19. Artificial intelligence techniques for supporting face-to-face and online collaborative learning

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INTRODUCTION

Collaborative learning is a term that refers to a variety of educational phenomena involving joint intellectual effort by peers interacting with each other and with teachers, for the purpose of learning about a particular topic, or learning to collaborate effectively (Dillenbourg, 1999). Collaborative learning provides particular opportunities for data-intensive, educational innovations (Dönmez et al., 2005; Chi & Wylie, 2014). This is in part because learners need to externalize some of their commonly hidden mental processes in the form of dialogue, drawings, and other representations (Stahl, 2006). Many types of problems may occur during collaborative learning, such as students failing to reach common ground, students engaging in superficial argumentation instead of deep argumentation in which they build on each other's reasoning, or the occurrence of free-riding so that the input from group members is unequal (Kreijns et al., 2003). Digital traces of these automatically captured externalizations can be analyzed using various Artificial Intelligence (AI) and collaboration analytics techniques for the purpose of making collaborative interactions more visible, finding recurrent patterns of behavior, and deepening our understanding of collaborative learning in various contexts and domains. This can further accelerate computer-supported collaborative learning (CSCL) research and the development of more effective tools that support collaborative learning.

Using analytics and AI techniques to support collaborative learning has some history in the field of artificial intelligence in education (AIED). For example, data-intensive techniques have been used to characterize effective collaboration (e.g. Perera et al., 2008), argumentation (e.g. Rosé et al., 2008), and team activity (e.g. Kay et al., 2006) in online collaborative situations. Modeling group interactions has also enabled the creation of mechanisms to adapt the support provided to groups (Kumar et al., 2007), form groups automatically (Amarasinghe et al., 2017), adjust collaboration scripts according to particular group needs (Rummel et al., 2008), and mirror group processes to students (Jermann & Dillenbourg, 2008; Jermann et al., 2005). Moreover, educational data-mining approaches have also been applied to identify patterns of interaction between low- and high-achieving groups in face-to-face situations (Martinez-Maldonado et al., 2013).

Within AIED and other data-intensive educational technology communities, such as ITS (Intelligent Tutoring Systems) and EDM (Educational Data Mining), there has also been a sustained interest in providing "intelligent support to learning in groups" (ISLG). Researchers across these communities organized thematic series of workshops (e.g. ISLG workshop series organized in ITS and AIED conferences between 2012 and 2018, Kim & Kumar, 2012) and special issues in high-impact journals (Isotani, 2011; Kumar & Kim, 2014). The rapidly growing field of Learning Analytics is also focusing on providing techniques for supporting collaborative learning under the new umbrella term Collaboration Analytics (Martinez-Maldonado et al., 2019).

This chapter brings together literature from these communities to describe what we mean by supporting collaborative learning in the second section. The third section discusses techniques currently available for supporting both face-to-face and online collaborative learning situations to: (1) form effective groups, (2) provide direct feedback to students, (3) facilitate adaptive scripting, enhance group (4) and teacher (5) awareness, and (6) perform summative assessments. In this section, we focus on techniques that have been used to *analyze*, rather than *collect*, data from collaborative scenarios. As such, this paper does not address the variety of techniques, challenges, and issues associated with using sensors to automatically collect data of different modalities (e.g. actions, speech, texts, affects) and from different contexts (synchronous vs. asynchronous collaboration.) The fourth section presents potential future trends for research and development in this area. The chapter concludes with some final remarks in the last section.

SUPPORTING COLLABORATIVE LEARNING

Collaborative learning situations involve the interaction between students, teachers, tasks students work on, and (digital and material) tools to support the collaborative processes (Stahl et al., 2006). The success of collaborative learning depends on the quality of this interaction. Therefore, studying collaborative learning does not only include the collaboration as it happens in the classroom or online, but also the preparation for this process and the reflection on the process afterwards. Kaendler et al. (2015) refer to these three phases as the pre-active phase, the inter-active phase, and the post-active phase. Although Kaendler et al.'s framework was originally proposed to describe teachers' competencies for implementing collaborative learning, we use it here to describe the various types of support students may benefit from.

Artificial Intelligence (AI) and analytics techniques may play a supporting role in all three of the phases described above and thereby contribute to the success of collaborative learning in various ways. The ways in which AI and analytics are commonly employed depend on the specific *type of support* for which they are intended. To explain this further, we present Figure 19.1 below. In this figure, the central unit is a group of collaborating students, in this case a triad. From the collaborative process, the captured activity data constitute the input for further analyses (e.g. students' utterances, non-verbal behaviors, and physiological measures). As can be seen by the arrows in Figure 19.1, there are several pathways for offering support, and the specific pathway determines what type of data can be used and what analyses are performed on those data. We will briefly mention these pathways here, and delve deeper into each of them in the next section.

Arrow 1 points at the importance of selecting a strategy for *grouping* students for the collaborative activity, which is often already done as preparation in the pre-active phase (Figure 19.1). Based on student characteristics or data obtained during previous collaborative sessions, AI and analytics techniques can help determine optimal group formations for a specific activity.

Arrows 2–5 point at various types of support during the inter-active phase (Figure 19.1). *Direct feedback* to students (arrow 2) for formative purposes means that the data obtained during the collaborative activity is used immediately and directly to offer support to the students, for example by providing a hint or a prompt. The AI and analytics techniques in this case

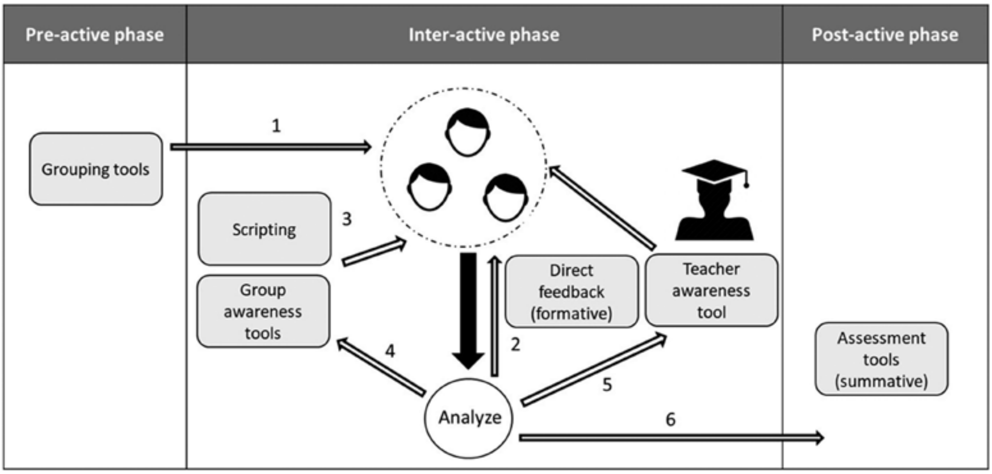

Figure 19.1 Overview of types of support in pre-active, inter-active, and post-active phases of collaborative learning

must be granular enough to detect specific occurrences of the event for which the feedback is designed. Arrow 3 represents support in the form of *scripting*, which means that part of the collaboration process is explicitly and dynamically structured so that students engage in the type of activities or processes that may not occur naturally, for example reflecting on the group's progress (Fischer et al., 2013). AI and analytics techniques in this case may help to detect which activities need scripting in the first place, and when scripting is implemented, to detect when each phase of the script needs to be activated.

Arrows 4 and 5 both point to *awareness tools*, the difference being that the awareness tool is either designed for students (arrow 4) or for teachers (arrow 5) (Figure 19.1). In general, these tools are, as their name suggests, designed to enhance the awareness that students or teachers have of the situation. Underlying the idea of student awareness tools is that many problems that may occur during collaboration are caused by a lack of awareness of each other's knowledge and activities within the group (Janssen & Bodemer, 2013). When information about the group's activities is visualized and provided to all group members, understanding and interaction can be enhanced. The idea of providing teachers with awareness tools as well stems from the generally acknowledged importance of teacher guidance during collaboration that may occur in addition to the support that students provide to each other or that technology can provide to students (Van Leeuwen & Janssen, 2019). Rummel (2018) described teacher awareness tools as technological tools that indirectly support collaborating students. By providing an overview of the situation to the teacher, s/he can better attend to the needs of the collaborating students. The role of AI and analytics techniques in the case of awareness tools lies in extracting relevant and actionable information that can be displayed to students and teachers.

Lastly, Arrow 6 points to the use of the data gathered during students' collaboration for purposes of summative assessment (Figure 19.1). In addition to grading the product that students have been working on (such as a collaboratively written text), the interaction process itself may also be assessed, and AI and analytics techniques may aid in this process.

An important issue to remark on is that collaborative learning can take place in various contexts (face-to-face, online, or both) and in various modes (synchronously and asynchronously). For example, computers can connect learners who are separated in time or space, so that all communication occurs online. In this case, communication could be synchronous (i.e. occur in "real time" as in a chat), or asynchronous (i.e. when learners are not necessarily online at the same time, for example in a discussion forum). Another example is when multiple learners share one computer screen and solve tasks together while communicating face-to-face. Each of these combinations has its own potentials and restrictions for the collaborative process (Van Diggelen & Overdijk, 2007), and each combination determines whether certain types of analysis are applicable and whether particular types of data are available. The context also determines whether certain types of support can be delivered or whether the output of the analyses needs to be presented in a certain way. For example, in a face-to-face synchronous setting a teacher awareness tool may take the form of a wearable device and to-the-point information may be preferable, whereas teachers in an asynchronous online context may benefit more from a dashboard with elaborate information.

AI TECHNIQUES TO SUPPORT COLLABORATIVE LEARNING

Group Formation

A key factor influencing group processes and performance is composition. Dillenbourg (1999) described group composition in terms of different *symmetries*: symmetry of action, symmetry of knowledge, and symmetry of status. The first refers to the extent to which members of the group are allowed the same range of actions. For example, groups with well-defined roles exhibit an asymmetrical action structure: leaders can give orders and redistribute workload but other members cannot. Symmetry of knowledge refers to the extent to which team members possess the same knowledge, skills, or expertise. Finally, symmetry of status is the extent to which individuals have similar status in the group.

Much of the early work on collaborative learning explored the effect of different symmetrical structures by varying group heterogeneity. For example, research in the Piagetian paradigm investigated the effects of pairing individuals together at similar developmental levels, but with different viewpoints, in efforts to incite cognitive conflict (Hmelo-Silver et al., 2013). Relatedly, researchers in the social-cultural tradition of Vygotsky often investigated learning that took place between pairs or groups asymmetrical in status, action, and knowledge, for example, by pairing children with older children or adults (Vygotsky, 1978).

Following this work, researchers have continued to argue that group composition can benefit collaborative learning by fostering certain collaborative interactions or hinder it through disproportional participation, demotivation and conflict (Cruz & Isotani, 2014). Consequently, the process of forming groups, and the effects of different formations, have been studied extensively.

In terms of AI, the problem of forming effective groups involves three components and can be generally construed as a constraint satisfaction problem (Amarasinghe et al., 2017) or multi-objective optimization problems (Moreno et al., 2012). First, a set of *characteristics* must be chosen that describe the individuals to be grouped. Researchers have considered a variety of such characteristics including cultural background, interests, knowledge, skills, roles, and gender. Second, a set of *constraints* is chosen to limit the possible number of group formations. Example constraints include the number of groups an individual can be in, homo/heterogeneity of knowledge, background, and gender. Finally, a particular *method* is chosen to form the groups such that they satisfy as many constraints as possible. Of course, one method for forming groups is a manual approach, as is often employed by educators in learning settings. However, given the potential for high numbers of characteristics and constraints, and thus high numbers of possible combinations, manual formation can be difficult and time consuming (Amarasinghe et al., 2017). In response, researchers have developed tools and algorithms for assisting in group formation.

In their systematic literature review of group formation algorithms in collaborative learning contexts, Cruz and Isotani (2014) categorized the kinds of methods that have been used to assist in group formation. They found that the largest portion of methods were probabilistic algorithms—for example, genetic algorithms (Moreno et al., 2012) and swarm intelligence algorithms (Lin et al., 2010), followed by multi-agent formation algorithms (Soh et al., 2008), which model student and teacher decisions. The remaining methods were general data mining approaches, such as k-means clustering (Filho et al., 2010), and finally a set of miscellaneous techniques such as semantic web ontologies (Isotani et al., 2013). The authors suggest that genetic algorithms may be preferable due to their ability to handle large numbers of variables and rapidly generate (semi) optimal solutions automatically.

More recently, researchers have continued to explore data mining approaches to group formation. For example, Lobo et al. (2016) used techniques that included decision trees, naive Bayes, support vector machines, and logistic regression to classify students into groups based on collaborative indicators, social interactions (as measured by social network analysis), peer ratings, and measures of affective states. The authors then suggested effective groupings of learners based on these classifications. Wu et al. (2021) used NLP to create heterogenous and homogenous groupings of learners based on their prior knowledge. By associating a list of "mastered" and "unmastered" topics with each student, they used pre-trained word embeddings to automatically create different groups based on the similarity/dissimilarity of their topic representations in the embedding space.

While the work on AI-based group formation has been insightful, to the present authors' knowledge, systematic comparisons of the different approaches have not been conducted. Thus, it remains an open question as to which algorithms are more effective in which collaborative learning situations.

Direct Formative Feedback to Learners

One of the ultimate aims of data-intensive educational solutions is to provide meaningful feedback to learners on how well they are doing to provoke reflection and improvement (Gašević et al., 2015). This has often been referred to as "*closing the analysis loop*" in which the outputs of the analysis are not only useful to conduct CSCL research, but can be transformed into visual or textual representations that can be understood by learners. This live feedback to groups of learners can affect their behaviors in many ways. However, while the idea of providing direct, formative feedback to students in a live setting has been conceptually proposed, its implementation in authentic settings is uncommon.

There are some notable examples of systems that automatically provide recommendations to groups of learners in synchronous and asynchronous online settings. For example, the AMOEBA system analyzes the collaborative programming work of computer science students and makes recommendations based on the similarity between some students for them to collaborate more closely (Berland et al., 2015). These recommendations contributed to maximizing meaningful student–student interaction and led to improved learning and better programming outputs. Research on intelligent tutoring systems (ITSs) has also focused on providing direct support to learners. Tchounikine et al. (2010) provided a review of ITSs that support collaborative learning tasks. They emphasized different ways in which students can be supported, for example, by providing adaptive intelligent hints (e.g.., detecting problems in the task product or the collaboration, and providing written feedback; Baghaei et al., 2007); or adaptive technological means (such as enabling dynamic communication prompts in the argumentation tool ARGUNAUT; De Groot et al., 2007). The most recent work by Olsen (2017) has also provided foundations for supporting learners while they engage in individual and group tasks while working at an ITS in the context of math learning.

Formative feedback can also be presented to learners in the form of visualizations that invite them to reflect on performance and collaboration, and reach their own conclusions or decide the actions they can take for improvement. These tools have been also known as open learner models like Narcissus (Upton & Kay, 2009). This system displays summaries of activity logs in the context of team software development, in ways that promote reflection on potential issues in team dynamics. The system also allows learners to navigate through their logs from a high-level view to particular instances such as the messages or allocations between two team members. A similar approach has been followed by researchers who have designed more contemporary student-facing dashboards for CSCL (see review by Liu & Nesbit, 2020). Bodily and Verbert (2017) reviewed student-facing dashboard systems, reporting mostly non-collaborative settings. In fact, there is just a growing number of student-facing CSCL dashboard currently available, with some notable exceptions of systems that mostly mirror basic summary statistics from logs captured in forums (May et al., 2011), social networks (Scheffel et al., 2016) and software development systems (Tarmazdi et al., 2015; Upton & Kay, 2009).

Adaptive Scripting

Collaborative learning is typically associated with one or more tasks, such as forming an argument, designing a product, or solving a problem. In educational and professional contexts, tasks are one component of a collaborative *script*. Scripts have been defined broadly as contracts to specify how the collaboration should proceed (Dillenbourg, 2002). More recently, however, scripts have come to be associated with computer-based scenarios that structure collaboration by associating groups with tasks, roles, and resources, and by constraining interactions between individuals (Koller et al., 2006).

Scripts can affect both the overall structure of the collaborative setting (macro-level) and the moment-by-moment collaborative interactions (micro-level). Scripts at the macro-level structure collaboration through task design, group composition, roles, and available resources. At the micro-level, scripts constrain collaborative actions through the mode of communication, by enforcing particular problem-solving steps, or by providing prompts and hints to learners. For example, the PISA 2015 collaborative problem-solving assessment involved scripting at both levels (OECD, 2017). At the macro-level, participants were teamed with automated collaborative agents in a computer-based environment to solve problems in a variety of scenarios. At the micro-level, interactions between the participant and the agent were limited to clicking, dragging, or selecting certain items on the screen. In particular, the participant could only communicate with the agent via a chat window with predefined responses.

Collaborative scripts like those described above were developed with at least two mechanisms for supporting learning in mind (Wise & Schwarz, 2017). First, the script is an external representation of effective collaboration processes. In other words, the script shows learners what good collaboration is. As such, the end goal for the script is to be internalized by the learners so it is no longer needed in the future. Second, research has long focused on the potentially negative effects of collaboration on learning that may arise due to unproductive conflict, unequal participation, and a lack of understanding of how to collaborate effectively. Scripts are meant to mitigate these factors by using constraints such as prompts, modes of interaction, and group composition, to control the setting.

Over time, scripts have evolved from static structures and rules into malleable systems for scaffolding collaboration. In particular, scripts have been designed that are *adaptable*, *adaptive*, or both. Adaptable scripts are those that allow educators or learners to modify the script in some way. For example, researchers have also explored allowing learners and educators to build their own scripts from a pool of components (Prieto et al., 2012).

Adaptive scripts are those that automatically adjust, based on learner actions and interactions. Adaptive collaborative scripting builds on the large body of work on ITSs, which typically use dynamic models to guide automated pedagogical decisions (Graesser et al., 2012). Such systems often rely on *model tracing*, the process by which a model of the problem is compared to the student actions and solutions. If the participant's actions or solutions match those of the model, the automated tutor deems them appropriate; if they do not match or if the participant acts in ways the model associates with struggling, the automated tutor provides prompts, hints, and eventually, solutions. For example, Diziol et al. (2010) implemented an adaptive support system that classified student interactions with the system as they collaborated to solve algebra problems. If interactions were classified as either "hint abuse" or "trial and error"—strategies associated with poor learning outcomes—an adaptive script message was presented to encourage collaboration.

Extending ITSs' features to collaborative situations may involve expanding the kinds of interactions traced by the model. In particular, conversation can be a key component of collaborative interactions. As such, some adaptive collaborative scripts have integrated natural language processing to classify conversational interactions and adapt the script in response. For example, Dowell et al. (2014) proposed integrating the automatic classification of group conversations in online collaborative environments using Coh-metrix (McNamara et al., 2014), a technique that measures features of communication such as cohesion. Similarly, virtual internships, online educational simulations in which students work as teams to solve design problems, use regular expression matching to evaluate collaborative contributions and suggest when groups are ready to change topics in a guided discussion (Saucerman et al., 2017). Research into scripting remains intensive, with a current focus on striking a balance between guiding collaboration and maintaining learner and teacher agency (Wise et al., 2016).

Group Awareness Tools

The central idea of group awareness tools is to make certain aspects of the collaborative process visible to its group members to enhance group members' awareness of these aspects

(Janssen & Bodemer, 2013). Providing group awareness tools is hypothesized to contribute to diminishing these problems by making the process visible, and thereby enabling group members to discuss and regulate the process more adequately (Janssen & Bodemer, 2013).

Many authors have aimed at providing typologies of the type of processes that occur during collaborative learning (and, thus, in what areas potential problems may arise). As group awareness tools can be seen as ways to enhance these processes, their development and empirical investigation can generally be considered in the same typologies. For example, Meier et al. (2007) distinguish between processes concerning: communication, joint information processing, coordination, interpersonal relationships, and motivation. Those processes are thus the aspects of collaboration that are also being analyzed, visualized, and fed back to group members through group awareness tools, making use of a variety of LA and analytics techniques. Some techniques fit better with visualizing certain types of processes, such as using (epistemic) network analysis to focus on communication and interpersonal relationships within a group.

Schnaubert et al. (2020) have recently provided a review for group awareness tools that focus specifically on cognitive aspects of collaboration, meaning tools that provide knowledge-related information. They report that different types of data processing techniques were used, among which aggregating data, categorizing and/or clustering data, and coding and counting data. Interestingly, they also identified studies in which the group awareness tool did not transform the collected data at all. For example, when group members fill in a concept map to display their knowledge over a certain topic, those maps can be provided to the other group members without any changes or transformations. In those cases, all interpretation is left to the user. As Schnaubert et al. (2020) note, in case of tools that use visualizations (such as group awareness tools), one must always consider that "while transformations may be a way of extracting relevant information from complex data or adding relevant information about a domain, they always bear the risk of being incomprehensible (due to complexity or non-transparency) or not acceptable to learners (due to incompatibility with the learners' self-conceptions)". This is also why there is a movement towards human-centered co-design of such tools, in which students are involved in the design and development of the tool to ensure its usability (Sarmiento & Wise, 2022).

A relatively new direction for group awareness tools is reported by, for example, Avry et al. (2020), who developed a tool concerning *emotional* group awareness. As the importance of affective processes during collaboration is increasingly recognized, this is reflected in the development of tools that allow group members more insight into the occurrence of emotions. As Avry et al. (2020) show, the occurrence of emotions indeed relates to specific interaction patterns, and providing emotional group awareness tools indeed influence the type of task-related interactions that occur. The tool described by Avry et al. (2020) relies on group members manually labeling their emotions.

Teacher Awareness Tools

As discussed above, there are a number of similarities between awareness tools aimed at students and those aimed at teachers. Their core goal is the same: to provide information to enhance awareness of the collaborative situation. Teachers generally struggle to monitor student activity in the context of collaborative learning (Kaendler et al., 2016). This is not surprising given that it is a demanding task. Teachers have to pay attention to multiple dimensions (i.e. cognitive versus social aspects of collaboration), and especially in synchronous settings, there are a multitude of activities occurring at the same time. Therefore, the aim of teacher awareness tools is to enhance teachers' overview of the situation (see Chapter 15 by Pozdniakov et al.). Whereas student group awareness tools detail information about one group, teacher awareness tools display information about the whole classroom. This means analyses and visualizations need to be performed not only at a group level, but also at a classroom level, and decisions have to be made about whether and how to aggregate data from individual and group level to classroom level.

Recent reviews (Sergis & Sampson, 2017; Van Leeuwen & Rummel, 2019) show that teacher awareness tools have focused on both cognitive and social aspects of collaboration, using a variety of LA and analytics techniques. For teacher awareness tools to be useful, they need to indicate information that is relevant and actionable. This is a delicate balance; information that is relevant for the collaborative process but hard to interpret for the teacher is not useful, but neither is information that is easy to understand yet can be easily obtained by the teacher through observing students (for example the number of students attending a class). This expresses the same idea as discussed above that involving stakeholders (in this case teachers) in the design process will be beneficial for the usability of the tool. In the sections below, we will discuss two examples of how AI and analytics techniques have been used to extract information from the collaborative process, *and* how this information has been displayed to the teacher.

The first example concerns a teacher awareness tool that visualizes *critical moments*: moments during collaborative learning where the teacher could provide support to enhance learning (Swidan et al., 2019). In a computer-supported, synchronous setting, the teachers received alerts on a dashboard of the following events: idleness; off-topic discourse; technical problems; occurrence of explanation or challenge; confusion; correct solution; and incorrect solution. To analyze these critical moments, several analysis techniques had to be used: textual analysis to detect certain types of discourse between students (such as providing explanations), and comparing student input to canonical solutions (for the correct and incorrect solution alert). Each type of critical moment was given its own color for easy recognition by the teacher. Two aspects are notable about this teacher awareness tool. The first is that the tool not only visualizes when groups do *not* perform expected behavior, but also when they show good progress. Another notable aspect is that the authors of the paper remark that their analyses are based not only on what educational theory describes as important learning events, but also on the boundaries of LA techniques. As the authors put it, they focused on events that are computable. We will reflect on this issue in the next section.

Similar to student group awareness tools, there has been a recent trend in developing and investigating teacher awareness tools that focus on affective measures (e.g. see Chapter 5 by Arroyo et al.). The second example we selected is therefore a teacher awareness tool, Emodash, that displays learners' emotions (Ez-zaouia et al., 2020). In contrast to the previous example, this tool is meant for use *after* learning sessions, so for asynchronous, reflective use by the teacher. The tool is based on facial recognition algorithms (perception-based estimation) in combination with learners' interactions with the learning environment. The resulting visualization was iteratively designed in partnership with teachers and offers several layers of detail: both concerning learners' overall emotions, and the ability to zoom in on emotions occurring during specific learning sessions. This level of detail fits the intended asynchronous use of the tool, when teachers have more time to reflect on the offered visualizations.

Summative Assessment

Finally, there has been interest in providing automated support to the summative assessment of collaboration and teamwork skills (see Chapter 21 by Fang et al.). Two broad goals of the assessment can be identified: (i) assessing communication and collaboration skills; and (ii) assessing the task performance or learning gains. The assessment of the former is critical, given that effectively communicating and working in groups are critical twenty-first-century skills that learners are encouraged to develop for workplace success (Griffin et al., 2012). The assessment of the latter also has an important role in encouraging learners to take responsibility for their participation in the group task and to help them understand the non-competitive nature of a collaborative learning process (Meijer et al., 2020).

Most of the techniques that support the summative assessment of computer-mediated collaborative learning tasks involve some analysis of the content of the conversations between group members. For example, foundational work by Soller (2001) suggested the assessment of collaborative learning conversation skills by mapping conversation skill types (active learning, conversation, and creative conflict) into corresponding sub-skills and actual sentences from learners' conversation. To achieve this, the author provided an interface that allowed learners to scaffold their conversation by explicitly letting them pick short sentence openers. This way, the system could automatically infer the kind of participation of each learner. Currently, with further advancements in text analysis and natural language processing, it is possible to automatically process learners' conversations without forcing them to interact through a constrained interface.

The research agenda led by Carolyn Rosé and her team has been foundational in bringing the advances of computational linguistics to automatically code instances of learners' conversation contributions with various purposes in both synchronous and asynchronous collaborative settings (see Chapter 17 by Rosé et al.). These include the automated classification of text to be mapped to collaborative skill development (e.g. Rosé et al., 2008; Rosé & Ferschke, 2016). Moreover, synchronous conversations have been analyzed to automatically assess participation and collaboration by measuring the semantic cohesion of sentences (Dascalu et al., 2014) and the extent to which the voices of the group members intertwine (Dascalu et al., 2015). Asynchronous team contributions (i.e. in a wiki), have also been modeled to automatically assess the quality of the collaborative writing process by performing regression analysis on linguistic metadiscourse features and features that reflect the depth of cognitive thinking (Hu et al., 2016). In computer science education, progress has also been made in automatically assessing collaborative programming tasks by analyzing the quality of the coding in terms of code writing skills and also problem-solving processes (Staubitz et al., 2015). Techniques for summatively assessing code have a long history (Pettit & Prather, 2017), but more work is needed to articulate various tools to support learners who are expected to work in highly collaborative development environments.

In addition to detecting and assessing what learners are doing while they collaborate, increased attention has been paid to understanding the interdependent nature of collaboration (Swiecki et al., 2019; Swiecki et al., 2020; Swiecki, 2021). For example, researchers have developed coding schemes that attend to *transactivity*, or the ways in which individuals in collaborative situations respond to and build upon one another's contributions (Wang et al., 2017). These coding schemes have been integrated with techniques such as dynamic Bayesian networks to measure the prevalence of transactivity in collaborative discourse (Gweon et al., 2013). Similarly, techniques such as cohesion network analysis (Dascalu et al., 2018), contingency graphs (Suthers, 2017), epistemic network analysis (Shaffer et al., 2016), and group communication analysis (Dowell et al., 2019) have been retrospectively applied to discourse data to create models of collaboration that account for the interdependence between individuals as they work together in terms of the semantic similarity of discourse or the co-presence of automated codes applied to the discourse.

Moving beyond speech- or text-based discourse, there have also been efforts to assess collaborative learning using other relevant data sources. For example, Chua et al. (2019) proposed a multimodal monitoring setting to perform audio and video analysis to extract conversational features, linguistic features, and posture and facial emotions cues to automatically identify the characteristics of team composition and predict the success of learners in the collaborative task. Olsen et al. (2017) also explored the use of dual eye-tracking to identify if features related to joint attention can be used to predict the learning outcomes and assess the level of collaboration of dyads. Moreover, Echeverria et al. (2019) also proposed a multimodal learning analytics ecosystem (based on physiological sensors, microphones, and positioning trackers) to automatically detect errors made by nursing students during a fully immersive healthcare simulation. Although these works point at the recent interest in assessing group work and teamwork in physical spaces, this work is still in its infancy. Particularly, more work is needed both in improving the accuracy of sensors and also the validity of the techniques that can be used to model the multimodal data in educationally meaningful ways.

Table 19.1 provided a summary of some of the AI techniques that have been used to support collaborative learning presented in the previous subsections.

Table 19.1 Summary of techniques for supporting collaborative learning

Type of support	AI techniques used	Contexts explored
Group formation	Genetic algorithms, swarm intelligence algorithms, multi-agent formation algorithms, clustering, semantic web ontologies, social network analysis, word embeddings, decision trees, naive Bayes, logistic regression.	Mostly online
Formative feedback to learners	Recommender systems, intelligent tutoring systems, adaptive intelligent hints, data visualization, dashboards.	Mostly online (some face-to-face cases)
Adaptive scripting	Adaptive scripting, end-user scripting, dynamic modeling, intelligent tutoring systems, classification of group conversations, NLP.	Mostly online
Group awareness	Data aggregation, clustering, basic statistics, data visualization, affective computing (e.g. facial recognition algorithms).	Mostly online (some face-to-face cases)
Teacher awareness	Data aggregation, clustering, basic statistics, data visualization, affective computing (e.g. facial recognition algorithms).	Mostly online (some face-to-face cases)
Summative assessment	NLP, automatic conversation coding, classifiers, multimodal analytics, dynamic Bayesian networks, cohesion networks, contingency graphs, epistemic network analysis, group communication analysis.	Mostly online (some face-to-face cases)

TRENDS AND FUTURE CHALLENGES

In this section we discuss several overarching challenges related to supporting collaborative learning through AI and analytics techniques. We also point at new directions in this field. An overarching issue for all types of support discussed above is that it is of vital importance in evaluating the validity, utility, and interpretability of emerging techniques for modeling and assessing meaningful aspects of collaborative learning (see Chapter 22 by VanLehn). One potential way to address this issue is by considering human-centered approaches when designing a support tool. Taking a human-centered approach is related to ensuring that the user of the support tool—learners or teachers—retains a desired level of agency (e.g. see Chapter 6 by Kay et al.). That is, there should be a balance between the support tool imposing certain actions upon the user, and the support tool acting as a way to inform the user's actions (Wise et al., 2016). Support through scripting (see above) is a clear example of the issue of agency, as the danger of *overscripting* is commonly discussed in the literature (Dillenbourg, 2002). As described in this section, some authors have argued for letting students design (part of) their own scripts, allowing for greater flexibility and agency.

Another dimension of human-centered design concerns the choice for which aspects of the collaborative process are analyzed and visualized by the support tool to facilitate interpretability (Santos & Boticario, 2014, 2015). These aspects should ideally be chosen and visualized in such a way that they are informative yet easy to interpret for the user. However, these two goals are sometimes at odds: what may be easy to visualize is not always informative, whereas complicated yet informative indicators may not be easy to understand. In both cases, the result is that the intended goal of supporting the user may not be reached.

One promising approach to resolving this tension is suggested by the emerging field of Quantitative Ethnography (QE) (Shaffer, 2017). QE provides a conceptual framework for mapping data to constructs in terms of *Codes*—the contextually defined meanings of actions. Critically, Codes may be defined in relation to *etic* concepts—those that are associated with relevant theory—as well as *emic* concepts—those that members of the community being studied use to understand their own actions. Thus, emic coding may help to alleviate the tension between informative and interpretable constructs in the context of collaborative learning support.

Coding alone does not fully address the issue, however. To understand and support collaboration, we need techniques that model and visualize the relationships between Codes that are expressed when learners interact. One such technique, epistemic network analysis (Shaffer et al., 2016), has recently been used to model connections between Codes in collaborative settings and automatically represent these connections to teachers in real time to help them support collaborating learners (Herder et al., 2018). Other promising techniques for modeling the relationships between Codes include dynamic Bayesian Networks (Gweon et al., 2013) and lag sequential analysis (Kapur, 2011). Furthermore, several network techniques exist that have been used to visualize connections between concepts in discourse, such as cohesion, semantic similarity and uptake (Dascalu et al., 2018; Dowell et al., 2019; Suthers, 2017). However, more work is needed to examine these techniques in relation to emic concepts in collaborative learning and, thus, help to address the tension described above.

There is a growing interest in capturing collaborative traces from the increasingly hybrid learning spaces in which group activities span across physical and digital settings. Future research and development of awareness tools could focus on automated detection of emotions, using, for example, physiological indicators (see Chapter 18 by Casas-Ortiz et al.). Multimodal sensors can be used to build more complete models of collaborators to not only consider what can be logged from clicks and keystrokes but also to generate a deeper understanding of the complexity of working in groups, particularly in collocated settings (Martinez-Maldonado et al., 2019). However, more work is still needed to ensure validity in the kind of metrics that can be extracted from sensor data. For example, theory-based dual eye-tracking innovations have been robustly used to predict joint attention as a proxy of effective collaboration (Schneider & Pea, 2013). However, these metrics cannot easily scale to groups of three or more. Metrics from positioning, posture, and affective aspects of group activity are also emerging. For example, Malmberg et al. (2021) used physiological sensors to automatically identify key socially shared regulation constructs. Yet, much work is still needed to fully understand the validity and utility of such metrics to directly support collaborative learning.

Finally, using more sources of evidence about learners' collaborative behaviors can actually lead to building more accurate models (Viswanathan & VanLehn, 2019b). Yet, a key trade-off to consider exists between achieving high accuracy in collaboration detection and the potential privacy and practical challenges that can emerge in authentic settings from collecting richer collaboration data (Viswanathan & VanLehn, 2019a). Bringing AI into authentic collaborative learning settings is already sparking deep discussions around ethics, biases, inequalities, and moral dilemmas (see Chapter 26 by Porayska-Pomsta et al.).

CONCLUDING REMARKS

This chapter presented an overview of AI and analytics techniques to support collaborative learning in face-to-face and online settings. Some of the current techniques have contributed to accelerating CSCL researchers' analysis cycles, but some have also been transformed into tools that support teachers and learners in various ways. This chapter grouped the techniques currently available according to their purpose. We particularly focused on techniques that provide intelligent support to: (i) form effective groups, (ii) provide direct feedback to students, (iii) facilitate adaptive scripting, (iv) enhance group and (v) teacher awareness, and (vi) perform summative assessments. We emphasize that several validity challenges are persisting and more work needs to be done in understanding how low-level group data can be modeled in educational meaningful ways that can serve to inform practice. Validity is a particular challenge for the emerging interest in capturing multiple sources of collaboration data to gain a wider understanding of the group activity. However, the more data is captured, the harder it can be for teachers and learners to understand the relationships between salient aspects highlighted by AI algorithms and this can lead to complex interfaces that are hard to interpret. We propose that human-centered design approaches can enable the creation of AI support tools that serve their purpose in effectively supporting teachers and learners by giving them an active voice in the design decisions of the tools they will end up using. This means there are several future avenues of research in developing techniques for supporting collaborative learning that address authentic educational needs, with integrity.

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