A Taxonomy of Team-Assembly Systems: Understanding How People Use Technologies to Form Teams

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The emergence of team-assembly technologies has brought with it new challenges in designing and implementing socio-technical systems. Our understanding of how systems shape the team-assembly processes is still limited. How do systems enable users to find teammates? How do users make decisions when using these systems? And what factors explain the characteristics of the teams assembled? Building on existing literature from CSCW, computer science, and management science, we propose a taxonomy to characterize how systems influence team assembly. This taxonomy argues that two dimensions determine how systems shape team assembly: (i) users' agency, to what extent the system enables its users to exercise their agency, and (ii) users' participation, how many users the system allows to participate in the team-formation process. The intersection of these two dimensions manifest four types of teams enabled by systems: self-assembled teams, staffed teams, optimized teams, and augmented teams. We characterize each one of these types of teams, considering their qualities, advantages, and challenges. To contextualize these types of teams, we map the current literature of team-assembly systems using a scoping literature review. Lastly, we discuss ways through which these two dimensions alter users' behavior, team diversity, and team composition. This paper provides theoretical implications and research questions for future systems that reconfigure the organization of people into teams.

CCS Concepts: • **Human-centered computing → Collaborative and social computing theory, concepts and paradigms**; *HCI theory, concepts and models.*

Additional Key Words and Phrases: team assembly, team formation, teams, conceptual framework, algorithms, diversity

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1 INTRODUCTION

Assembling a team is a challenging enterprise for managers, workers, teachers, students, players, and many others [15]. It requires iterating several possible team combinations, getting information about members' attributes and social relationships, and operating under the given conditions in a

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particular social context [15]. Furthermore, forming the most efficient team combinations from a pool of individuals is not always evident. For example: bringing together star-players or top experts will not necessarily imply a successful team [150, 215], forming a team from diverse students may lead to cultural conflicts and divisions [19], and finding the most appropriate teammates is not always possible because they may not be available at the same time [177]. Putting the issue of the best way to assemble teams aside, people are often not even aware of others' backgrounds and abilities. Gauging information about others' skills, values, points of view, or knowledge is difficult since those characteristics are intangible, and people often judge others based on stereotypes and demographics [41]. When people can choose their teammates, hardwired human tendencies create an attraction to people who are similar and familiar [86], leading to the formation of less diverse teams [203]. People must confront these multiple decisions, recognize the lack of opportunities to find suitable teammates, yet feel empowered to choose them freely, and learn more about potential teammates' repertoires (e.g., background, skills, information, experiences.) These problems are relevant for both people and organizations, since forming ineffective teams can have devastating consequences for its members (e.g., conflict, group faultlines, authoritarian leadership), for the entrusted task (e.g., failure, delays, extra-costs, lack of innovation, poor performance), and for stakeholders (e.g., reputation, expectations, value) [136, 137]. As modern work is increasingly carried out by teams, organizations and individuals must overcome these challenges to assemble effective teams.

Can socio-technical systems help people assemble effective teams? In the last three decades, computer science scholars have worked on different systems and methods that support the team-assembly task. As a result, different systems have been developed to leverage team-assembly processes by combining several data sources, analyzing users' trace data, and performing several calculations to find the most efficient team combinations. However, these contributions have not been synthesized and studied as a whole [82], and most technological solutions do not consider members' social contexts, which can make teams more efficient and viable [95]. In the light of the increasing number of technologies supporting teams, there is an opportunity to study how systems are helping people assemble teams. This pursuit can increase our understanding of how systems improve team formation by assembling efficient teams or suggesting suitable teammates, who might not have been considered in an offline context [69, 82].

From a theoretical standpoint, most conceptual frameworks in CSCW assume that groups are already assembled [75, 98, 121] and leave questions about team assembly unaddressed: What kinds of potential teammates would users like to seek? How would the team composition be shaped by using a particular team formation system? Should users know why they were assigned to a particular team? Should users be actively involved in the team-assembly process? Only a few studies have sufficiently accounted for the benefits and challenges of using socio-technical systems to assemble teams, and how users' contexts are translated into systems' components or designs for assembling teams, Most of this research corpus is based on case studies and does not provide theoretical conceptualizations for future innovations [82, 84, 158]. Although system designers, researchers, and developers can incorporate knowledge from previous CSCW frameworks, they would greatly benefit from a conceptual framework that integrates social considerations and knowledge from previous team assembly studies. In other words, CSCW scholarship needs to extend existing theoretical knowledge to incorporate the increasingly common practice of assembling teams using socio-technical systems. Therefore, we propose a conceptual framework to understand the role of systems in team assembly.

In this paper, we introduce a taxonomy that describes the impact of socio-technical systems on team assembly. Prior research shows that team assembly is driven in part by the number of individuals involved in forming a team, and their level of control over the formation process [15].

Therefore, the taxonomy we propose integrates two dimensions considering the role of systems: (1) *users' agency*: to what extent systems enable their users to exercise their agency during the team-assembly process, and (2) *users' participation*: how many users the system allows to participate in the team-assembly process. These two dimensions manifest four types of teams enabled by systems:

- *Self-assembled teams*, where systems enable users to self-organize in their own teams.
- *Staffed teams*, where a user customizes the team-assembly criteria used by the system to simulate and form teams.
- *Optimized teams*, where a system assembles teams given particular team-formation criteria, and,
- *Augmented teams*, where the system augments users' actions by suggesting potential teammates.

After introducing this taxonomy, we conduct a scoping literature review [14] to examine the corpus, volume, and contributions of prior studies on systems that support team assembly. After screening more than 2,100 articles found on the ACM Digital Library, IEEE Xplore Digital Library, and Springer Link, we identified 126 relevant studies that describe systems, algorithms, and methods to assemble teams, and then we mapped them based on our taxonomy's dimensions. We used this exercise to identify future areas of research within this taxonomy, hoping that these results empower CSCW practitioners, designers, and researchers to systematically examine how socio-technical systems affect team assembly.

The contributions of this paper are twofold. First, we provide a taxonomy that sheds light on how socio-technical systems facilitate team assembly based on the interactions between systems and users. For designers and developers, this taxonomy illustrates key features and relevant design considerations to take into account in order to enhance users' experience. For researchers, this taxonomy suggests promising directions for empirical research and system experimentation. Second, we complete a scoping literature review to assess how the design of prior team-assembly systems has evolved based on users' agency and participation. By understanding the challenges of assembling teams using socio-technical systems, CSCW research will be able to develop and refine how systems support the formation of more effective teams, considering the dimensions that better satisfy the team's task and users' needs.

This paper is structured as follows: First, we begin by elaborating on our theoretical background to position systems that support team assembly in current CSCW frameworks. Next, we introduce this taxonomy of team-assembly systems, describe its conceptual dimensions, and elaborate on their intersections. We proceed with a systematic literature review to map prior studies of systems supporting team assembly. Finally, after explaining and categorizing the articles found, we end this article by discussing theoretical and design implications for designing and implementing these dimensions that configure team assembly in socio-technical systems.

2 THEORETICAL BACKGROUND

We situate our work in the context of prior studies of team assembly and CSCW frameworks across CSCW, HCI, and management science literature.

2.1 What is a team?

Teams are a set of two or more individuals interacting adaptively, interdependently, and dynamically toward a common and valued goal [175]. Teams are considered a specific subset of groups (i.e., work groups) since (i) team members are required to work interdependently with one another, (ii) teams require adaptation and structure to exchange information and resources, and (iii) teams have limited life span during which team interaction must be promoted together to achieve specific goals [175]. Despite these differences, the terms "group" and "teams" have been used interchangeably in the literature [79, 115]. In addition, teams are brought together to perform organizationally relevant tasks and exhibit interdependencies with respect to workflow, goals, and outcomes. Team members have different roles and responsibilities, and are together embedded in an encompassing organizational system, with boundaries and linkages to the broader system's context and task environment [115].

Since teams are increasingly relying on technologies to carry out their work, team processes and dynamics have adapted to the social architectures and interaction possibilities provided by socio-technical systems. CSCW research has explored how technologies facilitate teams' communication, coordination, collaboration, and work [51, 67]. More recently, scholars have explored how technologies can help the formation of teams by taking advantage of the current computational infrastructure and the combination of users' digital trace data and network information [82].

2.2 Team assembly

Team assembly refers to the process of searching for, identifying, and choosing members for a team [76, 199]. When assembling a machine, designers must look for, identify, choose, and gather the most appropriate pieces for the machine's specific purpose. So too with team assembly. The process of assembling a team is understood as the deliberate combination of people to form an envisioned whole since different and almost infinite team combinations can take place in social settings. One of the most critical challenges is deciding *who* would be the most appropriate team members who could work together successfully in order to accomplish the team goal. Team builders must complete a multi-step process to assemble successful teams, including searching for, identifying, and choosing members.

Prior literature has emphasized the socio-technical aspects that should be considered in team assembly:

- Team's structures [93] (e.g., norms, hierarchies, membership requirements).
- Team's contextual constraints [15, 137] (e.g., maximum size, members' locations, communication channels).
- Team's task [136] (e.g., What kind of tasks would members perform? Would the members' average or the best member's result be considered?
- Team members' relationships [108, 170, 204] (e.g., Have they collaborated together in the past?)
- Team members' personalities [204] (e.g., Are their personalities compatible?)
- Team members' expertise [211] (e.g., Do members have the necessary skills to complete the task?, Do members complement each other with different skills?).
- Team members' diversity [90] (e.g., Do members provide different points of view? How is the gender balance in the team? Is there a diversity of languages, cultures, and ethnicities?).
- Leadership structures [27, 163, 228] (e.g., Are there members who can lead and coordinate? Can team members manage themselves without outside leadership?).
- Members' identification with the group [201] (e.g., Do members see themselves as part of the team? Are members committed to the team's task?).
- Membership boundaries [137] (e.g., Do teams have open or closed boundaries to membership? What are the requirements to be part of the team?).

The combination of these factors—and how team assemblers prioritize them—will ultimately determine which members will be part of a team. Thus, understanding the factors and the mechanisms that support team assembly help us (i) trace the decisions that led to the team's ultimate composition, (ii) identify team assemblers' bias while searching for, identifying, and choosing members, (iii) and analyze how team members' characteristics and relationships might influence future team processes (e.g., cohesion, performance).

Past research has defined team assembly as the initial phases of the team members getting to know one another, their task, and their environment, but it does not address how team members are chosen. The research on teams has focused almost exclusively on what makes teams more or less effective *after* they formed. The focus of this paper, by contrast, is focused on the theoretical framework that explains the formation of the team. As such, this paper's theoretical focus ends where most prior theoretical research on team processes and outcomes begins. In the 1960s, Tuckman [196]—in a four-step model to explain team development—defines *team formation* as the initial stage that anticipates a team's actions. From this perspective, assembling a team is understood as an initial phase of building a team: members must know each other, understand the tasks, goals, and adapt to their environment. However, in this model, the team is already assembled, and its composition is already given. Tuckman's notion of team building was focused on building relationships among team members who were already assembled. It was not referencing the building of a team in terms of assembling the team.

One of the benefits of assembling teams is allowing individuals to achieve goals collectively, beyond the scope of what could be achieved by any of the individual members. Collins and Guetzkow defined this group quality as the "assembly effect" [40]. In Hackman and Katz's chapter [79] on the history of group research, the authors discuss how this effect should be considered by examining individuals' attributes and their social relationships when they come together as a team. Moreland et at. [146] described this situation as studying the "chemistry" that members develop when they work in a group. However, no empirical measures are provided to assess these interactions among members. In this sense, the challenge is examining how members' attributes will affect team processes once they finalize their team membership. Additionally, Hackman and Katz cautioned that aggregating individuals' attributes would not predict the team's ultimate characteristics, since new characteristics can emerge as a product of team members' interactions (e.g., a team of students in which some of them learn from others). They provided some guidelines to consider when assembling teams: (i) the task to be accomplished and required expertise, (ii) the use of members' information and knowledge, (iii) how members will share their expertise (and therefore, build teams' transactive memory and shared mental models), (iv) training activities that increase stability in the team, (v) the social systems that members are situated in (e.g., norms, hierarchies, status), (vi) and the presence and exercise of leadership. Although the studies reviewed by Hackman and Katz do not consider the role of technologies, these authors recognized the benefits of using technologies to coordinate teams' activities and characteristics.

A separate stream of research explores team assembly as a socio-cognitive process in which individuals situate their place in a social structure by identifying themselves within specific groups. One such theory, the *social-categorization* theory [88, 197, 198] posits that individuals categorize themselves into groups according to specific shared attributes. Two examples are a football team sharing the same uniform and software developers contributing to the same repository. As a result, team members develop attitudes of belonging to specific groups (i.e., ingroups) and establish boundaries that separate them from others who do not share those attributes (i.e., outgroups). Here again, this theory considers teams that are already assembled, and whose members feel a sense of group identity. A second theory is the *similarity/attraction* paradigm [25], which posits that people look for those who are similar or familiar to them. In contrast to the prior theory, a team does not innately exist, but rather, members assemble themselves into teams according to their similarities [28]. Individuals will form a group if they share interests or characteristics, and newcomers can join if their current members feel they are compatible.

In their book, Arrow, McGrath, and Berdahl [15] described four foci that characterize team assembly: member selection can be driven by *external* forces or *internal* forces, and it can be *planned* by agents or *emerge* spontaneously in social settings. Given the combination of these four forces, the authors introduce four team assembly strategies: (i) *Concocted teams*, where external agents deliberately form new groups (e.g., ad-hoc teams); (ii) *Founded teams*, where one or more members of the team may deliberately assemble a new group by linking up with other individuals (e.g., inviting a new partner in a start-up); (iii) *Self-organized groups*, where people form teams from local interactions pursuing their individual agendas (e.g., a research team); and (iv) *Circumstantial groups*, where environmental circumstances dictate both the project and the membership of the team (e.g., a flight crew assembled according to members' availability and schedule). These four strategies of team assembly advance our understanding of how the environment and individual agency impact team formation. However, teams examined in this model were assembled in offline circumstances. Though technology can be seen as an external force, it is not clear whether or not technology would be considered part of the assembly process. Considering how systems' design affects users' behaviors and decisions [46, 122], we focus on the intersections between systems and users during the team-assembly process.

Although these studies provide valuable insights on team assembly in general, the specific impact of technology on team assembly has not yet been studied in depth. Most prior studies on team assembly were conducted in traditional workplace settings and are grounded in theories developed in offline contexts [65]. There are a few studies on team assembly supported by systems, and they vary by context [65]. More theoretical work on team-assembly systems is required because we know that socio-technical systems reconfigure team formation, member interactions, and the process by which team members become familiar with one another. However, we do not know how and why. While members are assembling teams using these systems, communication can be asynchronous, members can be located in different places [98], and not all members' characteristics are readily revealed [28]. One systematic literature review on team formation at CSCW [82] shows the sparsity of theoretical work contributed from 1990 to 2018. This review proposes a conceptual framework to classify CSCW systems according to three dimensions: *agency* (whether team members organically assemble their teams or are assigned to them), *scale* (from dyads to communities), and *supporting technologies* (from expert-finder systems to virtual worlds). While novel in its contributions, this review only covers articles published at the ACM CSCW conference and excludes articles from other relevant computer science conferences and journals. A second systematic literature review on group formation for collaborative learning [158] highlights the increasing use of algorithms for assembling student teams—some of those can be configured by users, and others are already pre-set by machine learning techniques. This review also shows how diverse team-assembly methods can be: from students being able to choose their teammates to instructors who assign membership and design student teams. As a further limitation, this review only covers articles related to collaborative learning, excluding other fields such as crowdsourcing, work organization, or research teams.

Since prior scholarship has not provided a complete picture of how systems support team assembly, and not synthesized the team-assembly literature among all computer science disciplines, this paper addresses this gap by providing a taxonomy on how team assembly unfolds on socio-technical systems.

2.3 CSCW conceptual frameworks

Once computer technologies became accessible in workspaces, CSCW scholarship began designing conceptual frameworks that represented systems' components, their relationships with their users, and their impact in the workspace. Since its creation, the field of CSCW has developed several taxonomies of collaborative systems. The goal of these taxonomies is to understand how the design of collaborative technologies influences people's work [162].

In the 1990s, groupware-centric models were the most prominent frameworks developed and emphasized systems' physical components. Multiple authors published theoretical frameworks to explain group functions. Johansen's taxonomy [98] became one of the most cited theoretical pieces to explain groupware systems. This taxonomy characterizes systems according to two dimensions: *time* and *space*. These two dimensions arrayed types of technologies that support groups as working: (i) synchronously or asynchronously, and (ii) face-to-face or distributed settings. Despite its theoretical contribution, little emphasis has been put on Johansen's work on small and large groups using these systems [121]. Ellis, Gibbs, and Rein [56] defined two different dimensions to describe groupware systems: *common task dimension* (i.e., to what extent users are focusing on the same specific task) and *shared environment dimension* (i.e., to what extent users are aware of the other members who are collaborating in a single online space). Grudin [75] developed a conceptual framework to distinguish the different kinds of technologies and their specific users, from an individual using a personal computer to an entire organization establishing its technological infrastructure. Grudin's taxonomy is diagrammed as four concentric rings characterizing types of systems within their respective fields of computer science research. The outermost ring shows the inherent nature of information studies at the organizational level, while the innermost ring shows the relationship between HCI research and PC applications at the individual level. According to this taxonomy, CSCW research emphasized the small-group level and analyzed applications that support teams' activities. Gutwin and Greenberg [77] proposed a *workspace awareness* framework to disentangle the generation and execution of tasks done by groups in digital workspaces. This framework is designed as a perception-action cycle, where the system's users must execute actions to affect the environment or explore the environment to gain more knowledge from it. As a result of this knowledge-construction cycle, this framework proposes specific mechanisms that help users maintain high levels of awareness.

The groupware architectures' shortcomings in not adequately examining the social dimensions that characterize everyday work practice soon became apparent to CSCW scholars [1]. In order to address users' requirements—and based on individual and group activities performed on systems—Schmidt and Rodden [180] outlined seven requirements for a CSCW platform that they argued are necessary for supporting cooperative work: allowing *informal interaction* to support distributed activities, *information sharing and exchange* among users, *decision-making* mechanisms to reach agreement on particular issues, *coordination and control protocols* to reduce the complexity of work, and *domain directories* to provide services to the users and to index objects on the systems.

Cruz et al. [44] completed a systematic literature review of CSCW frameworks considering studies from 1987 to 2002. They found how several disciplines—including many social sciences—have shaped the theoretical developments of the CSCW foundation. The review found six socio-technical dimensions frequently discussed in the CSCW literature: *communication, coordination, cooperation, time and space, regulation, awareness*, and *group dynamics*. These dimensions provide measures to analyze aspects of technological systems, but the authors emphasized the lack of terminological consensus. To update these conceptual dimensions according to the social technologies that have since been developed, Lee and Paine's Model of Coordinated Action [121] expands previous groupware-centric models by considering the following measures: In addition to time (which they relabel as *synchronicity*), place (*physical distribution*), and *scale*, this conceptual framework introduces the *number of communities, planned permanence*, and *turnover* to characterize the inclusion, local and temporal presence, and the addition and removal of group members.

As the CSCW research unfolded, conceptual frameworks began to address more specific socio-technical infrastructures. Furthermore, since multiple solutions started to emerge in the market—offering several functionalities and affordances for similar purposes—the digital ecosystem became more socially complex [71]. The development of cooperative technologies—which turn into more diverse, social, and contextual systems—allowed for the specialization of conceptual frameworks. In one article, Rae et al. [168] presented a conceptual framework to explain *telepresence* on collaborative systems using seven design dimensions: *initiation, physical environment, mobility, vision, social environment, communication*, and *independence*. Each dimension is described with several characteristics related to the technologies' configuration and interactional aspects with their users. In another article, Morschheuser et al. [147] created a classification for *gamification* features based on two dimensions: *cooperative* and *competitive* goal structures. In the first dimension, features promote shared goals for a group or promote individual goals. In the second dimension, the game promotes competitive features—where the goal is to defeat or have better performance than other users—or noncompetitive features—where no one is defeated, and comparisons are not made between teams. In another article, Wulf et al. [216] proposed a research framework to analyze social practices, design technological artifacts that support those practices, and investigate the appropriation of the designed artifacts. This framework can be applied in four domains: cooperative work, community support, social and ecological sustainability, and elder societies. In another study, Stuart et al. [190] proposed a conceptual framework for *social transparency*—which they defined as the availability of social meta-data surrounding information exchange—on the Internet, considering three dimensions: users' identity, content, and interaction. This conceptual framework provides theoretical explanations of how social cues displayed in these platforms can affect users' behavior and decisions. One last example is provided by Foong et al. [64], who propose a conceptual framework to highlight critical processes that affect *online feedback exchange* (OFE). Based on an end-to-end cycle, the model distinguishes five activities that impact the design, use, and success of OFE: deciding when to seek feedback, presenting work and asking for feedback, incentivizing providers to give feedback, adapting feedback to designers' work, and making sense of feedback and integrating into revisions.

Although these previous taxonomies provide theoretical developments for the CSCW field, the literature lacks a single systematic way to conceptualize and evaluate team assembly supported by systems [65]. The sparsity of CSCW bibliographical work—combined with the lack of emphasis on social processes—motivates the need to expand our understanding of how individuals team up with others and how teams emerge in cooperative-work systems [82, 182]. The goal of this taxonomy is to provide theoretical and practical guidelines on how people use systems to assemble teams.

3 A TAXONOMY OF TEAM-ASSEMBLY SYSTEMS

In this section, we introduce a taxonomy to classify team-assembly systems. The theoretical background and conceptual frameworks reviewed above emphasize the contextual factors that users face when they decide to work together. However, the extent to which the systems allow users to *control* the team-assembly process has not been extensively discussed, leaving out some of the social dimensions of forming teams. First, the team-assembly process can be initiated by the team members, by external actors who decide on team members' interactions, or by the system itself. Ultimately, system designers determine how each user can control the team-formation process, interact with other users, and act on the system. Second, team-assembly decisions are highly interrelated since choosing an individual for a team means excluding others from that team and disregarding alternative team members. System designers have to decide what role the system will have during this sequence of decisions, and which users can make the decisions that affect the final teams and their composition. The final team composition will become less predictable when the system allows multiple users to decide and influence the team-formation process. Because assembling teams is a collaborative process, which would require users' actions to define team memberships, we posit that a taxonomy for team-assembly systems must consider (i) to what extent systems grant users control of their searches, teammate preferences, membership, and final team composition; and (ii) the number of users that the system allows to participate in the team-assembly process. Socio-technical systems may provide varying levels of control to users ranging from full-control, where each user is free to decide which team she/he wants to belong to, to a no-control situation where each user is assigned to a team by a third-party or by an algorithm [82]. Therefore, we argue that understanding *what* users can do and *how many* users control these team-assembly processes is key to the design and implementation of team-assembly systems. More specifically, we argue that the level of users' control allowed by the system during the team-assembly process is particularly salient for understanding the final team composition. Thus, we introduce (i) users' agency and (ii) users' participation as two dimensions of this taxonomy.

3.1 Dimension 1: Users' agency

The first dimension, taken from Harris et al. [82] and Coyle et al. [42] studies, measures the extent to which systems enable users to exercise their agency during the team-assembly process. Coyle et al. [42] defined agency as *"a person's innate sense of being in control of their actions and through this control of being responsible for, or having ownership of, the consequences of those actions."* Thus, we understand users' personal agency as the control that users have over the team-formation process on the system. Harris et al. [82] provided a spectrum of assembly mechanisms arrayed by agency: from high user agency conditions, where the user has complete control over whom they team up with, to low user agency conditions, where users have no choice in whom they are assigned to work with. Users' agency—or lack thereof—is also discussed in Eftekhar, Ronaghi, and Saberi's study [55], which describes the formation of *organic* and *algorithmic* teams. Organic teams are formed by the members themselves, who are able to leave a team and join another at any time. Algorithmically teams are often assembled by an instructor, who determines the criteria and association rules. In contrast with their rigid definitions, our taxonomy provides nuances between users' and systems' decisions and considers the synergy between these two entities. Users can both exercise certain levels of agency and be supported by systems. Considering these previous studies, we aim to extend theoretical knowledge in users' agency for team assembly.

Clearly, users' agency has consequences for the team-formation process. On the one hand, when users have control over the team-assembly process, they exercise their agency by searching for potential team members, identifying potential candidates, and finally choosing members for their specific team. On the other hand, when users cannot exercise their agency, team-assembly processes are controlled by the socio-technical system often through the use of algorithms. We define *user-driven* team assembly when users can exercise their agency in the system, and thus, the teams are formed by the users themselves. In contrast, we define team assembly as *algorithmically-driven* when users cannot exercise their agency in the system, and therefore, their teams are assembled by the system itself.

In these socio-technical systems, users that exercise their agency can be *internal members* of a team (e.g., students choosing their teammates) and *external individuals* who use the system to form teams (e.g., an instructor creating teams for his/her students). Two examples of users driving the team-assembly process in concert with technology are: (i) users looking for potential teammates on a social networking platform, or (ii) an instructor simulating different team assembly criteria using a system. In contrast, when the team-assembly processes are driven by systems, the decision-making process is more likely to rely on independently specified optimization logics, such as minimizing individuals' differences, matching individuals' availability, or maximizing team members' skills.

Systems—and their algorithmic components—can be part of team-assembly processes to varying degrees, whether the team is assembled, or staffed, by an outside agent or self-assembled by the members themselves.

3.2 Dimension 2: Users' participation

The studies reviewed in the theoretical background section demonstrated that team assembly actions could be run by a single person (e.g., a leader, an instructor) or be carried out collectively (e.g., individuals voting for their teammates). We capture this distinction in the second dimension of this taxonomy, which calibrates how many users can participate in the team-assembly process. This dimension is also inspired by the *scale* dimension from Lee and Paine's model [121], which they defined as the number of users—from a single user to many—who are able to act on a social platform. In our particular context, this dimension identifies how the system outlines users' participation in team-assembly actions: from one single organizing user that assembles the team to a multitude of users that assemble their own teams. Overall, systems provide a spectrum of centralized or decentralized participation among its users.

Socio-technical systems must consider how many users are going to participate in the team-assembly process since each situation would require enabling different technological architectures that would allow specific users' actions. On the one hand, *low participation* in team assembly focuses on a single user. One or a few users will interact with the system aiming to assemble the required teams. Examples of low-participation architectures are an instructor providing input to the system to assemble student teams automatically or a manager forming a taskforce by exploring and selecting its members. Some systems can provide the managing user the control to simulate, test, and redo their team combinations several times without relying on the users who will be part of those teams. After the user provides the input of the task and members' attributes (e.g., skills, social relationships), the system will continue with the team-assembly process, performing its calculations based on the programmed criteria and providing the teams as an output. As a result, teams assembled under low-participation conditions could achieve higher levels of heterogeneity, diversity, and expertise since the team builder (i) controls the team assembly criteria, (ii) has access to more information about individuals' attributes, (iii) explores how the combination of those attributes will produce specific team compositions, and (iv) determines the membership of each individual [15, 140].

The focus of low-participation architecture is how the user (or a few users) in charge of assembling teams can decide upon the team assembly requirements: Should these teams be heterogeneous? Should the team count on the best experts available? Should team members have prior relationships? Based on the systems' information requirements and team-assembly criteria, the team assembly will be controlled by a single user aiming to provide the best team combinations possible. The outcomes of low-participation systems are more predictable than high-participation systems since they depend on a few users. Uncertainty can be reduced, and replicable and scalable results can be guaranteed if algorithms are used to assemble the teams, instead of users. Overall, systems that prioritize low-participation architectures of team assembly feature the most inner circle of Grudin's rings taxonomy [75]: the interaction between the user and software applications.

On the other hand, *high participation* in team assembly focuses on the collective. In this case, team-assembly processes rely on multiple or all users. Examples of high-participation architectures are numerous users sending and accepting teammate recommendations provided by a system, or Wikipedia users forming editorial teams according to their expertise and availability. When many users participate in the team-formation processes, the decision-making process is likely to rely on the information provided by the system and the prior knowledge of other potential team members. Past research shows that competence, similarity, and familiarity are the most likely factors that explain individuals' choice of team members [8, 86]. Users are more likely to choose to work with people whom they already know [70, 177], have collaborated with successfully in the past [80], are close friends [29, 179], and/or are popular individuals in their social networks [29]. As a consequence, high-participation architectures may produce more homogeneous teams compared to those assembled by low-participation architectures.

When multiple users are participating in the team-assembly processes, systems' group features (e.g., communication, interaction, coordination, and awareness) are fundamental to coordinate their efforts. In contrast to low-participation systems, high-participation systems enable its users to coordinate their interactions and decisions over time. Johansen's taxonomy dimensions [98]—time and space—become relevant aspects for the systems' design: developers must consider whether users have to agree synchronously or asynchronously, as well as whether they have to be in the same location or not. Schmidt and Rodden's requirements [180] are crucial to enable high-participation architectures, such as allowing informal interaction to articulate distributed activities, information sharing and exchange among users, decision-making mechanisms to reach agreement on team membership, and coordination and control protocols to assist the team-formation process.

Finally, the outcomes of high-participation systems are incertain and less predictable than the outcomes of low-participation systems since the final decision relies on multiple users. Even if algorithms can ease the assembly of these teams, users' preferences can be varied and only known once users make their decisions on the system. In summary, systems that prioritize high participation in the team-assembly process recall the second circle of Grudin's rings taxonomy, where the emphasis is the interaction between small groups and networked technologies.

3.3 Intersecting these two dimensions

These two dimensions—user's agency and participation—define a team-assembly systems "space." By dividing this space into quadrants, we identify four categories of teams: optimized teams, staffed teams, self-assembled teams, and augmented teams (Figure 1). We examine these categories in more depth here using examples drawn from previous CSCW and HCI literature.

3.3.1 Optimized teams. Teams assembled by systems' algorithms are examples of "optimized teams." In this case, users' agency and participation are limited in the team assembly process. Generally, only one user participates in the team-formation process by providing the input data required by the system. This user does not have control over the team-formation process, and her/his only responsibility is to provide the data to the system. Systems' algorithms assemble teams based on specific criteria, such as members' characteristics and social networks. As a result, team members cannot choose their team memberships nor establish the assembly criteria. Computer science research has devoted considerable attention to developing team-formation algorithms and frameworks in this quadrant. Considering all team combinations that systems can provide—of different sizes and memberships—the primary goal of systems' developers is to use an efficient method to assemble teams. This problem has been classified as an NP-hard problem by several scholars since finding the best answer requires computing all the possible team combinations (i.e., brute-force search), which cannot be done in polynomial time [55, 58]. Contributions in this field are based on what variables and mechanisms are considered to find optimal solutions that approximate the best solutions, using less computer memory and less time.

One main characteristic of optimized teams is that they depend on (i) the input that the user provides to the system, (ii) the team assembly criteria established in the system, and (iii) the algorithms used by the system. Some systems consider the sum of individuals' skills as part of the optimization problem (e.g., forming a team of experts from a research community) as well as assigning members according to their specific roles in the team [171]. Other systems consider users'

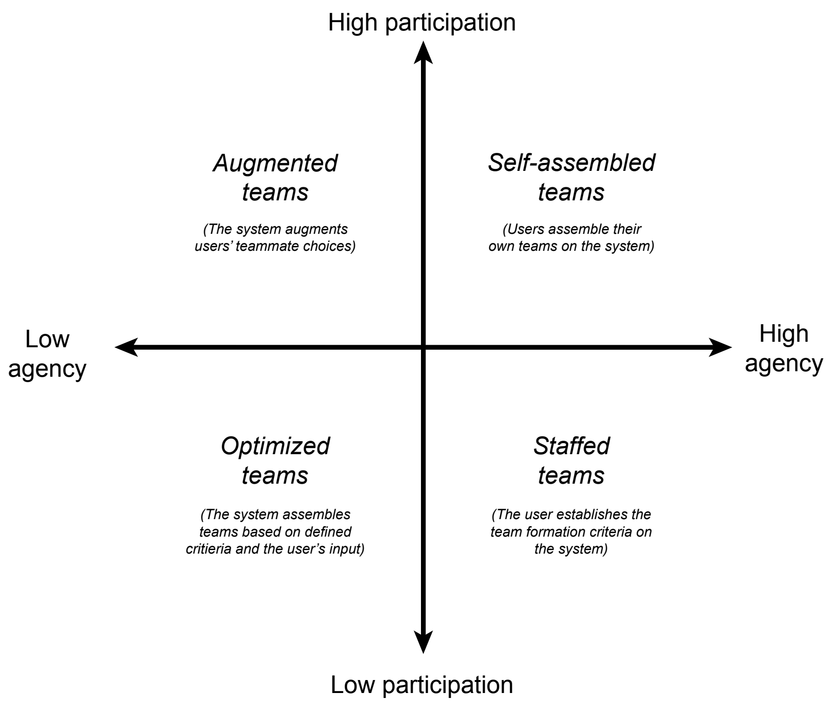

Fig. 1. The Taxonomy of Team-Assembly Systems presents two dimensions: (i) users' agency: to what extent users can exercise their agency during the team-formation process, and (ii) users' participation: how many users the system allows to participate in this process. Each quadrant defines four types of teams: optimized teams, staffed teams, self-assembled teams, and augmented teams.

social networks to assemble their groups. One example is Lappas et al. [117], which considers the team-formation problem using members' skills and social networks. The systems' goals are not only to assemble groups that meet the tasks' skill requirements but also to assemble teams that can work effectively together.

Through several methods and algorithms, these systems' objective function is to maximize a specific team's characteristics (e.g., social connections, skills covered by the team) subject to communication or personnel costs. Some crowdsourcing systems fit into this category since one of their challenges is to divide projects' tasks and assign them to crowd-workers according to their skills and availability [112]. Multiple studies consider the role of social networks, previous collaborations, and the intensity of interactions among a pool of individuals to assemble teams. Other developed systems consider how members can complement their personalities and skills to create balanced teams [129]. Furthermore, systems can alter existing teams' structures to be more effective for the current members of the team [233], and swap members between teams to facilitate new points of view in the teams [176]. Latorre and Suárez [119] develop a framework that facilitates team assembly in a systematic and reproducible way. This framework uses workers' social networks, prior experience, and previous collaborations to build compatibility networks among participants, where each connection represents whether the workers have compatible (or incompatible) social skills.

Based on previous collaboration or interactions, systems aim to assemble the most appropriate teams. In conclusion, assembling optimized teams becomes a process driven by algorithms that determine specific team combinations.

Pros: Team assembly is fast, objective, and reproducible. Helpful for assembling massive groups. It finds team combinations based on the users and task information, which are only computationally manageable. Team assembly criteria can be adjusted beforehand.

Cons: Solutions are fixed and do not provide other alternatives. Team members are usually excluded from this process. Lack of transparency for the users. Users cannot provide feedback.

3.3.2 Staffed teams. An instructor using a system to assemble student teams is an example of "staffed teams." In this quadrant, users' agency is high and users' participation is low. The users of these systems are usually one individual (e.g., instructor, manager, captain, leader). Teams can be formed on the system by a person who will not be part of a team (e.g., a manager using the system to assemble a task force), or by someone who is looking for new teammates (e.g., a lead engineer using the system to find new members for her/his team). Systems are employed to support users' decisions, simulate team combinations, or reach more members for their teams. Ultimately, the user makes the final choices based on the systems' output. Systems can provide a unique team solution or several team recommendations to the user, who has control over the input and the team-formation criteria. In contrast to optimized teams, the team-formation criteria are established by the user, who can configure the system's parameters, and the system provides results according to the user's requests. Another key aspect of this quadrant, which contrasts with optimized teams, is the presence of graphic user interfaces (GUI), which allow users to control and customize the parameters to assemble teams.

One example is a sales-team builder developed by IBM [9]. This system allows users to search for potential team members, simulate possible combinations, and assign members to specific teams. Once the user selects members for a potential team, the system provides future sales predictions based on the team members' previous collaborations and sales. Another example is CATME [120], which allows instructors to form teams by surveying students' work styles, skills, and demographics. Based on the instructor's criteria, the system suggests several team combinations, which the instructor can choose from.

Other systems for staffed teams help users find experts in a specific domain. Termed *expert-finding* systems in the literature, they allow users to search for experts who are likely to succeed in the team's tasks [6]. Expert-finding systems are used to support recruitment activities, where a user can see candidates' profiles and choose team members based on the information provided. One example is "TeamBuilder" [105], which enables groupware users to find other experts in the network. Another example is SCSMiner [206], which allows users to find expert developers on GitHub, considering their coding skills and prior projects. One study [223] proposes a system to measure potential teammates' willingness to collaborate. This system evaluates recommendations based on the users' shared contacts with other candidates (i.e., closeness), their expertise differences, and the benefit that could be gained through collaboration. In summary, systems for assembling staffed teams provide structured information or recommendations to users to facilitate the assembly of these teams.

There are limitations to staffed teams. First, they might face dissonances between the overarching users' criteria and the team members' expectations. In a CATME study, students desired more control over the criteria selected by the instructor and explanations as to why they were assigned to a particular team [95]. In another study, Fuller [66] conducted interviews and observations in software organizations and found that assembling teams based on the company's functional structure caused project teams to exhibit counterproductive behaviors that affect their work and cohesion. In contrast to optimized teams, even when team members are not able to control the team-assembly criteria embedded in the system, they may find the team-assembly process more objective when it is done by a machine, rather than by a human user [192]. Second, since most assembly information depends on users' networks and inputs that they put into the system, users' bias could cause the selected team members to be too similar to the team builders, excluding more diverse memberships from the group [70, 78].

Pros: Team assembly criteria adjustable. The team-builder user can iterate several team combinations. Heterogeneous teams are easier to assemble. Supported by the system, the team-builder user can get information from members' characteristics in a feasible way.

Cons: Lack of transparency from the user who assembled the teams. Team members' feedback is limited. Teams' viability and members' agreement depend on how much they trust the user who assembled the team.

3.3.3 Self-assembled teams. Players assembling their own teams in a virtual game is one example of "self-assembled teams." In this quadrant, users' agency and participation are high. These teams arise more or less spontaneously from self-organized activity that flows within existing patterns of relations among users, tasks, and systems. For more planned teams, systems enable users to search for, invite, and choose their teammates as they interact and meet each other on the platform [70]. The teams' final composition does not emerge until the team assembly stage is completed since membership relies on the sequential choices made by users. For less planned self-assembled teams, users' membership can vary over time as they navigate and use the system. These teams are more likely to change their composition over time since multiple members are entering and leaving the team [121]. As a result, these self-assembled teams of many sizes, characteristics, and purposes will emerge [172].

Systems facilitate self-assembled teams by relocating users' face-to-face interactions to virtual spaces in which interactions can be synchronous or asynchronous. Since systems coordinate users' decisions and interactions, users can search for, select, and choose their teammates at different moments and in different locations. One example is *MyDreamTeam* [49, 68], which enables students to assemble teams by themselves. In other open platforms, teams can emerge from users' interactions and systems' affordances. Wikipedia is another example where editors work on the edition of thousands of articles. Keegan et al. [109] found that articles drove the assembly of editorial teams, which brought those with prior editing experience. Other examples can be found in multiplayer game systems in which players team up with others based on their skills, expertise, and relationships [110]. One study of *e*-sports [65] found that novice and professional teams have different self-assembly strategies: While novice teams' members asked their friends or relatives to be part of their teams, professional teams' members conducted interviews and had face-to-face meetings—lead by current team members—to find new members. Designing open spaces for self-assembly can also be found in social media platforms, which provide open socio-technical architectures in which users are allowed to have interactions among themselves with lower barriers [161].

These teams have drawn scholars' attention because team members are allowed to choose teammates, and their choices are more likely to be driven individualistically rather than collectively. As a result, the formation of heterogeneous teams is not guaranteed. Prior studies show that self-assembled teams are more likely to have lower levels of cognitive and demographic diversity because most users will team up with other users who are similar and familiar to them [54]. Therefore, self-assembled teams are more likely to be homogeneous than the other types of teams [55]. In the context of start-ups and firms in the high-tech sector, Hart [83] found that foreign-born founders are more likely to team up with others who are foreign-born, and more likely than white founders to team up with women and other minorities. Gómez-Zará et al. [70] found that users tended to self-segregate members when they were assembling teams in online environments based on their human and social capital. Although most users were aiming to work with competent and social individuals, they selected other users whom they already knew. As a result, unskilled and less-connected users were less likely to find a team and they required the assistance of the system's administrator. In other words, segregation is also likely to occur when users are self-assembling teams on these systems.

Self-assembled teams' performance has also been an aspect of research interest [33]. Research questions about their performance have been addressed mostly in offline contexts. For example, Rusticus and Justus [174] found that students' self-assembled teams had better academic performance and group work contributions than teams assembled by teachers. Kim et al. [111] studied self-assembled teams playing the online game "League of Legends" and found that these teams were very competitive when they include a female team member and when their members have higher levels of social perceptiveness. Wax et al. [212] studied teams on Dragon Nest (a web-based MMORPG) and found that players were more likely to assemble teams with those geographically closer, which can be explained by reducing time-zone and cultural differences. Future research should explore whether self-assembled teams on these platforms outperform teams assembled by algorithms or third-parties.

Pros: Systems enable users to choose their teammates. Team members are more likely to be committed to the team's tasks when they can choose. Users' decisions are transparent.

Cons: Team composition is only known at the end of the team-assembly process. Segregation and discrimination are likely to occur among users. Teams are likely to be homogeneous. Some users can end up without a group and feel excluded.

3.3.4 Augmented teams. A system that helps users find the most appropriate teammates results in "augmented teams." In this quadrant, users' agency is low but user's participation is high in the team-assembly process. Rather than providing all the possible choices, the system narrows users' teammate options by highlighting potential candidates and hiding less feasible candidates. We call these teams "augmented" because the systems are designed to augment users' choices and interactions with others [153, 181]. Since users have to choose from a vast number of team combinations and potential teammates, systems can facilitate users' searches and choices by narrowing their options. By analyzing users' traits and social networks, systems can highlight potential teammates who are more likely to succeed in working with the user. For example, systems could suggest competent teammates who are already familiar with the users [177], or recommend teammates who provide the right combination of psychological traits [39]. As users explore and choose from the options curated by these systems, these augmented teams emerge.

Compared to self-assembled teams, users' choices are strongly influenced by systems. In particular, systems determine, curate, and present potential teammates to the users based on their operating algorithms. As a consequence, some teammate alternatives will not be visible to the users. Because of this intervention, users' agency is more limited since their options are reduced and determined by the socio-technical system. The focus of these systems is the algorithmic intervention performed in the team-assembly process, which might introduce algorithm bias and reduce transparency [155].

In contrast to optimized teams, augmented teams systems allow users to participate in the team-formation process, supporting them to find teammates, express their preferences, and provide feedback about the teammate candidates suggested. Instead of a single user controlling the team-assembly process (e.g., instructor, manager), team members participate in the assembly process and take advantage of the systems' computational capabilities to discover suitable teammates. Another difference is the final outcome. While forming optimized teams is reproducible and predictable, forming augmented team systems leads to unknown teams' final composition because it depends on the sequential decisions that each member makes, which is unknown *a priori*.

One way in which augmented teams can be assembled is through *recommender systems*, which attempt to recommend the most suitable potential teammates to users according to specific criteria [22]. Recommending teammates is not easy since each recommendation is correlated to other users' decisions (e.g., one recommended candidate may already be in another team). Recommendations also are temporary and become narrowed over time since other users are assembling their teams too. One example of a recommender system is a social platform that assembles taxi drivers teams [230]. After registering, users decide whether they want to be a leader of a team or not. Leaders have two options: they can self-assemble their teams without input from the system, or choose teammates from a list of recommendations that the system provides based on users' driving data. Members can accept or decline a leader's invitation.

Despite the low agency that users exercise in this quadrant, systems promote users' participation by asking for their teammate preferences. Users' teammate preferences can be used as an input to assemble their teams. One example is Joseph et al.'s system [99], which first asks students with whom they would like to work, and then, assembles the team to maximize their preferences. A second example is a team formation system developed by Wang and Zhang [207], which allows leaders and team members to negotiate their team membership. This system mediates this negotiation by identifying the best candidates for the team's objective, the required skills for the project, members' competence, and available vacancies. In a third study by Cavdur et al. [30], a two-phase allocation system allocates students and academic advisers to project teams based on their teaming preferences and qualifications. The system creates balanced teams based on students' preferences and optimization parameters, and then allocates academic advisors to each team in the same way. The sequential combinations of users' decisions and algorithmic calculations allow the assembly of the final teams. These are examples of systems in which users are constantly choosing those with whom they would like to work and providing feedback to the system, while the system curates this information to assist the assembly of these augmented teams.

A final design example of augmented teams considers interactions between users and computational agents. Based on multi-agent systems, scholars have provided hybrid solutions that enable users and agents to facilitate the team-assembly process. An exemplary study by Durfee et al. [53] presents a system in which agents mediate between a staffer user who requests a team of experts and the experts who use the system. The system is comprised of four computational agents who mediate the interactions between the staffer and the experts: a matchmaking agent (who consults potential experts in the system's databases), an expert agent (who mediates between the expert users and the system), scheduling agent (who finds the experts most likely to be available for the requested team), and a collaboration agent (who mediates interactions between the staffer and the other computational agents).

Overall, increasing users' participation is likely to provide higher levels of satisfaction with the team-formation process and increase the chances of success of those teams [31]. Despite the fact that users can participate, their agency is limited since their teammate options are dictated by those presented by the system. Therefore, their agency is lower compared to self-assembled teams. Moreover, the curation of recommendations can raise concerns about systems' fairness and transparency [21]. Augmented teams depend mostly on the systems' features and team formation criteria established by the developers, which ultimately defines the interactions that users are allowed.

Pros: Systems augment users' choices by managing information about users' attributes, relationships, and availability. Team assembly criteria can be designed by the systems' developers beforehand. Heterogeneous teams are likely to be assembled. Users can participate in the team-assembly process.

Cons: Teammate recommendations might lack transparency and fairness. The final team composition is only known at the end. Some users may end up without groups.

4 EXAMINING THIS TAXONOMY THROUGH A SCOPING REVIEW

To position this taxonomy within the current computer science literature, we mapped relevant articles into their respective quadrants. This decision was made to account for the increasing quantity and evolution of these systems over time, as well as to identify potential paths for future research. We followed the review methodology done by Harris et al. [82], which performed a scoping review methodology [14] and used the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines to report methods and results [145]. Scoping reviews are used to map literature in a specific field or area of research and to identify gaps in the research that may lie [14, p. 2].

4.1 Eligibility Criteria: Inclusion and Exclusion of Articles

Inclusion. This review includes articles that refer to team assembly. Articles were eligible for inclusion if they: (i) described, analyzed, or developed technologies, systems, or algorithms involved in searching for, selecting and incorporating members into a team; (ii) its research questions or hypotheses considered the processes or consequences of adding, modifying, or removing team members; (iii) there was at least one human user involved; and (iv) were published between January 1990 and March 2020. If the article has multiple publications, we selected the most recent or complete version. Similarly, if it has both a conference and journal version, we selected the journal version.

Exclusion. We excluded articles that (i) did not study any aspects of team assembly; (ii) developed or analyzed technologies to support teams already assembled; (iii) analyzed formation as processes that take place after the team is assembled, such as group identity, transactive memory, or shared mental models; (iv) consisted in assembling robot teams or machine teams; (v) consisted of multi-agent systems; (vi) analyzed teams with only two members; (vii) were meta-analyses or literature reviews; and (viii) were presented in a language other than English.

4.2 Search Strategy and Data Sources

We conducted the first step, "Identification." Unlike Harris et al. [82], who only reviewed articles in the ACM CSCW proceedings, we expanded the search databases and included articles published on the ACM Digital Library, IEEE Xplore Digital Library, and Springer Link. First, we performed several searches to assess the volume of potentially relevant studies according to the eligibility criteria. We built and identified keywords and search terms from the research topic, our theoretical background, and suggestions by other scholars [195, p. 215]. After several iterations, we used "*(team formation) OR (team assembly) OR (group assembly) OR (group formation)*" as our final search query. After defining the search query, we searched and exported the results from each library. Following [82]'s search strategy, we only included Research Articles (excluding posters, extended abstracts, and shorter contributions) to ensure that our review only included work in advanced research stages. Finally, to make a more comprehensive corpus for analysis, we added the following filters in each library:

- *ACM Digital Library*: Results within "Research articles."
- *IEEE Xplore Digital Library*: Results within "Conferences," "Journals," and "Magazines."
- *Springer Link*: We selected "Chapter," "Conference Paper," and "Article," as Content-Type. Since the first search gave us more than 2,000 articles and the search system only allowed

us to download 1,000 articles, we added as an additional filter, "Computer Science" as the discipline, and "User Interfaces and Human Computer Interaction" as subdiscipline.

As a result of these searches, we found 961 articles from the ACM Digital Library, 595 articles from IEEE Xplore Digital Library, and 625 articles from Springer Link. While we exported the results from IEEE Xplore Digital Library and Springer Link to a CSV file, the results from the ACM Digital Library were exported to an EndNote file. We merged the three files into a single CSV file resulting in 2,181 articles. We then removed one duplicated article using the articles' DOIs. Using the articles' titles, we identified 29 articles with the same authors duplicated. Some of these articles were published in two online sources. Other articles had a conference and journal version, which we kept the latter. This left 2,150 articles for screening.

We tabulated articles in a Microsoft Excel spreadsheet, capturing metadata such as title, publication year, authors, DOI, abstract, and keywords. Once we recorded the metadata, we hid the authorship information to avoid any potential bias during the coding phase.

4.3 Article Selection

One of the authors (henceforth, referred to as the coder) manually screened all retrieved articles' titles and abstracts. The coder proceeded to screen articles for inclusion through a three-stage process. First, the coder reviewed the retrieved articles' titles and keywords (i.e., level-one screening). Articles whose titles or keywords met the Inclusion & Exclusion eligibility criteria were retained. From this stage, the coder selected 264 articles. Then, in the level-two screening, the coder performed a second review that included the articles' titles, keywords, and abstracts. If the coder found that an article met the Inclusion & Exclusion criteria, it was coded as 1, if not, as 0. From this process, the coder selected 163 articles for full-text article review (i.e., "Eligibility" phase).

In the third stage, the authors went through two cycles of revision. First, the coder read each article in its entirety. Based on a full-text analysis, the coder again classified each article as either 1, included, if it met the inclusion criteria, or 0, if it did not. Ultimately, the coder selected 126 articles. The coder then presented the selected articles to the other authors, who reviewed the coder's classification in a second cycle together. The authors agreed to analyze the 126 articles, and the coder continued with the data extraction and synthesis stage.

4.4 Data Extraction and Synthesis

The coder extracted data from all included articles using a pre-designed electronic form. The coder extracted data pertaining to (i) the computational method used by the system to assemble teams, (ii) systems' input, (iii) team-assembly criteria, (iv) whether the article presents a model or tool [166], (v) the dataset used, and (vi) context of the study. In order to classify each article according to this taxonomy, the coder answered the following questions: (vii) Who participates in the team-formation process?, (viii) Who generates the teams?, (ix) Can users decide on their team membership?, and (x) Can members express their teammate preferences in the system? The coder used the answers to these questions to classify each article according to its respective (xi) taxonomy's quadrant (optimized teams, staffed teams, self-assembled teams, or augmented teams). During this data extraction process, the coder took open notes and memos to synthesize the article's key findings. The coder managed and analyzed the data using a Microsoft Excel spreadsheet, which is available in the Supplementary Materials.

After the coder completed the full-data extraction, the authors met again and discussed the coder's main results. To ensure that the coder's classification was reliable and exhaustive, the authors discussed and reviewed each article's classification until they reached an agreement. Discrepancies were resolved by discussion, and the authors reached a consensus on the final classification of papers.

5 RESULTS

The coder identified 2,150 unique articles that were screened for inclusion, from which 163 full-text articles were retrieved for further assessment. From these articles, 126 were included in the final review (Figure 2). These articles addressed the architectures, mechanisms, processes, and users' behaviors on systems that supported team assembly. The most common reason articles were excluded in the eligibility stage was that they did not focus on team-assembly strategies. Thirty-seven articles passed through the screening stage but were not included. Many of the excluded articles did not use a socio-technical system, were not available to download, had another version that was already included, or were not in English.

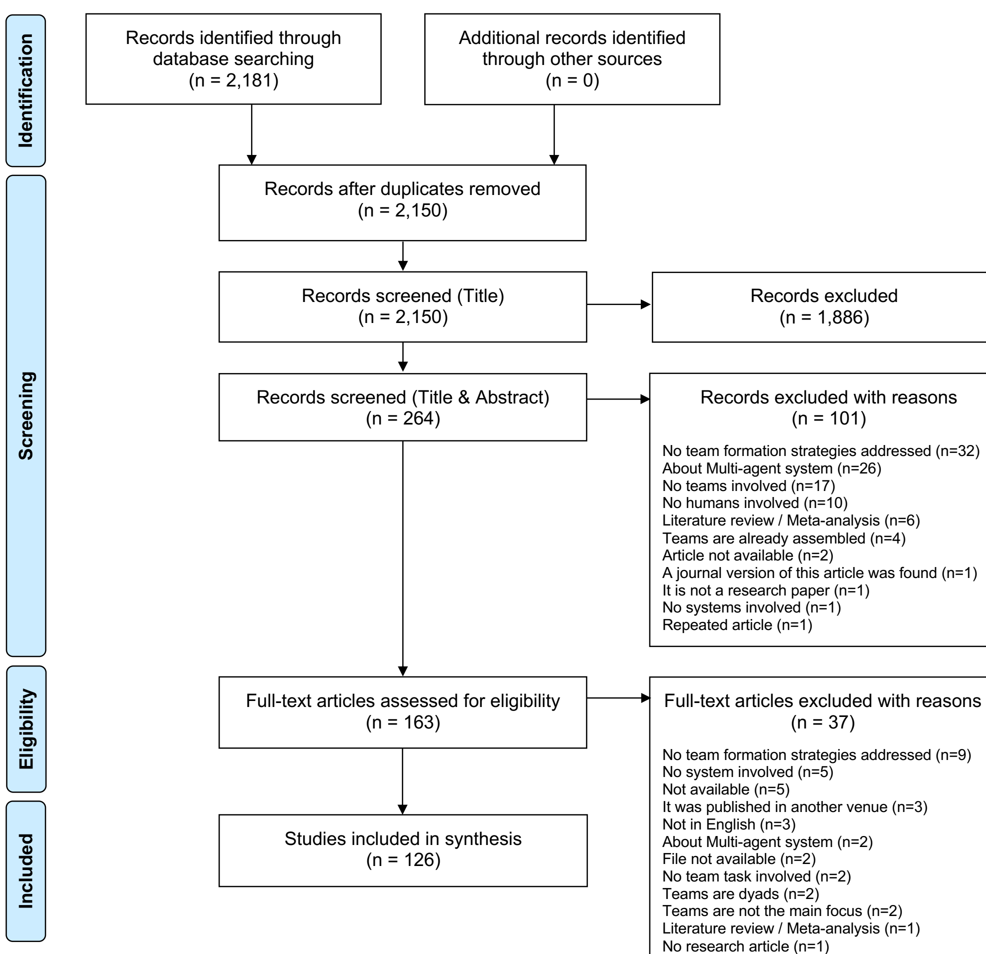

Fig. 2. PRISMA Flow Diagram for this study. It presents the details of the article selection process.

5.1 Description of the Included Articles

Table 1 provides a description of the included articles. Most of the articles were published in the IEEE Xplore Digital Library (57.94%), followed by the ACM Digital Library (30.95%), and finally, the SpringerLink (11.11%). The majority of the articles were published from 2015 onwards (53.17%), one-third were published between 2010 and 2015 (34.92%), and only 3 articles were published before 2005 (2.38%). We found that 41.26% of the articles were written about student teams, 29.46% on expert teams, and 11.90% on teams in the industry.

From this corpus, 63.49% of the articles presented a model, in which only the system's method is implemented and evaluated with existing datasets, and 36.51% of the articles presented a tool, in which the entire system is implemented, designed, and evaluated by real users. Regarding the databases used, the majority of the articles tested their systems using their own databases (65.87%), including synthetic databases or using data from students. The second most common database was the DBLP database (12.70%), which provides computer science bibliography metadata. We also found articles using databases from crowdsourcing platforms, such as GitHub, Upwork, and Wikipedia. Finally, eight studies analyzed videogames databases (e.g., Battlefield4, DOTA, FIFA 2018).

The methods proposed in these articles were varied, showing diverse approaches to assist team assembly: from genetic algorithms, clustering algorithms, dynamic programming, fuzzy algorithms, greedy algorithms, and stochastic algorithms. No one of these techniques represented more than 5% of the corpus. More details of each article are available in the Supplementary Materials.

	Augmented teams	Optimized teams	Self-assembled	Staffed teams	**Total**
Year period (5 years)					
1990	-	-	1	-	1
1995	-	-	1	-	1
2000	-	-	-	1	1
2005	2	4	1	3	10
2010	5	23	3	13	44
2015	15	33	8	11	67
2020	-	2	-	-	2
System type					
Model	14	49	8	9	80
Tool	8	13	6	19	46
Source					
ACM	8	17	5	9	39
IEEE	11	41	7	14	73
SpringerLink	3	4	2	5	14
Context of the study					
Community	-	-	-	1	1
Crowdsourcing	5	3	2	1	11
Expert teams	2	25	3	7	37
Health	-	2	-	-	2
Industry	2	8	1	4	15
Learning	12	22	3	15	52
Virtual games	1	2	5	-	8

Table 1. Characteristics of the included articles

5.2 Classification based on this taxonomy

To characterize the articles included in our scoping literature review, we classified them according to one of this taxonomy's four quadrants. Each article was classified in only one quadrant. We found that the distribution of systems was not homogeneous among the quadrants (Table 2).

Most of the included articles focused on "optimized teams," 62 articles in total (49.21%). Overall, these articles proposed different methods and algorithms to resolve the team-formation problem, subject to communication and personnel costs. The goal of these articles was to find fast and efficient methods to assemble one team or to group individuals into several teams. In the majority of these studies, authors implemented their method and compared their speed and accuracy with other algorithms, and then evaluated them using databases. We found 28 articles that enabled "staffed teams" systems (22.22%), which developed tools for instructors and managers. Overall, these papers present different systems that support users to assemble heterogeneous teams or teams with the most suitable experts. These articles provide tools to simulate and explore different team combinations. The next type of team was "augmented teams" (17.46%), with 22 articles. Most of these articles were published after 2015 and developed recommender systems. Users' social networks and team preferences feed systems' recommendations. Finally, 14 articles of this corpus enabled "self-assembled" teams (11.11%), which were mostly related to multiplayer games. These studies aimed to understand how users chose teammates and analyzed which factors were most likely to explain their choices.

From the classification process, it is clear that in most existing systems' designs resulted in limited user's agency (84 articles). In only one-third of the articles, the systems delegated team assembly decisions to their users, enabling them to decide who would be part of the team (42 articles). Moreover, in 90 articles, the systems allowed only the participation of a single user. And in 36 articles, systems enabled the participation of multiple users in the team-formation process. Since this classification was unbalanced, we checked other conceptual frameworks from prior studies to see if they had balanced or unbalanced article classifications. We found that López and Guerrero [128] used Johansen's taxonomy to classify CSCW articles related to awareness. In this study, most articles were concentrated in the distributed (rather than co-located) dimensions, showing that they also had an unbalanced distribution.

	Included papers	**Most frequent keywords**
Optimized teams (n=62)	[3–5, 10, 12, 16, 17, 26, 32, 34, 35, 37, 59–61, 73, 81, 84, 87, 94, 97, 100–102, 106, 117, 118, 123, 125, 127, 131, 133, 141, 144, 148, 149, 152, 154, 156, 157, 167, 169, 176, 183, 185, 186, 188, 189, 194, 210, 213, 218–222, 227, 229, 231, 232, 234]	*Problem, Social, Algorithm, Task, Experts, Cost, Students*
Staffed teams (n=28)	[9, 11, 13, 23, 24, 38, 43, 45, 47, 57, 85, 92, 95, 107, 113, 114, 116, 124, 132, 138, 159, 164, 173, 184, 214, 217, 224, 225]	*Students, Collaborative Learning, Criteria, Model, Experts, Data*
Self-assembled teams (n=14)	[7, 8, 18, 55, 62, 65, 70, 89, 91, 104, 165, 205, 223, 226]	*Social, Online, Games, Networks, Choose, Communities*
Augmented teams (n=22)	[36, 39, 48, 52, 63, 72, 99, 126, 129, 130, 134, 139, 142, 143, 160, 177, 178, 191, 193, 200, 208, 209, 230]	*Workers, Social, Algorithm, Preferences, Network, Crowd*

Table 2. Classification results from the scoping literature review

6 DISCUSSION

In this paper, we established the need for CSCW scholarship to extend existing theories to account for the increasing use of systems to assemble teams. We provide a taxonomy to understand the role of socio-technical systems and users during team assembly. Based on CSCW and team research literature, we propose users' agency and participation as the two dimensions of this taxonomy. These two dimensions manifest as four types of teams enabled by systems: optimized, staffed, self-assembled, and augmented teams. After developing this taxonomy and situating it within the current literature, we now elaborate on the implications of this conceptual framework.

First, our taxonomy extends theoretical work on socio-technical systems to account for team-assembly processes. Based on our review of prior literature on team assembly, we found that assembling teams using socio-technical systems has not been systematically explored, nor analyzed vis-á-vis systems' affordances, algorithms, and designs that influence the final team compositions. After exploring CSCW conceptual frameworks, we observed how systems that organize people together into teams have been barely addressed or discussed. Just recently, Harris et al. [82] examined group formation in CSCW proceedings and found that users' agency, the scale of socio-technical systems, and the several collectives that individuals can forge are fundamental dimensions that system developers and designers should consider. However, their study only covered contributions published in the ACM CSCW proceedings and excluded relevant findings from other computer sciences subdisciplines, such as human-computer interaction, recommender systems, or learning sciences. Moreover, the need to uncover the relationship between users and their contextual factors leads to a greater understanding of how team-assembly processes unfold [15]. For example, Harris et al. [82] did not consider how users participate in the team-formation processes. This has consequences for users' teammate expectations and team composition. Integrating research in computer and social sciences is fundamental to understanding team assembly facilitated by systems through a holistic perspective. Ultimately, the systems' architecture and features must integrate users' agency and participation, and their larger social context, in order to enable the assembly of more effective teams. While we built this taxonomy from multiple pieces of CSCW, HCI, and management science literature, this work is only an early step along a larger path to contribute to our theoretical knowledge of teams assembled using socio-technical systems.

Second, our taxonomy disentangles the influence of socio-technical systems on team assembly. We found that systems' architectures and components have a deep impact on users' choices and, ultimately, define the teams to which they will belong. While the studies reviewed in our theoretical background have shown that forming teams depends on their context, task, and members, this taxonomy shows that forming teams using socio-technical systems depends heavily on the architectures, algorithms, interfaces, information, and affordances that systems provide. Thus, the degree of users' agency and participation in the team-assembly stage have consequences for users' interactions, recommendations, options, expectations, and decisions. Only when system designers consider these two dimensions based on the teams' context, goals, norms, and tasks, they can leverage users' choices for teammates through the use of relevant information and opportune teammate recommendations. Alternatively, when these dimensions are not considered, they can exacerbate users' biases and dissatisfaction, resulting in less efficient teams. In light of these socio-technical repercussions, this taxonomy encourages system designers to reflect on if the systems' affordances must enable users' agency based on the creation of homogeneous or heterogeneous groups. Additionally, system designers should examine how many users will participate in the team-assembly process, as this will affect users' motivation and engagement with the system, and ultimately, with the teams they create. Ultimately, the configuration of users' agency and participation in the system—such as allowing users to reach out to one another, or by displaying how many contacts they have in common—has significant repercussions in users' teammate decisions and in the teams' final composition. By using this taxonomy, we want to make users' agency and participation an important part of systems' architectures that facilitate team-assembly processes.

6.1 Theoretical implications

After introducing each one of the taxonomy's quadrants and the systems they contain, we provide implications that leverage our understanding of the role of users and systems in team assembly.

First, research about self-assembled teams shows that when users are allowed to exercise their agency, they are likely to follow similar rules as to when they are forming teams offline. Similarity and familiarity were the most likely factors to explain users' teammate choices [7, 55, 62]. Consequently, this inclination for similar and familiar people has led many systems to consider users' traits and social networks as part of their solution in their algorithms and features. In other words, many systems have been designed to exploit users' characteristics to enable more likely teammate connections. By making visible users' previous collaborators, friends, common relationships—and highlighting similar characteristics—systems provide more natural ways for users to find and choose partners [70, 103]. Certainly, there is a tradeoff. Allowing users to drive team assembly efforts increases the likelihood of homogenous teams. Systems can reduce users' inclination for similar people by promoting a *conscious* reflection on how diversity can help them achieve teams' goals, and how to choose the teammates who are best suited for those tasks [69]. Other design alternatives to prevent homogenous teams include presenting the most diverse teammate recommendation at the top of the search results [74], or consider embedding users' attributes at the cognitive level (e.g., teammates' complementary skills, backgrounds, or personalities) in assembly algorithms [111, 187].

Second, multiple solutions were found in the staffed-teams quadrant, where the user's agency is allowed, although the user's participation is diminished. The focus of these systems was to provide features to a single user, who could assemble teams multiple times, adjust the team's structures, or explore several team combinations [9, 92, 132]. Most of these articles were motivated to create expert teams and heterogeneous student groups. The research reviewed revealed the importance of providing algorithms that could quickly find the best solutions possible. In order to enable the user to change the team-formation criteria, these systems provided multiple control parameters and visualization components to iterate the team-assembly results [24, 107, 124]. Although assembling staffed teams can avoid team members' bias for similarity and familiarity, this team assembly configuration can present dissatisfaction and conflicts between the individual who creates the teams and the members that are assigned to them [95].

Finally, the increasing development of systems for augmented teams in the last decade—compared to the stable development of systems for staffed teams and optimized teams—reflects the high interest in developing solutions that help users choose the most suitable teammates. The current computational infrastructure, the growing use of artificial intelligence in socio-technical systems, and the relevance of user-centered designs foreshadow the creation of more organic teams that could achieve higher levels of heterogeneity. Not only do technologies automate tasks, support collaboration, or increase connectivity, but they can also augment user's decisions to address organizational problems [96]. We found multiple studies showing how systems can form efficient teams when users' feedback, choices, and teammate preferences take into account [72, 143, 191]. Incorporating systems that enable augmented teams will be relevant for crowdsourcing markets, gig economies, and organizations that need to assemble teams from large groups in real-time. This provides new research opportunities for the CSCW field to explore (i) whether systems can help users reach more suitable teammate candidates, (ii) find potential teammates who complement their skills (rather than being just similar to them), and (iii) reduce the cultural and language barriers between users who can work together as an outstanding team. As the research included in this category show, socio-technical systems can help people find the most appropriate team members based on their attributes and relationships by curating teammate options and using exponential computational power, such as Hackman and Katz envisioned [79].

6.2 Design implications

This paper provides multiple guidelines for future research and design implications. Several system's qualities can be examined from this taxonomy's four quadrants. We start from users' self-presentation (e.g., How do users present themselves on systems?) and systems' user representation (e.g., How do systems represent users?), which affect users' likelihood of being chosen by other users as teammates or being recommended by the system [202]. Systems' values and norms will affect teams assembled algorithmically. For example, systems' fairness determines whether users are assigned to particular teams without discrimination [151]. Also, the displayed transparency and accountability of these systems affect their trustworthiness and how users perceive systems' recommendations or the teams that they assemble [20]. Our taxonomy also reflects on the inclusion of minorities and discriminated groups, overcomes the obstacles for isolated users and newcomers face to be accepted by other users, and addresses the lack of diversity that these assembled groups may experience [2]. The intrinsic users' desire to work with similar and familiar people can lead to these issues, which are ultimately built upon users' prejudices. By adjusting users' agency and participation, these issues can be mitigated. However, systems' algorithms can exacerbate segregation patterns among users. For this reason, algorithms' criteria, methods, and results should be transparent so they can be held accountable [50]. Based on these implications, in Table 3 we propose design considerations and future research questions that envision team assembly on socio-technical systems.

Our taxonomy's two dimensions—users' agency and participation—provide practitioners, designers, developers, and scholars with a taxonomy that can be used to disentangle the decisions that bring teams to life, and their consequences on team composition, which are relevant for teams' performance, cohesion, and viability.

6.3 Limitations

Two main limitations in this paper must be considered. First, the operationalization of this taxonomy with only two dimensions can be considered a substantial limitation. Including other characteristics that have been studied in previous CSCW studies—such as affordances, awareness, scale, time, and location—are also essential for team-assembly processes enabled by socio-technical systems. Nevertheless, we believe these two dimensions shed the most light on the systems' influence on the decision-making processes to support team assembly, while previous CSCW taxonomies have already covered other dimensions.

Second, a scoping literature review conducted by only one coder affects the reliability of this classification process. Bias, misfits, and errors are less likely to occur by counting on multiple coders. We acknowledge that having two or more coders could have increased the reliability of the final analysis. Unfortunately, finding a second coder was not possible, given the circumstances during this paper's development. We addressed this issue in order to increase the classification's objectivity:

- To ensure search replicability, a member of our research group (who was not a co-author) peer-reviewed the search strategy using another computer and followed the Peer Review of Electronic Search Strategies (PRESS) checklist [135].
- All the authors of this paper reviewed the final list of articles to include and arrived at a consensus before proceeding with the full-data extraction.
- With the help of the coder's notes, the discussion held by all the authors enabled an insightful reflection to determine the articles' final classifications.
- We have made the results of our scoping review public to the research community in the Supplementary Materials, hoping that this analysis can be revisited, extended, and enhanced.

	Design considerations	Example of future research questions
Optimized teams	Users may not know what algorithms and criteria were used, and why they are assigned into specific teams.	How can systems provide more transparency about their decision-making process? How can users be aware and conscious of the information used by systems? How can systems provide higher levels of fairness?
Staffed teams	Users may not know who the team assembler is (e.g., manager, instructor, leader), and what criteria were used by the team assembler.	How can systems control users' information overload? How can systems address users' bias at the moment of searching for and selecting members? How can team members perceive fairness in this process?
Self-assembled teams	Users may choose candidates who are similar or familiar to them. Systems may highlight specific users' characteristics and information. Users' self-presentation may influence their likelihood of being chosen as a teammate.	How can users be encouraged to work with others who are not similar and familiar to them? How can diverse teams emerge in this process? How can systems help in avoiding the creation of segregated teams?
Augmented teams	Defining how system affordances will determine team assembly mechanisms.	How can systems learn from users' characteristics and relationships to assemble teams? What kind of feedback is required to update systems' team assembly mechanisms? How can users and systems be aware of their biases?

Table 3. From this taxonomy, we highlight four kinds of teams assembled in computer-mediated environments and offer takeaways for system developers as well as questions for future research.

As part of future work, charting and categorizing each one of the included articles with more than one coder would help identify themes and summarize the extensive literature on team assembly. We conducted this mapping exercise to contextualize this taxonomy based on the prior literature. Hence the lack of inter-coder reliability of this mapping exercise should not necessarily undermine the taxonomy presented in this paper.

7 CONCLUSION

As more technologies are being used to assemble teams, we need a better theoretical and empirical understanding of how socio-technical systems shape team-assembly processes, which will ultimately have consequences on teams' composition and users' experiences. Drawing upon a synthesis of multidisciplinary literature in team assembly, this paper offers a conceptual framework that sheds light on the social dimensions and challenges people face when using socio-technical systems to assemble teams. Building on prior research of the team-assembly processes and CSCW conceptual frameworks, we built a taxonomy based on two dimensions—users' agency and participation—that manifest as four types of teams enabled by socio-technical systems: self-assembled teams, optimized teams, staffed teams, and augmented teams. By conducting a systematic literature review, we mapped the current literature on team-assembly systems onto this four-quadrant taxonomy. While we found an overwhelming number of systems that assemble teams without considering users' participation and agency, we discovered that in articles published in the last five years, there has been increasing research interest in combining the use of algorithms with users' participation to form augmented teams. Our taxonomy's dimensions enable system developers to reflect on the design components of socio-technical systems. We hope that this taxonomy provides guidelines for the design and use of systems that support team assembly, which have the potential to facilitate the formation of more effective, diverse, and viable teams.

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