaluated against three experimental problems that differ as a function of the percentage of positive relationships in the people available. In nearly all cases, the VNS algorithm slightly outperforms the CP and LS algorithms although performance issues begin to occur as the problem grows in size.

At large, the MFTP can be understood as the problem of allocating multiple people (either full-time or in smaller time fractions) categorized into one or several skills to multiple teams or projects (groups) that require a specified amount of people per skill. By considering multiple projects and fractions of people's time this research introduced two new dimensions to the Team Formation Problem. Moreover, by considering the social structure of teams, the proposed MTFP model may provide an ideal method for future work in social network analysis.

Liemhetcharat, S., & Veloso, M. (2014, May). Team formation with learning agents that improve coordination. In *Proceedings of the 2014 International Conference on Autonomous Agents and Multi-Agent Systems* (pp. 1531-1532).

Liemhetcharat & Veloso consider the learning team formation problem where there are a certain number of training instances for learning pairs to improve coordination and the goal is to form a team with maximum performance after all training instances are allocated. Learning agent pairs are defined as pairs of agents that simultaneously learn and consist of a learning and a regular agent. Within a set of agents, learning pairs are considered to have heterogeneous rates of coordination improvement, such that a team with low performance but with learning pairs that improve quickly may outperform other teams with slowly improving learning pairs after training.

This work extends research on the Synergy Graph model which views team performance as a function of single-agent capabilities and the coordination among pairs of agents, removing the typical assumption in the MAS literature that the capabilities of single-agents remain fixed. Although the model was originally proposed to analyze improvements in an agent's capabilities as the agent learns more about the task through experience, the current work is concerned with improvement in the coordination as the agent learns to work better with its teammates. More specifically, this differentiation allows for models to consider how team performance may change over time as team members learn from each other through their repeated interactions.

In this problem, the synergy model is represented by a graph where the distance between agents is an indicator of how well they work together. Each learning pair has an initially unknown learning rate whose estimate is improved after every training instance is observed. Using two models of coordination (both linear and geometric to consider marginal improvement decreases), the current approach iteratively allocates training instances and updates the estimated learning rates with the use of a Kalman filter. Importantly, the proposed algorithms can learn from only a partial set of agent interactions in order to learn the complete synergy model such that they can be used to balance exploring (improving the estimate) and exploiting (allocating training to the pairs that improve team performance).

Rangapuram, S. S., Bühler, T., & Hein, M. (2013, May). Towards realistic team formation in social networks based on densest subgraphs. *In Proceedings of the 22nd International Conference on World Wide Web* (pp. 1077-1088).

Rangapuram, Bühler, and Hein contribute to the literature solving the team formation problem in the context of social networks by offering a new method, Formation of Realistic Teams (FORTE). Their goal is to provide a more flexible and realistic setting for modeling team requirements such as inclusion of leaders, restriction of size, and ease of communication and to do so they present a new method for solving the team formation problem. Their approach is based on a classic problem in computer science, the densest subgraph problem, which aims to find a subgraph of maximum density. Put another way, the goal is to find a team within the larger network of candidate individuals that is the most connected and therefore has maximum density. In employing this formalization, the authors can make a series of generalized constraints that are flexible enough to handle many different decision settings.

First, in their method, team size can be given an upper bound. Similarly, constraints can be put on the number of people within the team who have a certain skill of a certain level. For instance, preference can be given not only to those who have a skill, but to those who have the highest competence in that particular skill. Importantly their setting also allows for a team to be formed around a specific person or even a group of experts, a constraint important in creating teams that have a leader either previously determined or identified in the course of creating the team. Their most general constraint is one that constrains distance – whereas in previous work that notion of distance was specified in terms of communication or collaboration history, their distance constraint could be used to create a team that was geographically close or socially close. They also note that the distance constraint could be applied in the opposite sense, to exclude members who have high incompatibility with others.

As with all other computational methods proposed in the papers annotated here, the methods are only useful if they have efficient solutions. The authors demonstrate that although the "densest subgraph problem" on which their formulation is based is classically difficult to solve, they can use a linear programming relaxation to find a solution and check the optimality of that solution (we direct interested readers to the text for details).

Stylianou, C., & Andreou, A. S. (2012, September). A multi-objective genetic algorithm for software development team staffing based on personality types. In *IFIP International Conference on Artificial Intelligence Applications and Innovations* (pp. 37-47). Springer, Berlin, Heidelberg.

Recognizing that humans are a critical component of team success, these authors build on previous work (Gerasimou et al., 2012) to include a social factor as one of the primary objective functions in their consideration of software development team formation. A multi-objective approach was utilized to consider the sometimes conflicting need to optimize both team member skill and personality traits. Using an implementation of a non-denominated genetic sorting algorithm (cited authors send interested readers to Deb et al., 2002), the proposed method will produce a set of optimal solutions assigning different collections of project developers to assignment tasks while ensuring that the best solution is preserved. Each solution is evaluated by three objective functions: two maximization functions based on assigned developer's technical skills and personality traits[5] and a third minimization function based on team size that is included to maximize resource utilization and prevent over-assignment to a team. Feasibility of the solutions is based on two constraint functions that ensure that all skills are covered by at least one developer assigned to the team and that each developer is available during the proposed schedule.

Results from two experimental trials suggest that the proposed algorithm is capable of producing adequate and feasible solutions. Moreover, researchers found that when the algorithm failed to produce an optimum solution of available developers, the product manager of the participating company confirmed that they often lack the human resources necessary to prevent project overrun. Thus, this algorithm may provide directions for a decision support tool for project team staffing that can both help to form teams to meet the demands of each project and help managers to decipher where there are potential human capital deficits. Integrating some of the objective and constraint equations developed in their previous work (Gerasimou et al., 2012), authors used this approach to develop IntelliSPM.

Existing Tools

Dimiduk, T. G., & Dimiduk, K. C. (2011, December). Effectively assign student groups by applying multiple user-prioritized academic and demographic factors using a new open source program, GroupEng. *In 2011 WEPAN Nat. Conf. Advancing Women: Transforming Eng. Educ* (pp. 1-12).

GroupEng is a tool introduced by Dimiduk and Dimiduk (2011) that approaches team composition in a way similar to that of Team-Maker. Two particular features of Team-Maker are addressed in GroupEng's design: (1) GroupEng introduces privacy improvements by keeping data inputted by students and teachers local, unlike Team-Maker which stores it externally, and (2) it addresses a weakness of Team-Maker's group value determination where groups which have satisfied certain rules are allowed to be weaker on average than other groups. The underlying algorithm employed by GroupEng is a heuristic guided stochastic greedy algorithm and the structure allows for flexibility in team size and in sequence of team formation preference rules. Four grouping rules are allowed by the program and the instructor must decide the order of grouping rules. The first, distribute, spreads students with an attribute (e.g., a needed skill) across groups such that each group is equal in that attribute. The aggregate rule groups students with some attribute (e.g., project choice) together in the same group, while the cluster rule ensures that students with a particular attribute are not isolated (e.g., imposes a minimum of two women

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[5] Authors note that the desired personality traits that were associated with each occupation were selected based on career handbook suggestions and were not validated. Rather they argue this aspect could easily be changed and the focus is on how well their encoding approach optimizes team assignment.

in a group). The balance operation ensures equal strength of groups based on a criterion (e.g., GPA). This program has been released in a beta version as a python tool and is free to users: https://www.groupeng.org.

Donsbach, J. S., Tannenbaum, S. I., Alliger, G. M., Mathieu, J. E., Salas, E., Goodwin, G. F., & Metcalf, K. A. (2009). ***Team composition optimization: The team optimal profile system (TOPS)*****. Army Research Inst For The Behavioral And Social Sciences Arlington Va.**

This article outlines one of the few published articles outlining and providing an example of an automated team decision developed to handle the range of team staffing decisions that need to be made using both qualitative data and team composition theory as a guide. Authors interviewed 21 subject matter experts from both the military and private sector to determine the most common staffing scenarios and the accompanying factors and constraints that are commonly faced when staffing teams. Results were organized into a team staffing taxonomy that highlights five elements that should be considered when staffing teams: 1) types of team staffing decisions, 2) factors decision makers consider when staffing teams (e.g., Individual knowledge, skills, abilities, and other (KSAOs), functional diversity among the team, criticality of the task/mission), 3) factors that define the team staffing process (i.e., centrality of the decision making; availability of candidate information; temporal dynamics), 4) factors that define the candidate pool (e.g., internal vs. external), and 5) constraints placed on team staffing decisions (e.g., costs, missing information, timing).

They break down the types of team staffing decisions into 6 domains that can be further categorized by whether they are concerned with staffing team member/s to an existing team, a new team, or a reconfiguration of teams. The objective of the team optimal profile system (TOPS) is to aid military commanders in making those decisions that involve staffing existing and new teams. Existing team decisions include: 1) team member placement where a person is assigned to an existing team, 2) multiple member replacement where people are assigned to multiple positions on an existing team, and 3) talent distribution where new people are assigned to several existing teams. On the other hand, new team decisions include: 4) single team formation where multiple people are assigned to a new team, and 5) multiple team formation where people are assigned to several new teams. A TOPS Framework was developed to specify the functional characteristics and interlinking modules of the decision making system proposed. For a more detailed description of each module, we direct readers to the text; however, a major strength of the proposed framework is that it would provide a user-friendly software application that is customizable to be scalable across situations and applications. For example, in addition to the standard candidate and position information that should be pre-populated, the decision maker is able to identify and adjust the importance of different key attributes across team roles in addition to customizing interdependency weights to reflect the influence that different positions have on the performance of others on the team.

A generic TOPS algorithm is proposed that will be built in and will function as the underlying engine to the TOPS system with each subsequent module introducing the selected constraints. A major contribution of this algorithm to the team composition literature is it allows for: 1) a recognition that team performance is a joint function of members' individual job performances and their contributions to combined team activities; 2) incorporation of the relative interdependencies of members' individual job performances in a network fashion; and 3) a differentiation of members' job versus team related KSAOs. Although the authors were unable to fully demonstrate the algorithm due to limited computational power (see Tannenbaum et al., 2010), this work is novel in that it outlines how a team optimization system could be applied in practice to help those in charge to work through real team staffing scenarios.

Hertz, J. L., Davis, D., O'Connell, B. P., & Mukasa, C. (2019, June). gruepr: An Open Source Program for Creating Student Project Teams. In *2019 ASEE Annual Conference & Exposition*.

Hertz et al. (2019) offer another algorithm to solve the team formation problem, *gruepr*. Their set-up is similar to that of Team-Maker, among others, with an instructor gathering information on students, indicating desired scoring rules, and then specifying their preferred weighting of those rules. Hertz and colleagues solve the assignment problem using a genetic algorithm (GA). As implied by the name, a GA is a method modeled after natural selection wherein genomes (arrays of student IDs representing group membership) are evaluated according to a fitness function (a group compatibility score) and those with higher fitness scores pass on part of their genome to the next generation. As evolution within the model proceeds, random mutations occur (students are randomly swapped between teams) and over generations, the optimal distribution of students to teams emerges. The details of how fitness is assessed reflect how the instructor has weighted their group membership preferences. The authors demonstrate dominance of *gruepr's* team allocation over both random and instructor-selected assignment. They have made the source code available here: https://bitbucket.org/joshuahertz/gruepr/wiki/Home.

Layton, R. A., Loughry, M. L., Ohland, M. W., & Ricco, G. D. (2010). Design and validation of a web-based system for assigning members to teams using instructor-specified criteria. *Advances in Engineering Education*, *2*(1), n1.

Team-Maker is a team composition tool that is integrated with the more general Comprehensive Assessment for Team-Member Effectiveness (CATME; Ohland et al., 2012) tool for classroom group assignment (Layton et al., 2010). Users begin by inputting relevant classroom information and are able to identify what set of criteria are important to them when forming their teams. For instance, they could prioritize Grade-Point Average (GPA) distribution in groups such that teams either have students of similar or dissimilar GPAs. They could also decide that allocation according to that GPA rule was more important – or should receive greater weight – than allocation according to gender. To select a set of optimal groups, Team-Maker employs a hill-climbing algorithm, an optimization technique that finds local maxima by making incremental changes to its solution from a random initial starting point. The algorithm begins with a random allocation of students to groups and then swaps two students at a time, recomputing the "compliance" or group fit scores each time. Several weaknesses of Team-Maker's method of composition are addressed in subsequent work (see e.g., Thio et al., 2017; Dimiduk & Dimiduk, 2011). One specific drawback from a usability standpoint is that instructors are not able to manually move students among groups – they may only re-specify criteria and preferences and run the algorithm again. The Team-Maker tool is currently marketed as part of a larger CATME package and is available to users for an annual fee: https://www.catme.org/login/index.

Stylianou, C., Gerasimou, S., & Andreou, A. S. (2012, November). A novel prototype tool for intelligent software project scheduling and staffing enhanced with personality factors. In *2012 IEEE 24th International Conference on Tools with Artificial Intelligence* (Vol. 1, pp. 277-284). IEEE.

Building on their previous work, these authors developed a decision support tool, IntelliSPM, intended as a means of helping software project managers to optimally assign developers to tasks using both technical aspects (i.e., developer skill levels, duration, and team size) and social factors (i.e., developer personality traits and required personality traits of tasks). IntelliSPM offers users the option to choose from two functionalities using several optimization techniques (namely, single-objective GAs, multi-objective GAs, and/or a single-objective PSO). The parameter settings for both functions are tailorable to the degree that the user is familiar with the optimization algorithm but in all cases requires that the user enter information regarding project tasks (e.g., expected time and effort), the dependency between tasks, and the required skills and preferred personality types for each task.

The first functionality utilizes a multi-objective genetic algorithm (the constrained Non-Dominated Sorting Algorithm) and a pre-existing project schedule to optimally assign the minimum number of developers to teams based on the competing nature of the required skills and “right” personality. Users are then provided with a visualization of multiple solutions from which the best staffing strategy can be decided. This functionality can also be used to help managers to pinpoint where there are personnel or resource shortages in the case where no feasible solutions can be found to meet the scheduling demand. The second functionality performs two different operations. First, this functionality provides a set of staffing solutions in the same manner as the first. However, this time the implementation does not include the project schedule restriction (i.e., the assignment conflict constraint) allowing users to identify if their available personnel is adequate enough to complete a project based on their skills and personality. If so, the user can then use the provided solutions to create a project schedule using a specific staffing strategy. In this step, users are able to choose between a genetic algorithm or a single-objective particle swarm optimization algorithm to generate a set of assigned tasks with the minimum project duration (as visualized by a Gantt chart).

After two experiments confirmed the effectiveness and efficiency of the two functionalities of IntelliSPM, an empirical validation of the tool was conducted to confirm its applicability, usability, and scalability to the activities of scheduling and staffing. Although the participating project managers desired the ability to have more control over the objectives used during optimization, including the incorporation of a project cost constraint, the consideration of how a certain personality trait aligns with a specific task represents a novel addition to an automated tool for helping project managers to better assign their personnel to meet project demands.

Tannenbaum, S. I., Donsbach, J. S., Alliger, G. M., Mathieu, J. E., Metcalf, K. A., & Goodwin, G. F. (2010). Forming Effective Teams: Testing The Team Composition System (TCS). Algorithms and Decision Aid. *US Army Research Institute*, 1-7.

This paper provides an overview of a program of research and the development of an automated tool to help military commanders (and others) make effective staffing decisions. The team composition system (TCS) algorithm described is designed to integrate the three team staffing approaches introduced by Donsbach et al. (2009) and can be scaled to focus on a number of team composition constraints. As a step beyond the previous model, researchers also introduce a team role profile measure developed as an additional team-related predictor to be included in the decision aid. The Team Role Experiences and Orientation (TREO) survey is a 48-item diagnostic survey which asks candidates about their past experiences and personal preferences when working on a team in order to predict their propensity for six team roles (organizer, innovator, doer, challenger, team builder, or connector).

The TCS algorithm and TREO assessment tool were empirically tested across three different samples (a flight simulation, student business teams, and Army Transition Teams). Results provided suggest that together the algorithm and TREO results have the potential to predict team performance above that attained through traditional individual models of position-readiness. A first generation TCS prototype was designed to support the formation of a single team based on both individual position readiness and team fit indicators. Although the state of the PC computing power at the time required that some constraints be programmed (e.g., limiting the total team size and number of candidates considered) to reduce system run time, the TCS can be used to generate a list of possible teams with the highest predicted performance score while allowing users to easily readjust their specifications and re-run their analysis to examine the best solutions. For example, the TCS can be adjusted to account for the user's considerations such as more central team roles, number of people on the team with a specific skill, or people who cannot (or should not) work together. As a whole, the TCS is suggested to be an important first step in developing an efficient tool for helping military commanders and others to make more effective team staffing decisions.

Thio, C. (2017). Teammatic: A Mixed Initiative Interface for Team Composition with Multiple Constraints. University of California, San Diego.

Thio and colleagues (2017) offer a tool, Teammatic, that has a "mixed initiative approach" that allows instructors more flexibility when interacting with team formation. Similar to others, their tool begins by having instructors upload information about their students (e.g., their schedules, topic interest, gender) and then create constraints to govern team formation. Allocation proceeds according to a greedy algorithm that maximizes a score function that reflects the instructor's constraints. Importantly, after the teams have been generated, instructors can move students to different groups. To support these swaps, Teammatic suggests potential exchanges that will still yield groups scoring high on the specified criteria. The tool is available in a beta stage here: https://projects.invisionapp.com/share/JZCWS2XNQ#/screens.

Zhou, Q., Li, L., Cao, N., Buchler, N., & Tong, H. (2018, September). Extra: Explaining team recommendation in networks. In *Proceedings of the 12th ACM Conference on Recommender Systems* (pp. 492-493).

These authors developed an interactive prototype, EXTRA, whose purpose is to explain why the underlying algorithms of network-based team recommendation systems give the specific results given the team optimization scenario. More specifically this tool can be used to explain the recommendations according to random walk graph kernel which measures the similarity between two graphs (e.g., the team networks before and after a replacement). For example, in team replacement, the objective is to find a person with a similar skill to the team member they are trying to replace as well as a similar collaboration structure with the existing team members. The graph kernel approach is then used to find the candidate that makes the new team most similar to the old team. EXTRA provides users with a visual explanation of the recommendation results based on underlying network to help the end-user understand why the replacement algorithm recommended a candidate as a good fit (e.g., can show the key connections with existing team members or the key skill similarities that the candidate brings to the team). This system is designed to function across three different team recommendation scenarios and can provide an explanation from three different perspectives according to the influence of the edges, nodes, or attributes of the resulting graphs (outlined below).

	Team Replacement	Team Expansion	Team Shrinkage
Edges	important common collaborations shared by the candidate and the departure member	new collaborations that the new member might establish	the most important collaborations the candidate is lacking
Nodes	key existing team members both candidate and departure member collaborate with	key existing team members the new member will work with	key existing team members that the candidate should have collaborated with
Attributes	common and important skills shared by the candidate and the departure member	the unique skills the new team member brings that are critical to the team's new need	the most important skills that the candidate lacks

Organizational Science

Bell, S. T. (2007). Deep-level composition variables as predictors of team performance: a meta-analysis. *Journal of Applied Psychology*, *92*(3), 595.

This author conducted a meta-analysis on the relationship between the configuration of relatively enduring deep-level characteristics (i.e., personality, values, and mental ability) and team performance. Results pooled from 89 different sources revealed that the relationship between team personality and values with team performance held greater magnitude in field settings as compared to that of a lab whereas emotional intelligence and general mental ability were more related to performance in a lab-based setting. In regard to team personality, team agreeableness and conscientiousness were the strongest predictors of team performance. Moreover, results suggest that the mean operationalization of the composition variables (e.g., average of team member conscientiousness) produced the strongest correlation with team performance except for team agreeableness, where the lowest scoring team member reflected the strongest predictor of the relationship with team performance. Results of this meta-analysis also suggest that having team members with a collectivist orientation and a preference for team-work should be beneficial to team performance. Although there are other contextual factors important to team composition that this research was unable to capture (i.e., tenure, task-type), these findings can be used to consider team characteristics during the initial design, formation, and subsequent staffing stage of teams.

Harrison, D. A., Price, K. H., Gavin, J. H., & Florey, A. T. (2002). Time, teams, and task performance: Changing effects of surface-and deep-level diversity on group functioning. *Academy of Management Journal*, *45*(5), 1029-1045.

This article suggests that time plays a key role in increasing team collaboration. More specifically, as team members interact over time, they start to focus less on surface-level diversity (e.g., race, gender) and more on deep-level attributes (e.g., attitudes, beliefs). In turn, this affects the role that team member diversity has on performance. These authors examined the effects of both perceived and actual diversity and team reward contingency (i.e., the degree to which outcomes for individual members depend on outcomes for their teams) on team integration and performance across 144 student project teams over the course of approximately 4 months. Results found that actual diversity was positively related to perceived diversity (both surface and deep), which in turn negatively impacted team performance through its negative effect on team integration. However, as team collaboration increased, the negative impact of perceived surface-level diversity on team integration was diminished whereas that of perceived deep-level diversity was strengthened. Team-based rewards were in turn found to increase team-member collaboration suggesting that organizations and team leaders can use structure to increase cooperation in teams. Taken together, results suggest that early perceptions of both demographic and psychological differences among team members leads to negative consequences in how diverse groups of individuals will get along even months later. However, differences in psychological attributes such as personality and job-related attitudes, beliefs, and values become more consequential over time as team members continue to work together.

Humphrey, S. E., Morgeson, F. P., & Mannor, M. J. (2009). Developing a theory of the strategic core of teams: A role composition model of team performance. *Journal of Applied Psychology*, *94*(1), 48.

These authors present a theory that supports the use of a compilation (relative contribution model; Mathieu et al., 2014) or "role composition" approach to team staffing in which some members are more crucial to overall team effectiveness than others. Unlike previous models of team composition that have focused on individual attributes, the proposed theory suggests that there is a strategic core of teams which represent the role/s on a team that: 1) encounter more of the problems needed to be overcome by the team; 2) have greater exposure to the tasks that the team is performing; 3) are more central to the workflow of the team. Combined with an individual attribute approach, this article suggests that team member experience and job skills are more strongly related to team performance when these characteristics are possessed by the strategic core than by non-core team members. Based on a sample of 778 major league baseball teams across 29 years, these authors found that core resource allocation increased team performance by an additional 3% after accounting for total resource allocation. Results further suggest that paying core role holders more than non-core team members might improve team performance if pay variance is derived from a focus on the critical roles. Taken as a whole, the theory of the strategic core suggests that those in charge of team staffing should place priority on the core roles when they consider building or changing teams.

Mathieu, J. E., Tannenbaum, S. I., Donsbach, J. S., & Alliger, G. M. (2014). A review and integration of team composition models: Moving toward a dynamic and temporal framework. *Journal of Management*, *40*(1), 130-160.

This article represents one of the initial attempts of researchers to bridge the science-practitioner gap to connect team composition theory to team staffing. These authors review the literature and present four composition models (including the corresponding heuristic formula), to predict team effectiveness based on individual and/or team-related staffing decisions. Although there are advantages and disadvantages to each approach, the preferable model will depend on the type of team being considered, including the skills and team-member interdependency required for team performance. Individual models include the *traditional personnel-fit model* and the *personnel fit model with teamwork considerations* which focus on the individual team member's fit with the job requirements or on the member's team-generic KSAOs such as team orientation or cooperativeness. According to the traditional approach, team performance is improved through the selection of individuals with high levels of task specific skills for their role, regardless of the team context. The latter model extends the individual approach to consider how the member contributes to the team as a collective such that team effectiveness is enhanced to the extent that members all possess generic team-related competencies. The two team-based models adopt a holistic or comparative view of individual members' KSAOs (e.g., averages, diversities) or consider more complex combinations or team profiles of KSAOs. The *relative contribution model* assumes that team member contributions to performance are unequally weighted. This represents a *compilation* model in which particular individuals can carry or undermine the entire team's effort (i.e., the competencies of the weakest or strongest member; attributes of occupants in critical roles). Finally, the *team profile model* advocates a collective perspective and attempts to optimize the blend, synergy, and profiles of the team members. For example, it may not matter exactly who performs specific tasks, only that at least one or a certain percentage of individuals on the team have the necessary skills to complete the team's mission.

The authors go on to recognize that teams, and team members, are dynamic and that current compositional models fail to take this into account. Changes in team membership and team-relevant tasks can influence team development, team member dynamics, and the effect that team member characteristics have on overall team performance. As such, different team compositional profiles are likely to be more important at different stages of a team's lifespan. To help account for this, the authors provide a temporal vector that can be integrated into the team composition algorithms to help predict the impact on effectiveness that different team member combinations have over time. This article concludes with a consideration of areas in need of future research to better understand how team composition affects team-related outcomes over time.

Mathieu, J. E., Tannenbaum, S. I., Kukenberger, M. R., Donsbach, J. S., & Alliger, G. M. (2015). Team role experience and orientation: A measure and tests of construct validity. *Group & Organization Management*, *40*(1), 6-34.

This work is built off the assumption that team composition serves as a foundation upon which other team factors are built such that teams with an optimal combination of member's KSAOs are better positioned for more effective teamwork and performance outcomes than those with a sub-par combination of member attributes. Moreover, the attributes that make up each individual on a team motivate and enable them to occupy different team roles. These authors reviewed and synthesized prior team role taxonomies to offer and develop a measure for a more comprehensive six-dimensional framework of team role classifications (defined below). Using a sample of both military and non-military participants they then developed and validated a 48-item measure that uses both the individual's previous team role-related experiences and their predispositions to certain role-related behaviors to predict their propensity to occupy the roles. Moreover, they were able to show discriminant validity from measures of the Big 5 Personality Scale (NEO-FFI) despite finding some of the hypothesized correlations between some of the factors – among these were Organizer and Doer with Conscientiousness, Innovator and Openness to Experience, Team Builder, Connector, and Innovator with Extraversion, and Team Builder with Agreeableness, Innovator, and Openness to Experience.

Although not tested here, empirical research suggests that different team member combinations or profiles may be more or less advantageous according to the situation. Thus, the Team Role Experience and Orientation (TREO) measure is suggested as an additional tool that can be used for future research on optimal team compositions. A team role behavior-based observation tool for measuring the TREO taxonomy has also been developed for future research and organizational utility (Griggs et al., 2021).

Team Role Definitions:

1. **Organizer:** An organizer acts to structure what the team is doing, keeps track of accomplishments, and monitors how the team is progressing relative to goals and timelines.

2. **Doer:** A doer is someone who willingly takes on work and can be relied upon to complete work, meet deadlines, and take on tasks to ensure the team's success.

3. **Challenger:** A challenger is a member who asks "why" in order to push the team to explore all aspects of a situation and to consider alternative assumptions, explanations, and solutions.

4. **Innovator:** An innovator actively generates new and creative ideas, strategies, and approaches for how the team can handle various situations and challenges.

5. **Team Builder:** A team builder is a member who endeavors to establish norms, support decisions, and maintain a positive work atmosphere within the team, calming and motivating team members as necessary.

6. **Connector:** A connector bridges and connect the team with external people, groups, or other stakeholders. They ensure good working relationships between the team and external individuals.

Munyon, T. P., Summers, J. K., & Ferris, G. R. (2011). Team staffing modes in organizations: Strategic considerations on individual and cluster hiring approaches. *Human Resource Management Review*, *21*(3), 228-242.

Similar to Zaccaro et al. (2012), these authors bring to light that despite the significance of teams to organizations, very little research exists to help guide organizations who wish to implement human resource practices to facilitate the effective staffing of teams. After briefly reviewing the history of team staffing, this article takes a firm level approach drawing upon resource based theory to consider the competitive contribution of team human capital based on the team staffing approach used (we direct interested readers to the full text for an overview of the strategic outcomes discussed). While authors include the more traditional approach of individual staffing to teams in their review, a significant contribution of this piece is the inclusion of cluster hiring. This refers to an organizational effort to staff entire teams at once through the acquisition and fitting of pre-existing teams (either internal or external to the organization). Although outcomes are at the macro-level, the discussion provides a more in-depth explanation of how the different staffing approaches impact individual and team level factors (i.e., team embeddedness; shared mental models). Taken as a whole, authors propose that although the traditional, individual approach to team staffing may be less costly during the initial acquisition stage of the team, cluster hiring should prove more cost efficient in the long run in the form of enhanced labor productivity resulting from mitigated socialization processes and higher levels of coordination. On the other hand, cluster hiring may result in a stagnant role structure and shared knowledge base that can impede team creativity.

Trainer, H. M., Jones, J. M., Pendergraft, J. G., Maupin, C. K., & Carter, D. R. (2020). Team membership change "events": a review and reconceptualization. *Group & Organization Management*, *45*(2), 219-251.

This paper describes team composition as a dynamic process through which team membership shifts as team members join and leave over time. From this perspective, each team-membership change can be conceptualized as a discrete team-level event that can alter team functioning at varying degrees (i.e., along the dimensions of novelty, disruptiveness, and criticality). The impact of team-membership change can also be characterized according to whether the change is associated with team member entry, team member departure, or team membership fluidity (i.e., high levels of team member replacement). With these differences in mind, authors identified and reviewed 83 articles to advance an integrative framework that depicts the impact of individual, team, and organizational factors that can influence the overall impact of a team membership change. For example, this review suggests that there tend to be more favorable team outcomes when an outgoing team-member is replaced with a member who is similar across both task-role and individual level attributes. Moreover, team membership changes to positions that carry a heavier load in the team have the ability to cause more disruption to overall team effectiveness. Taken as a whole, there are both positive and negative outcomes that can occur across the different types of team membership change that can be influenced by both the existing team composition, team structure, and the attributes of the new or replacement team member.

Zaccaro, S. J., & DiRosa, G. A. (2012). The processes of team staffing: A review of relevant studies. *International Review of Industrial and Organizational Psychology*, *27*, 197-229.

Although team researchers acknowledge that team composition should be a consideration in staffing decisions, the process of selecting and/or assigning individual(s) to meet the demands of team-related tasks and team-member interdependencies is more complex than individual selection, with few best practices for practitioners to follow. This chapter represents one of the first attempts to discuss the value of staffing from a team's perspective using empirical examples as support for practitioners moving forward. These authors provide an overview of 5 primary steps to consider for team-based staffing: 1) conduct a team-task analysis; 2) identify requisite member attributes and attribute configurations; 3) recruit candidate members; 4) assess member characteristics; 5) select the best fitting mix of member candidates. While the steps outlined in this chapter do not provide a standard step by step manual for practitioners to use, the authors provide a guiding framework that introduces and discusses different team-related factors (e.g., contextual considerations; task interdependency) that should be considered when deciding how to select and configure individuals for team-based assignment.

Appendix B: Collection of Comprehensive Reviews

Andrejczuk, E., Rodriguez-Aguilar, J. A., & Sierra, C. (2016). A concise review on multiagent teams: contributions and research opportunities. Multi-Agent Systems and Agreement Technologies, 31-39.

This article reviews and classifies the most recent advances made in the computer science literature dealing with the composition and formation of multi-agent teams (e.g., crowdsourcing applications; human-agent teams). This paper provides a "who, what, when, where, why" approach to synthesizing the state of the literature. As a whole the multi-agent system (MAS) literature is described as one that has focused on building systems whose agents interact to achieve a common objective or to exploit the other's features to achieve self-interested goals but without a consideration of the quality of human factors or resources.

Andrejczuk, E., Berger, R., Rodriguez-Aguilar, J. A., Sierra, C., & Marín-Puchades, V. (2018). The composition and formation of effective teams: computer science meets organizational psychology. The Knowledge Engineering Review, 33.

This paper integrates some of the major contributions from the computer science literature and the organizational psychology literature on the topics of team formation and team composition. As in their 2016 review, the authors approach the topic from a "who, what, when, where, why" perspective to compare and contrast the driving factors of the research in both fields in order to help pave the way for future collaboration.

Costa, A., Ramos, F., Perkusich, M., Dantas, E., Dilorenzo, E., Chagas, F., ... & Perkusich, A. (2020). Team Formation in Software Engineering: A Systematic Mapping Study. IEEE Access, 8, 145687-145712.

These authors used a snowball based systematic mapping approach to review the literature on team formation specific to software project management. Based on 51 identified articles, this article describes the most common approaches and concerns for software team formation. Overall, the most commonly used solutions match software engineers (or tasks) to teams based on some sort of technical attribute using some sort of search and optimization technique (namely a genetic algorithm) to approach the problem. Authors conclude that one of the major constraints to the team formation problem in software engineering is the scalability of the solutions that try to incorporate more subjective attributes.

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

This review takes a system's perspective to advance our understanding of how users interact and assemble teams within more advanced team-assembly technology. They highlight four types of teams assembled in computer-mediated environments (optimized teams, staffed teams, self-assembled teams, and augmented teams) according to how systems allow users to shape team assembly based on user agency and participation. Based on a systematic literature review, the socio-technical considerations are discussed for each. As it stands, the authors conclude that although there appears to be an increasing interest in combining the use of algorithms with user's participation to form teams, the majority of team assembly systems do not consider user agency. Full results of the scoping literature review can be downloaded as supplemental material at https://dl.acm.org/doi/abs/10.1145/3415252#sec-supp.

Harris, A. M., Gómez-Zará, D., DeChurch, L. A., & Contractor, N. S. (2019). Joining together online: the trajectory of CSCW scholarship on group formation. Proceedings of the ACM on Human-Computer Interaction, 3(CSCW), 1-27.

This paper reviews all of the articles (n= 35) published at CSCW (Computer Supported Cooperative Work) that are identified as focusing on technology and team formation. Using thematic analysis, the reviewers identify and discuss four group formation periods that occurred from 1990 to 2018: 1) groups interacting with technology (e.g., groupware); 2) enabling online groups and communities (e.g., social networking sites); 3) enabling crowds (i.e., assigning skilled workers to micro-tasks); 4) the renaissance of small groups (i.e., using group formation to support group performance and effectiveness). Six main themes (group composition, self-presentation of users and groups, recruitment mechanisms, assembly mechanisms, organizing structures, and group culture) were also identified across the progression of CSCW articles with additional sub themes discussed for each.

Juárez, J., Santos, C., & Brizuela, C. A. (2021). A Comprehensive Review and a Taxonomy Proposal of Team Formation Problems. ACM Computing Surveys (CSUR), 54(7), 1-33.

These authors review the last two decades of research on the team formation problem, recognizing the two major contributing fields to be that of Operations Research (identifying a team with the "best" match between candidates and specific jobs or positions according to the organization's needs) and Data Mining (identifying candidates via social network data with tightly knitted interactions whose combined skillset meet the demands of a given task). Moreover, they offer a taxonomy to organize the existing research into two collections based on how the problem is modeled. The first refers to assignment based models where the goal is to maximize the suitability of the matching between a set of candidates and a team or team position. This research is typically found in the Operations Research and Decision Science literature and can be further categorized based on the considerations of the TFP (single team, multiple teams, or kindred teams that also recognize the social aspect). The second collection refers to the TFP in Social Networks and is largely rooted in Data Mining and Data Science research. This literature can be further classified by how candidate skill levels are included into the problem (binary skills, weighted skills, or probabilistic skills). A more in-depth discussion of the common components and application of TFPs follows.

Wang, X., Zhao, Z., & Ng, W. (2015, April). A comparative study of team formation in social networks. In *International Conference on Database Systems for Advanced Applications* (pp. 389-404). Springer, Cham.

This review offers a comparative study of the metrics and algorithms used to solve the Team Formation Problem for Social Networks. These authors examine a particular set of team formation algorithms, namely RarestFirst, EnSteiner, MinSD, MinLD, MinDiaSol, MinAggrSol, MCC, ItRepace, LBRadius and LBSteiner and categorize them into four groups according to communication cost functions (radius distance, steiner distance, sum of distances, and leader distance). Experiments and case study results suggest that there is not one best algorithm but that some perform better in different situations. The code and datasets used to evaluate the performance of the algorithms are publicly available at www.cse.ust.hk/~xwangau/TF.html.

Appendix C: Table of Algorithmic Approaches Coded for Content

Table C1

Algorithmic Approaches to Team Formation

Reference	Exogenous/ Endogenous	Algorithmic Approach	Optimization Criteria	Inputs	Context	Tool Name
Multiple Team Formation						
Anagnostopoulos et al. (2012)	Exogenous	Steiner coordination-cost algorithm, Diameter algorithm, set-cover Steiner algorithm	Minimize communication cost, balance workload	Skills, communication cost, workload	Ad hoc team	---
Andrejczuk et al. (2016b)	Exogenous	Greedy algorithm	Heterogeneity	Skill, personality, gender	---	---
Andrejczuk et al. (2018b)	Exogenous	Heuristic algorithm	Heterogeneity	Skill, personality, gender	---	SynTeam
Andrejczuk et al. (2019).	Exogenous	Linear programming, heuristic algorithm	Team size, personality	Skill, personality, gender	---	---
Bahargam et al. (2019)	Exogenous	Heuristic algorithms	Minimize faultline potential	Variable (e.g., gender, major)	Team diversity	Faultline Splitter
Chalkiadakis & Boutilier (2012)	Endogenous	Bayesian reinforcement learning	Joint outcome utility	Skills, level of expertise	Learning	---
Farhangian et al. (2015a)	Exogenous	Agent based model	Skill coverage, personality-role fit	Skills, personality	---	---

Farhangian et al. (2015b)	Endogenous	Agent based model	Joint outcome utility	Skills, personality, task type	---	---
Gilal et al. (2018)	Exogenous	Logistic regression, decision tree, and rough sets theory	Team performance	Skills, personality, gender, team role	---	---
Gutiérrez et al. (2016)	Exogenous	Constraint Programming, Local Search, Variable, Neighborhood Search	Skill coverage, peer affinity	Skills, sociometric matrix	---	Multiple Team Formation Problem
Liemhetcharat & Veloso (2014)	Endogenous	Synergy graph	Coordination	Skills	Learning	---
Marcolino et al. (2013)	Endogenous	---	Joint action utility	Individual preferences	---	---
Peleteiro et al. (2015)	Endogenous	Network-based, contract net algorithm	Skill coverage, synergy, minimize cost	Skills, synergies, reputation	Ad hoc team	---
Rangapuram et al. (2013)	Exogenous	Network-based, dense subgraph problem algorithm	Minimize communication cost	Skill, team size	---	---
Rokicki et al. (2015)	Endogenous	General algorithmic approach	Solution quality, minimize cost	Skills, hiring cost	Ad hoc team	---
Spradling et al. (2013)	Endogenous	Heuristic optimizer, greedy algorithm	Joint action utility	Skills	Ad hoc team	Roles and Teams Hedonic Games

Single Team Formation						
Anagnostopoulos et al. (2017)	Endogenous	Linear Program; heuristic algorithms (LumpSum, TFO)	Skill coverage, minimize personnel cost	skills, tasks, costs (salary and hiring/ outsourcing fees	Online crowdsourcing	---
Crawford et al. (2016)	Exogenous	Greedy heuristic algorithm, genetic algorithm, linear programming	Robustness, minimize team cost	Skills	Robust team formation	Task-Oriented Robust Team Formation
Dorn & Dustdar (2010)	Exogenous	Network-based, simulated annealing, metaheuristics	Skill coverage, connectivity	Skills, level of expertise	Expert team	---
Gerasimou et al. (2012)	Exogenous	Particle swarm optimization	Skill coverage, availability	Skills, schedule	---	---
Kargar (2011)	Exogenous	Network-based, approximate and exact polynomial algorithm	Skill coverage, minimize communication cost	Skills, team role	Expert team with leader	---
Kargar & An (2013)	Exogenous	Network-based, approximation algorithms	Skill coverage, minimize personnel cost and communication cost	Skills, hiring cost	Expert team	---
Kargar & Zihayat (2012)	Exogenous	Network-based, minimal cost contribution algorithm	Minimize communication cost and recruiting cost	Recruiting cost	Expert team	---
Lappas et al. (2009)	Exogenous	Network-based, greedy heuristic and approximation algorithm	Skill coverage, minimize communication cost	Skills	Expert team	---

Okimoto et al. (2015)	Exogenous	Branch and bound search-based algorithm	Robustness, minimize team cost	Skills, hiring cost	Robust team formation	---
Stylianou & Andreou (2012)	Exogenous	Multi-objective genetic algorithm	Skill coverage, personality fit	Skills, personality factors	Project management	---
Team Member Replacement						
Agmon et al. (2014)	Endogenous	Recursive modeling, simultaneous repeated game	Joint action utility	Depth and width of agent recursion	Ad hoc team	---
Barrett et al. (2013)	Endogenous	Transfer learning algorithms	Joint action utility	Agent recursion	Learning	---
Chen et al. (2015)	Endogenous	---	Rate of learning and completion	Skills, task, and agent turnover	Ad hoc team	---
Li et al. (2015)	Exogenous	Network-based, graph kernels	Skill and structure matching	Skills, relationships	---	---
Malinowski et al. (2008)	Exogenous	Probabilistic latent semantic analysis	Predicted trust	Trust	---	---
Sapienza et al. (2019)	Exogenous	Deep neural network	Minimize the loss function	Skill level and its error of certainty	Virtual games	---
Wax et al. (2017)	Endogenous	Network-based, exponential random graph models	N/A	N/A	Virtual games	---
Tool						
Dimiduk & Dimiduk (2011)	Exogenous	Heuristic guided stochastic greedy algorithm	Variable	Variable	User tool	GroupENG
Donsbach et al. (2009)	Exogenous	General algorithmic approach	Variable	Variable	User tool	Tops

Hertz et al. (2019)	Exogenous	Genetic algorithm	Variable	Variable	User tool	gruepr
Layton et al. (2010)	Exogenous	Hill-climbing algorithm	Variable	Variable	User tool	Team-Maker w/ CATME
Rad et al. (2021)	Exogenous	Variational bayesian neural network	Skill coverage, history of collaboration	Variable	User tool	PyTFL
Stylianou et al. (2012, November)	Exogenous	Particle swarm optimization, genetic algorithm	Skill, personality fit	Skills, personality traits, schedule	User tool	IntelliSPM
Tannenbaum et al. (2010)	Exogenous	General algorithmic approach	Variable	Skills, team role, synergy	User tool	TCS
Thio (2017)	Exogenous	Greedy algorithm	Variable	Variable	User tool	Teammatic
Zhou et al. (2018)	Exogenous	Network-based, graph kernels	Minimize communication cost	Variable	User tool	Extra