TSCL: A conceptual model to inform understanding of collaborative learning processes at interactive tabletops

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ABSTRACT

Emerging systems for tabletop interaction have the potential to support small groups of students in collaborative learning activities. We argue that these devices have the potential to support learning by exploiting the interaction data that they can capture. The capture, analysis and presentation of these data can provide new ways to gain understanding of the collaborative processes. This is particularly important for teachers at two levels. First, they can gain a deeper level of awareness of the progress of individual students and groups in their class and, based on this, make real-time informed decisions. Second, they can do post-hoc reflection and analyse aspects of the class. This paper presents Tabletop-Supported Collaborative Learning (TSCL), a conceptual model that provides foundations for building tabletop-based systems that can inform understanding of the collaborative learning process. The model provides guidance for building the infrastructure to: (i) capture traces of student activity; (ii) exploit these through data analytics techniques; and (iii) provide useful information about the collaborative processes. We illustrate the usefulness of TSCL in its use to create a learning environment that was evaluated in two studies conducted in tertiary education contexts. The first was a laboratory study, where 60 students in 20 groups worked on a concept mapping task, with data from their interaction used to create visualisations of the group processes. The second study was conducted in-the-wild, involving 140 students, working in 8 class sessions.

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1. Introduction

The current proliferation of surface devices, such as tablets, smartphones and more expensive tabletops, is causing a shift in the ways people interact with computers (Hilliges et al., 2010). This is creating opportunities to make computers more ubiquitous and pervasive, rather than the centre of the activity as is often the case with most desktop/laptop computers. In particular, interactive tabletops can enrich a typical face-to-face setting in several ways: by supporting convenient, unconstrained orientation of people around a shared device; allowing the placement of physical items on the table; affording persistence of the interface status when working with virtual content, so that it can be retrieved for later reuse; and offering each group member equal opportunities for participation (Müller-Tomfelde and Fjeld, 2012; Piper and Hollan, 2009).

A particular focus of our work is to support group work in a learning context. Indeed, collaborative skills are important for students (Scheuer et al., 2010) and are not straightforward to learn (Dillenbourg, 1998). Students require close attention and timely feedback from their teachers. Unfortunately, in regular classrooms, the multiple responsibilities that teachers face can make it difficult for them to provide timely attention to the students who need it most (Dillenbourg and Jermann, 2010). Teachers often see only snapshots of student progress and have severely restricted insights into their collaboration. At tertiary education level, this issue can be exacerbated by even larger student numbers enrolled in the courses (Salmi, 2001). A particularly promising way that interactive tabletops have the potential to support collaborative learning is by exploiting the interaction data that they can capture whilst students work face-to-face, in small groups.

The introduction of new technologies in education needs to be thought through carefully to realise their potential benefits and take account of their limitations. Similarly to other learning technologies, tabletops by themselves do not necessarily provide a direct improvement in learning, collaboration or instruction (Dillenbourg and Evans, 2011). Rather they offer the potential for new ways for teachers and researchers to design and conduct activities (Dillenbourg and Jermann, 2010). Dillenbourg et al. (2011) described the tendency to over-generalising the possible benefits of tabletop devices to address a number of educational challenges, and the over-expectation of their affordances. These
acknowledged challenges point to the need to gain understanding of the ways that these devices can be used to enhance learning and teaching. They also suggest the need for a grounding, based on established educational theories, to build effective classroom tools using such devices. At the core of our work is a deep awareness of these risks and a commitment to build from solid theoretical foundations.

This paper proposes an approach that consists of a conceptual model which we call Tabletop-Supported Collaborative Learning (TSCL), to echo the name of the established field, Computer-Supported Collaborative Learning (CSCL). TSCL exploits the particular affordances of interactive tabletops and guides the design aspects of the infrastructure that can effectively inform understanding of the collaborative learning process at tabletops. Our vision for TSCL is to facilitate the creation of systems that support collaborative learning processes at a quite new level. The core affordances of tabletop learning applications are to support student collaboration. However, that support has not previously made rich use of the learner’s digital footprints of collaboration at the tabletop. TSCL changes this. It enables a new level of information to be made available to teachers, as in the work we report in this paper. Beyond that, insights can also be provided to students. It is also a foundation for adapting the interface or system behaviour, depending upon student progress and characteristics of collaboration. It can, further, drive the choice and timing of alerts to learners and teachers.

**Fig. 1** illustrates the core elements in the tabletop-based learning contexts. These need to be understood in order to support the collaborative activity. These include the learners, who are central actors of the learning activity. According to teacher-centric approaches (e.g. Dillenbourg et al., 2011) teachers are also key actors because they commonly manage the resources available in the learning setting; they have an influence on the learner, due to their roles during the design of the tasks and during the activity, particularly, in providing feedback. Learners, teachers and other stakeholders (such as learning designers, researchers, or academic directives) can benefit from using the data-based support to be provided by an implementation of the TSCL. It is also required to understand the context of the learning situation; this includes the particular features of the learning tasks, the learning goals and the each learner’s needs. The identification of the above elements can underpin the definition of a Conceptual Design that matches the many different learning contexts, each with their particular group dynamics, learning goals and tasks. Inspired by literature on interaction analysis (Harrer et al., 2009), the TSCL establishes the elements and mechanisms needed for capturing traces of students’ interactions at one interactive tabletop, or a number of them in the classroom setting; analysing these data through analytics techniques; and accomplishing the Interface Design to present distilled key indicators to the teacher to improve their awareness, decision taking and management of students’ collaborative learning processes. Finally, this approach proposes that learning theory should strongly influence the implementation of the Conceptual Design and all the elements of the model.

We explored how to achieve our vision, with the TSCL emerging in parallel with our creation of systems that tackle challenges of enhancing a teacher’s awareness. We demonstrate the utility of the model by showing how it can enable the creation of interfaces that help teachers see valuable information of students and the learning activity. We do this in two case studies, both conducted in tertiary education contexts. We created two new forms of information: visualisations for post-hoc analysis for a small group of learners at a single tabletop (Fig. 2, left); and real time visualisations of students’ progress at a multi-tabletop classroom deployed in the wild (Fig. 2, right). The model builds on theoretical foundations from Computer-Supported Collaborative Learning (CSCL) research. It is also strongly influenced by research on tabletops for collaborative work, taking an HCI perspective and building upon the previous work on analysis of indicators of collaboration.

The key contribution of this paper is the TSCL conceptual model that can be used as a basis to build tabletop-based collaborative learning systems. Associated contributions come from two implementations of it, each demonstrating its use to capture and exploit tabletop learning data collected unobtrusively, to provide useful forms of information about collaboration. In both case studies, the learning activity was based on the collaborative concept mapping technique. This is a well-established learning technique that has proved effective in promoting meaningful learning among students (Novak, 1990), and it is specially valuable for learners when maps are built in group (Chaka, 2010). It provides an excellent means for a learner to externalise knowledge and build meaningful understanding about...
almost any domain (Novak and Cañas, 2008). This technique is thus representative of group learning activities that require students to share their individual perspectives, visually represent their ideas and agree on a group solution (Chaka, 2010).

This paper is organised as follows. The next section describes the interdisciplinary context of our model. Section 3 presents the conceptual model. Section 4 describes our technological infrastructure. Section 5 presents a laboratory study that illustrates our model. Section 6 presents another case study, using another instantiation of our model. This study was conducted in the wild, where we illustrate the use of a second set of visualisations to help a teacher manage their attention and decisions to intervene with the group they consider is most in need of their support. The paper concludes with Section 7 that presents a discussion of our current and future avenues of research.

2. Background

There has been a steady growth of interest in the use of interactive tabletops in educational contexts, with research into various aspects of tabletop applications for learning, exploring this new design space (Dillenbourg and Evans, 2011). At the same time, there is a mature body of research on the automatic analysis of students’ logs of collaborative learning activity, mostly recorded by networked remote learning systems, to support teachers’ awareness of learners’ progress and collaboration levels (Baker and Yacef, 2009; Siemens and Baker, 2012). In spite of this, there has been little research exploring how students’ data captured from collaborative learning systems can help teachers and researchers understand the processes of students working face-to-face (Jeong and Hmelo-Silver, 2010). As commercial tabletop hardware becomes cheaper and more readily available, tabletops may offer new opportunities to exploit these data, by using data analytics to enhance awareness of the face-to-face learning activities. It is important to understand both the limitations and the benefits of using tabletops in collaborative learning. We discuss both the positive and negative affordances of tabletops in the next subsection. The rest of the section presents an overview of the state of the art of the interdisciplinary background this paper builds upon.

2.1. Affordances of interactive tabletops

Interactive tabletops have positive affordances for supporting face-to-face group work (Müller-Tomfelde and Fjeld, 2012; Piper and Hollan, 2009). However, their effectiveness depends on the nature of the collaborative activity performed by the group members. Benko et al. (2009) conducted a survey with design researchers and developers and this highlighted the main limitations of tabletops, in order of importance:

• the keyboard for text entry, be it physical or digital, presents difficulties;
• the lack of availability of standard applications (desktop standard applications are very often not suitable for horizontal devices and the market of tabletop users is still too small for sustainable development of commercial tabletop applications);
• problems in precise pointing (which can be improved by using a stylus, but this compromises the advantages of the natural and always-available fingers for interaction);
• and issues with ergonomics (with users complaining of neck strain) and orientation (especially for reading text).

On the other hand, the same survey identified advantages of tabletops over traditional personal computers, including:

• direct touch input (enhanced awareness of other users’ actions);
• large display and interactive areas;
• long-term personal use (large interaction areas and combined with touch and pen inputs suggest their suitability for everyday personal usage);
• and their horizontal orientation (to provide space for users to collaborate in different areas).

We aim to take advantage of the positive affordances of tabletops to provide a medium for students to collaborate face-to-face and to support teachers by enhancing their awareness of students’ collaboration. Such awareness can help teachers make better informed, and potentially more effective, decisions that consequently may improve instruction, collaboration and overall student performance.

2.2. Tabletop research to support collaborative learning

Interactive tabletops have been a focus of HCI research for more than two decades (Müller-Tomfelde and Fjeld, 2010). As described in the previous section, the unconstrained display orientation of this shared device can enable users to interact with each other, using a rich digital environment, with egalitarian access, while maintaining face-to-face communication with each other. These benefits have also attracted CSCL researchers interest to investigate the use of interactive tabletops in education (Dillenbourg and Evans, 2011). However, even though interactive tabletops are novel, original, and exciting, as mentioned above, the technology itself does not provide a radical change in learning or teaching (Dillenbourg and Evans, 2011; Higgins et al., 2011). Indeed, there has been little research exploration on successfully integrating tabletops into authentic learning environments (Kharrufa et al., 2013b). In this case and for the rest of the paper, we use the term, authentic learning environments, to mean those where students do learning activities that are linked to the regular curricula and the class is run in their regular scheduled weekly time. This is in contrast to lab studies; these are performed in special settings where students and teachers participate in extra-curricular tasks.

Our goals pose challenges at two levels. They require a strong design for effective tabletop interfaces, grounded on usability principles (HCI perspective). But they also draw upon educational principles for supporting collaboration and learning (CSCL oriented design). This overlap, at the intersection of these two fields in general, has not yet been deeply explored (Rick et al., 2013). A second challenge in CSCL research was described by Jeong and Hmelo-Silver (2010), who reported the limited number of CSCL studies targeting face-to-face collaborative settings (according to this report only 36% of CSCL studies examined face-to-face collaboration in the period 2005–2007). This is an area where the development of emerging interfaces (e.g. interactive tabletops) can enrich the learning setting to enhance research and practice. Fig. 3-A marks the overlap between CSCL and HCI disciplines that is relevant to scaffold our research to support collaborative learning at the tabletop.

From a very different research perspective, there has also been a lack of exploration of the analysis of students’ face-to-face collaboration using either artificial intelligence or analytics techniques (Baker and Yacef, 2009). Educational Data Mining and Learning Analytics (which we will refer to as Educational Analytics) are both emerging fields that have mostly focused on discovering patterns of
interaction between individual students and learning systems (Siemens and Baker, 2012). However, some important work has tackled problems for collaborative learning in networked and online learning systems (Magnisalis et al., 2011). This can serve as a basis to build support for face-to-face settings. In recent years, there have been serious attempts to formalise this emerging research area (Kumar and Kim, 2013), focusing on providing intelligent support for group learning in the form of visualisations, teacher's dashboards, data mining, learner modelling and tutoring systems (see Fig. 3-B, Educational Analytics and CSCL). As noted above, from the CSCL perspective there has also been little work on implementing approaches to automatically analyse students' collaborative interactions (Jeong and Hmelo-Silver, 2010). The data analysis in these kinds of face-to-face settings has typically consisted of very expensive manual video coding. Our model and its implementation aims to exploit the development of emerging large touch devices and sensing technologies to offer alternative approaches to support collocated collaboration.

According to Müller-Tomfelde and Fjeld (2010), interactive tabletop systems and similar touch technologies will be increasingly used in a wide range of areas in the near future. While almost all existing touch tabletop hardware cannot determine which user has done each action, there has been work to change this (Blazica et al., 2013; Clayphan et al., 2013; Martinez-Maldonado et al., 2011a). One alternative approach to address this is to use pens for interaction. But this compromises the benefits of direct touch interaction. If student touch input can be differentiated and logged (along with raw input, environmental data, and interpreted student's actions), then it is possible to apply a whole new level of analytics and mining techniques to this student data to better understand students' behaviours and discover patterns of interaction (Kharrufa et al., 2013b), similarly to approaches previously used with networked learning systems (Mostow and Beck, 2009). Our model aims to highlight the importance of adding seamless accountability and awareness capabilities to tabletop systems to facilitate the application of analysis techniques on collaboration data (see Fig. 3-C, Educational Analytics and HCI).

Overall, there is a lack of authentic deployments of tabletop technologies in the classroom for real activities and the analysis of students’ data that can be automatically captured, processed and shown to the teacher to support small-group collaboration. We tackle this issue, at the intersection of the three fields depicted in Fig. 3 (HCI, CSCL and Educational Analytics), by grounding our conceptual model on the metaphor of classroom orchestration (D). This term is used to describe the role that teachers take as managers and coordinators of the cognitive, pedagogic and technological resources in the classroom (Prieto et al., 2011). It establishes the unit of usability at a classroom level rather than individual students, or the teacher alone (Dillenbourg et al., 2011). The effectiveness of orchestration and the extent to which teachers can respond to the ways students perform the class tasks is critical because it directly impacts these student’s activities, and therefore, their learning (Dillenbourg et al., 2011).

2.3. Visualisation of small-group collaboration

There has been significant research exploring visual representations of small group activity that can reveal various aspects of the collaborative work (Reithmeier, 2013; Soller et al., 2005). Erickson and Kellogg (2000) introduced the concept of social translucence to support computer-mediated communication by showing simple quantitative aspects of user participation. This approach builds on three properties:

- **visibility**, which refers to the notion that users can more readily direct their attention on socially significant information that is visually presented in the form of figures;
- **awareness**, which considers the impact of showing users aspects of the activity that can trigger modification of their actions or social rules;
- **accountability**, which refers to the processes of regulation that can occur as a result of user’s awareness of their own actions or those of others.

Reithmeier (2013), in the the most recent review of literature mostly produced by HCI and Computer-Supported Cooperative Work research, showed the varied ways in which aspects of face-to-face and distributed group work can be mirrored to promote reflection. In these areas, most of the group visualisations have focused on presenting features of the content of the dialogue between group members (Bergstrom and Karahalios, 2009a, 2009b) or conversation patterns, not related to the content of the speech, such as speaking time, response patterns and turn taking (DiMicco and Bender, 2004; Kim et al., 2008; Roman et al., 2012). Other visualisations have included information about which person looked at the speaker (Sturm et al., 2007) or the actions of the group members during the activity (Ichino et al., 2009). The last type of general visualisations of small group work includes the provision of cues about the level of agreement between group members (Bergstrom and Karahalios, 2007; Leshed et al., 2007) or the quality of collaboration (Streng et al., 2009).

In educational settings, sociograms have been extensively used in the CSCL field to visualise learner interactions (Jermann et al., 2009). They have also been applied to represent the lines of interaction.
communication within social networks (Sundararajan, 2010). Janssen et al. (2007) explored the effects of visualisation of participation in groups of learners. They found that visual representations of activity, mirrored to the group, can be useful for encouraging coordination and regulation. Donath (2002) went a step further by showing qualitative aspects of user’s participation in a visualisation that can facilitate the identification of dominant group members or possible patterns of interaction. Kay et al. (2006) designed a set of visualisations to identify anomalies in online team work by mirroring aspects such as participation, interaction between members and leadership. The authors found that the compact visualisation of information, showing useful interaction between members and leadership, could help teachers and students become aware of the long term processes in a group project. Narcissus (Upton and Kay, 2009) introduced a “scrutable” visualisation presenting broad information about each student’s actions, depicted as vertical timelines. This enabled learners and teachers to scrutinise the group activity, by navigating through the visualisation to see the detailed evidence that contributed to each part of the visualised group actions. A key contribution of this project was the deployment of the tool within an authentic university course where it improved group success. This highlights the importance of showing end users (students and teachers) key information, at different levels of detail, to promote reflection and awareness of the group processes.

Regarding the design aspects of most of the visualisations mentioned above, abstract objects have been widely used to present information about small group work (e.g. circles, lines, rectangles). Simple diagrams have also been used such as o-meters, pie charts and connected node-graphs. Some complex charts have also been effective for inviting deeper analysis of the data. In some cases, the visualisations make use of metaphors, for example, representing contributions by the flourishing of trees (Kay et al., 2006; Streng et al., 2009), groups of users with avatars (Brandon et al., 2011; Leshed et al., 2009) or the quality of collaboration in terms of weather forecasts (Brandon et al., 2011).

Finally, we build upon key work on visualising individual student’s data for online collaborative learning and extend this to face-to-face environments. So, we draw upon research on Open Learner Models (Bull and Kay, 2007; Bull and Vatrapu, 2011) and analysis of collaborative interactions (Soller et al., 2005). The visualisations presented in our the case-studies build on the previous general work on visualising aspects of face-to-face group work. They also take account of the specific requirements for representing the key features of collaborative learning, with a particular focus on supporting teacher awareness.

3. The conceptual model (TSCL)

As stated above, the main contribution of this paper is the Tabletop-Supported Collaborative Learning – Conceptual Model (TSCL). This provides guidance for building the infrastructure to capture traces of student activity at the tabletop, exploit these traces through data analytics techniques and provide useful information about the collaborative processes. TSCL deals with learning contexts where small groups of students are intended to work collaboratively to build common understanding, mediated by learning activities at interactive tabletops. Examples of these settings can include a multi-tabletop classroom, but also single-table settings. In such contexts, students mainly work face-to-face on a task to create and refine a joint solution; and students can have equal opportunities for participation and they work towards shared goals. The main components of the TSCL model are shown in Fig. 4. At the bottom is the Theoretical Foundation (TF) that contains the main theories, principles or paradigms that drive the design, development and implementation of the learning activities and the educational technology and the three operational modules. These modules are: the Data Capture Foundation (DCF), the Data Analytics Foundation (DAF) and the Data Presentation Foundation (DPF).

At mid-right of Fig. 4, we show the elements of the DCF. The Data Sensing System (SS), captures data about each individual’s activity and group interactions from the face-to-face learning system. The Data Pre-processing System (DPS), is responsible for filtering, combining and interpreting, as needed, the raw data captured by the SS. The is all in preparation for subsequent deeper data analysis or to create interfaces that mirror distilled information for the target users.

The lower box of Fig. 4 shows the main elements of the DAF whose main purpose is to analyse the pre-processed data from the DCF to either directly summarise group indicators or to discover
hidden patterns from interaction data. The DAF has one element for Group Indicators (GI); these must be carefully designed to capture salient aspects of students' interactions. DAF also has a set of Statistical Analysis tools (SA) that include both descriptive and inferential statistical models. The third part of DAF is a set of Data Mining Analysis algorithms (DMA) that can be used to discover more sophisticated models of students' data.

The mid-right box of the figure shows the DPF, which aims to provide useful forms of the processed data by the other parts of TSCL. One goal is to present this information so that it helps people (in this paper, teachers) make better informed decisions. Equally the DPF could produce information in the form needed to drive automated and personalised actions by a system. The input data for the DPF may be the results of sophisticated and data mining algorithms. But it may also be useful in the form of simple group indicators that can be easily visualised in various forms. The information, or automated actions generated by the DPF has the potential to be useful for (i) the learners, (ii) their teachers, (iii) researchers, or (iv) automated agents. The two implementations of the TSCL presented in this paper focus on teachers. In the following sections we describe the details of each element of the model.

3.1. The Learning Context

The Learning Context that this model aims to support is defined by (i) the type of group activity that learners are intended to perform; (ii) the learning scenario; (iii) the learning and teaching problems; and (iv) the sources of available student data. We now consider each of these.

i) Type of group activity: According to Dillenbourg's work (1998), a learning context is collaborative when it is characterised by the following four aspects: (1) group members have similar opportunities for participation and the activity is meant to be open for all to contribute; (2) students have similar levels of knowledge, status or expertise; (3) students share, or at least have similar, learning goals; and (4) there may be a horizontal division of labour (Dillenbourg, 1998). However, there can be other types of group activities, such as team work (Salas et al., 2005), where learners have set roles that imply asymmetric status. Another form of asymmetric work is when group members have relationships such as masters and apprentices or between teachers and students. There are also competitive contexts where there is a goal or reward that only one or a few students can achieve; or cooperative situations, with vertical division of work, meaning that students can work on independent sub-tasks (Oxford, 1997). We acknowledge that tabletops may be suitable for all these types of group activities. In this paper we describe examples of collaborative group work.

ii) Physical environment: The Learning Context can also vary greatly depending on whether the tabletops are used in the classroom or in a single-tabletop scenario. The learning scenario also defines the type of support that needs to be offered to the users. In the classroom, the teacher and their pedagogical decisions have a crucial impact on student's learning processes and outcomes. In this scenario, teachers need tools to manage the technology when available, opening opportunities to support the teacher's overall classroom orchestration from the design perspective (Dillenbourg et al., 2011). By contrast, in a single-tabletop setting, where the teacher is not always present, the design of the system can focus on different needs such as providing scaffolding directly to the group's activity or generating overviews of student's work for further detailed analysis or reflection.

iii) Learning and teaching problems: A third core element that defines the Learning Context is the relationship between the learning/teaching goals and the problems that need to be addressed to achieve them. For example, in some contexts the learning activity or the pedagogical approach emphasises collaboration over results (e.g. in brainstorming activities or when the learning goal is to learn to collaborate). In such cases, the type of support that teachers or learners need is to help all students to participate. This makes it valuable to enable teachers to identify the groups that are facing collaboration problems. By contrast, if the learning goals are for task achievement or collaborating to learn, then the type of support should focus on problems students experience with the topic-related aspects. Here, the system should help teachers gain awareness of the student progress towards the product and possible misconceptions. In this regard, there is no universal solution for all the learning and teaching contexts. But the student data can be exploited to facilitate the solution of the problems that students and teachers may be facing in each particular case.

iv) Sources of student's data: The Learning Context imposes limitations on what data is available and what data can be captured. For example, in authentic classrooms, it is not easy to capture the same rich data that can be captured in controlled laboratory settings (Kharrufa et al., 2013b). But in the classroom there may be other important sources of information, such as teacher's decisions, feedback they provided, interactions between groups and, in general, richer environmental and, many times, unexpected data (Mostow and Beck, 2009). The Learning Context also includes the data sources from which information can be captured by the technology and their different levels of detail. These levels of student's data include the group's activity as a whole, individual contributions, the digital artefacts that students individually or collaboratively constructed before, during or after the group work.

3.2. Theoretical foundation (TF)

The Theoretical Foundation (TF) offers principles for the implementation of the model for specific aspects, such as what student data should be captured, the type of group indicators that can provide valuable insights into the collaboration processes or what information can be most useful for a teacher who wants to attend to learning or teaching problems.

Our model is strongly linked to principles of classroom orchestration (e.g. teachers' awareness and minimalism) and HCI (usability and user perception). As described above, the notion of Classroom Orchestration (Dillenbourg et al., 2011) particularly emphasises the importance of offering simple but practical solutions to authentic problems in the classroom. It promotes what is called modest computing (Dillenbourg et al., 2011). This is the application of minimalist approaches to mirror key aspects of learners' activity, aspects that would otherwise remain unseen. In its original conception (Dillenbourg and Jermann, 2010), Classroom Orchestration appeared to be limited to the handling of the class in a physical classroom. However, this approach has been taken over by several researchers in the Learning Sciences and CSCL communities, embracing a wider definition of orchestration (Prieto et al., 2011). This includes online activities, blended learning activities, instructional design, and, most relevant for our case, teacher awareness (Rodríguez Triana et al., 2014) and distributed orchestration (Sharples, 2013) (where the orchestration load is not only placed on the instructor's).

Under the umbrella of classroom orchestration, other researchers have focused on the development of tools to enhance
classroom management of multiple tabletops (Do-Lenh, 2012; Higgins et al., 2011; Kharrufa et al., 2013a). But little has been done in regard to supporting teachers, to enhance their awareness, or providing automated ways to capture traces of learning activity and behaviours for research purposes.

In addition, the theoretical design and implementation of the various elements to capture, analyse and present key student’s information should be influenced by learning theories or principles. These define an epistemic perspective underpinning the design. This is illustrated in Table 1, which presents the main principles of the TF that were used in the two implementations of our model described in this paper. These are the theory of Group Cognition (Stahl, 2006) which itself builds on well established principles of collaborative knowledge building (Scardamalia and Bereiter, 2006), mediated cognition (Vygotsky, 1978) and distributed cognition (Suchman, 1987; Winograd and Flores, 1985). The theory of Group Cognition provides a solid theoretical grounding for all the elements of the model, including the definition of the Learning Context: small-groups of students (3–6 in each group) engaged in a problem solving activity, aided by an interactive tabletop, both in and outside the classroom. The second main theoretical foundation comes from work on Computer Based Interaction Analysis (Dimitracopoulou et al., 2004). This seeks to develop various forms of support, ranging from visualisations of group indicators that can be unobtrusively displayed, to more intrusive actions, such as alerts issued by the system to inform students of likely problems, as they are detected (Soller et al., 2005).

3.3. Data Capture Foundation (DCF)

The Data Capture Foundation (DCF) defines the infrastructure needed to collect and gather rich student data from the tabletop setting. It requires various ways to record the low level raw interaction data, along with contextual information that can provide meaning, in terms of learning or collaboration, to user interface activity logs. The analysis of utterances has proved powerful for understanding what is actually ongoing within a group (Stahl, 2006). A large number of studies in the CSCL field highlight the importance of analysing the conversation between group members (Jeong and Hmelo-Silver, 2010). But this type of analysis still requires the manual scrutiny of video recordings. While this is adequate to conduct research, it cannot be applied in real classrooms as it cannot deliver information to help teachers or students in real-time. Moreover, in face-to-face settings, group members use multiple channels to communicate. These certainly include verbal utterances, but learners also make use of important non-verbal cues.

Previous studies have shown that even quite modest indicators of speech can be effective to describe several aspects of collaboration at non-interactive tabletops (Roman et al., 2012). The automated analysis of speech is an important aspect to analyse collaboration at interactive tabletops but it is still challenging and not yet a mature enough technology to use in collaborative settings (Rosé et al., 2008). Alternatively, previous research has also investigated how the touch activity captured by the tabletops can provide evidence about important aspects of collaboration, such as equity of participation, self-regulation (Marshall et al., 2008), or collaboration strategies (Martinez-Maldonado, 2014). This suggests that a model to support collaborative learning at the tabletop should consider the connection between three elements: the artefacts produced by students; their verbal activity; and physical interactions on the device. The challenge is to define what and how to capture the student’s data that is needed to design an effective support tool without interfering with the learning activity.

To address this challenge, an initial key question for the implementation of the DCF is: What data should be captured to derive useful group indicators? Dimitracopoulou et al. (2004) defined a taxonomy of group indicators that can be captured from online/remote learning systems. This taxonomy provides a starting point. This can be extended to face-to-face collaborative systems. It distinguishes five sources of information: (i) individuals (the actions and products of each learner), (ii) undifferentiated group (information that concerns the whole group, without identifying individual contributions or roles), (iii) differentiated group (information in which the contribution of each learner is identified), (iv) the community (considering multiple groups), and (v) the society. Our work concerns the first four of these.

A second question is: What are the sources of these data? The internal sources of data include the group activity, individual participation and artefacts constructed in the tabletop. However, there can also be external sources, such as other learning tools that can be inter-connected within the learning ecology. These can include desktop-based or online-based Personal Learning Environments (PLEs) that students can use in learning activities before or after the use of tabletops. Other learning tools, for example those available on mobile devices, can be used outside or within the classroom (Valdes et al., 2012). Importantly, centralised Learning Management Systems (LMSs) or Virtual Learning Environments (VLEs) (e.g. Moodle or BlackBoard) can also provide valuable information about other learning activities performed by groups or individual students beyond the face-to-face learning environment.

The DCF should aim to accomplish two main operations: sensing and pre-processing. We now describe its components.

3.3.1. Data Sensing System (SS)

The Data Sensing System (SS) relates to the hardware and software that can be used to capture specific aspects of students’

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<tr>
<td><strong>Group cognition theory</strong></td>
<td>Group cognition considers the small-group activity as a process that focuses on constructing new understanding and in which shared meaning is created through learners’ dialogue. Both abstract and physical artefacts created by learners capture parts of this mutual understanding generated by the group and are used as mediators of the collaborative activity.</td>
<td>Stahl (2006); Vygotsky (1978); Scardamalia and Bereiter (2006)</td>
</tr>
<tr>
<td><strong>Computer-based interaction analysis</strong></td>
<td>This body of work informs what information needs to be provided to the participants in learning activities (usually students or teachers), so that they can better self-assess their performance or improve the learning process overall. This work comes from the fields of Artificial Intelligence and Data Mining in Education.</td>
<td>Dimitracopoulou et al. (2004), Soller et al. (2005), Soller and Lesgold (2007), Baker and Yacef (2009)</td>
</tr>
<tr>
<td><strong>Classroom orchestration</strong></td>
<td>Orchestration can be defined as the process of productively coordinating the available resources and possible interventions for multiple learning activities occurring at multiple social levels, learning contexts and with a set of different technologies.</td>
<td>Dillenbourg and Jermann (2010), Dillenbourg et al. (2011), Prieto et al. (2011)</td>
</tr>
</tbody>
</table>
activity (or inactivity) from the physical environment or by accessing students’ data from other online learning systems or teachers’ notes.

In face-to-face environments, there is substantially more information that is externalised by learners, in comparison with networked applications. For example, hand gestures, body language and gestures of assent, among others are all important (Olson et al., 2002). Table 2 presents an overview of the main categories of sensing technology that have been used to enrich interactive tabletops.

One form of fundamental contextual data, which is generally not captured by interactive tabletop hardware, is information about user-differentiated, or identified touch. This is important for analysis of the nature of the collaboration, as it is key to determining what each learner did and how each learner interacted with the others, in using the application at the tabletop. Notably, research on tabletops in education has not dealt with this. Most of current tabletops reported means for identifying who is doing what are intrusive (Marquardt et al., 2010; Meyer and Schmidt, 2010), require training (Zhang et al., 2012) or are restricted to the touch sensitive technology, notably the Diamond-Touch (Dietz and Leigh, 2001). These limitations pose a serious problem for classroom implementation of TSCL, since most emerging tabletop devices do not support touch identification.

Speaker differentiation has been explored in non-interactive tabletop collaborative systems, for example (Evans et al., 2010; McCowan et al., 2005; Roman et al., 2012) where it proved to be effective in providing useful quantitative information for deep conversation analysis. Another source of students information comes from analysing the evolution of the artefacts produced on the tabletops to provide insights on group collaboration.

Various sensing technologies can augment tabletops to collect interaction data. The automatic analysis of speech, for example, can give useful results (Rosé et al., 2008). Eye tracking technologies have been used at tabletops to improve the interaction with distant objects (Holman, 2007; Mauderer et al., 2013). However, these papers did not report deployment in authentic settings with multiple users. New sensing technology does not necessarily provide useful data for collaborative learning environments; more studies are needed to determine that, including where it can be practical for real classrooms.

3.3.2. Data Pre-processing System (DPS)

The second element of the DCF is the Data Pre-processing System (DPS). This is strongly influenced by the Theoretical Foundation, which informs what information and, more specifically, which indicators offer promise to provide insights about the nature of collaboration and learning within groups. The three main objectives of this component are: (i) data filtering; (ii) synchronisation and combination of data coming from multiple sources; and (iii) interpretation of low level application logs. These logs may include the traces of touch activity, differentiated speech capture, live assessments of the group artefacts or even external observations. Sensors may be permanently active collecting data. However, some dimensions of these data are likely to be relevant for teachers, researchers or students themselves. Data filtering steps are frequently needed to select the information that is relevant for the analysis tools or to be displayed to the users. This makes it easier to analyse and show the students’ data by hiding the data that is not relevant for the target users.

Secondly, multiple sensors can record events in parallel. In that case, it is important to synchronise and integrate student’s data across multiple sources and levels. We illustrate this in Fig. 5. For example, at a single tabletop, students’ actions might be recorded in the form of user-differentiated audio logs (such as the second set of bars, in orange) and touch interaction (such as the top set of bars, in red).

<table>
<thead>
<tr>
<th>Sensing information</th>
<th>Description</th>
<th>Key previous explorations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Touch identification</td>
<td>Associating individual touches with the user who did them, without necessarily identifying the person.</td>
<td>Dietz and Leigh (2001), Zhang et al. (2012), Marquardt et al. (2010), Meyer and Schmidt (2010)</td>
</tr>
<tr>
<td>Speaker differentiation</td>
<td>Speaker differentiation has been used in collocated environments to automatically mirror levels of participation. No previous exploration in interactive tabletop environments.</td>
<td>Bachour et al. (2010), Roman et al. (2012)</td>
</tr>
<tr>
<td>Analysis of artefacts</td>
<td>The analysis of the progress towards the solution created by a group at the tabletop. This can capture key information of group members’ understanding.</td>
<td>Kharrufa et al. (2009)</td>
</tr>
<tr>
<td>User identification</td>
<td>Association of touch activity with an authenticated user at the tabletop. Not yet much explored.</td>
<td>Ackad et al. (2012)</td>
</tr>
<tr>
<td>Automated analysis of speech</td>
<td>For multi-modal interaction only. Not yet much explored.</td>
<td>(Tse et al., 2007)</td>
</tr>
<tr>
<td>Gaze tracking</td>
<td>Gaze tracking has been explored in tabletop settings to enhance users’ reach and text orientation.</td>
<td>Holman (2007), Mauderer et al. (2013)</td>
</tr>
<tr>
<td>Connection with other user applications</td>
<td>Some previous exploration of access of tabletops to data previously generated by users through other environments (e.g. web and mobile interfaces).</td>
<td>Valdes et al. (2012)</td>
</tr>
</tbody>
</table>

Fig. 5. Diagram representing the multimodal data capture and integration of collaborative multi-user data at the tabletop. (For interpretation of the references to colour in this figure, the reader is referred to the web version of this article.)
application logs, in blue). Continuous measures of quality can be obtained from the learning artefacts built by students or external observers can record key events into the logs.

Moreover, in settings with multiple small-groups working in parallel, all the software being used by each group should be synchronised in a store for that group. Then, a common service covering the whole classroom can provide the teacher with real-time indicators and also highlight events that occur at a class level. Additionally, all the tools and the actions performed by the teacher through any controlling tool should also be synchronised. Then, analysis tools can triangulate evidence to discover key aspects of learning and teaching. This synchronisation also allows the system to associate the multiple sources of information with the higher level meaning of student's actions. This is critical to provide deep insights on collaboration, compared to what can come from just the low level action data (such as touch events), which may not be informative enough to be useful.

The output of DCF consists of rich contextual data that contains contextual students’ information synchronised across all the data sources. From a technical perspective, these output data should be immediately recorded into a shared Central Data Repository to allow other services to access the information in real time.

3.4. Data Analytics Foundation (DAF)

This component is built upon the theoretical foundations from Educational Analytics adapted to face-to-face settings. The Data Analysis Foundation describes ways to analyse the captured data to produce key indicators of interaction or patterns linked to the strategies students used. The data analysis uses the same Central Data Repository discussed above as this integrates from multiple sources, both raw and processed data, making both readily available.

The first element of the DAF is a set of Group Indicators (GI) that provide information about various aspects of students’ work and relationships. The Theoretical Foundation (TF) influences the design of each part of the DAF, specially for the definition of these Group Indicators (GI). The set of GIs can mainly be borrowed from the extensive research in the field of Computer Based Interaction Analysis. Some of these indicators may include quantitative measures of participation and contribution in the verbal or physical layers, the symmetry among students’ actions, interweaving of the stream of conversational activity and actions on the shared device, and the degree of collaboration of the group.

Other derived aspects can be considered, such as parallelism, turn taking, patterns of communication and leadership. These GIs can be generated by simple statistical analysis or, if warranted, by applying more complex processing techniques. The two operational elements of the DAF that address this are the Statistical Analysis (SA) and the Data Mining Analysis (DMA) systems. The first (SA) refers to approaches from descriptive statistics that can be used for grouping measures, extracting averages and making simple comparisons of students’ data that can also be easily visualised. Inferential statistics can also be applied to provide deeper data analysis such as finding correlations or trends in large amounts of data. The DMA includes the application of tools that can address questions about possible activity trends obtained from multiple instances of data, or when it is desirable to find models that better describe aspects of collaborative learning. Some of the techniques that can be applied include: classification algorithms, clustering approaches, sequence pattern mining and process mining models.

Regardless of the methods used to generate GIs, these generally should include aspects of collaboration, argumentation, participation, awareness and content (Dimitracopoulou et al., 2004). Table 3 presents an overview of some of these categories of GIs proposed by Dimitracopoulou et al. (2004) as a result of a detailed literature review of online learning systems. Low level actions are those performed by students and can be captured by the system with contextual information about their learning impact. High level actions provide more information about the quality of collaboration or participation in terms of learning concepts. The higher level an indicator has, the more interpretative value it is likely to have. Low level indicators may provide information that requires more interpretation from the users perspective. This may be desirable in some situations; for example, a teacher may be able to make effective use of simple indicators in order to decide which group seems most to need their attention.

### Table 3
Main groups of Indicators of Group Interaction; adapted from (Dimitracopoulou et al., 2004).

<table>
<thead>
<tr>
<th>Indicator level</th>
<th>Description</th>
<th>Example indicators</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Low level indicators</strong></td>
<td>Include general indicators of individual amount and proportion of student’s participation</td>
<td>Learner’s ratio of participation, participation count, non-verbal actions, number of messages per participant, student contribution, interactions, active students, authorship awareness</td>
</tr>
<tr>
<td>Indicators of participation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Content related indicators</td>
<td>Provide information from the content or artefacts generated by students as a result of their collaborative activity.</td>
<td>Conversation versus action balance, division of labour, actor’s degree of centrality, network density, collaboration level in the group.</td>
</tr>
<tr>
<td>Cognitive indicators related to strategies</td>
<td>Indicators with high levels of abstraction that are processed manually (but that can still aid groups’ analysis).</td>
<td>Amount of collaborative work, argumentation, coordination, cooperation, collaboration.</td>
</tr>
<tr>
<td><strong>High level indicators</strong></td>
<td>Describe advanced aspects of participation and collaborative strategies.</td>
<td>Initiative, elaboration, creativity, conformity, opinion difference visualisation.</td>
</tr>
<tr>
<td>High level indicators related to collaboration</td>
<td>Describe measures of aspects of discussion that happened within the groups. Their automatic generation mostly apply to systems that scaffold argumentation.</td>
<td>Average number of contributions, average contribution size, group interactivity, contributions answered by others, follow-up contributions.</td>
</tr>
<tr>
<td>Elaborated indicators of collaboration quality</td>
<td>Quantify qualitative aspects of argumentation. Automatic generation mostly apply to systems that scaffold argumentation.</td>
<td></td>
</tr>
<tr>
<td>Elaborated indicators of argumentation quality</td>
<td>Reflect quantitative measures of argumentation activity that can be captured through a number of learning systems.</td>
<td></td>
</tr>
</tbody>
</table>
Therefore, in the studies we report, focus on providing key information for use by teachers. The model also focuses on the principle of non-intrusiveness. The output of the DP depends on the context of usage. In a classroom, teachers need real-time information, if they are to use it to intervene in the learning processes in a timely manner, so as to enhance the learning–teaching experience. The data can also be used for after-class reflection. In this case, the target users may be the teachers, who want to be able to study certain aspects of the sessions in detail. Post-hoc use is also valuable for designers or researchers, aiming to improve the learning or instruction approaches.

The granularity of the information displayed to the target users also depends on the context of usage. Tools to visualise detailed student progress might be desirable for post-hoc analysis if the teacher is concerned about some groups and wants to explore possible causes (Schneiderman, 1996). However, a teacher cannot devote attention to large volumes of information in class, as they need to focus on their main teaching and facilitation roles. Teachers need different volumes and forms of information for in-class use compared with after-class exploration (Bull et al., 2012).

The instantiations of our TSCL model presented in Sections 5 and 6 focus on providing key information for use by teachers. The model also focuses on the principle of non-intrusiveness. Therefore, in the studies we report, students are not provided with any indicator or visualisation.

3.5. Data Presentation Foundation (DPF)

The Data Presentation Foundation (DPF) includes the user interface elements that can provide the target users with key information about group work. These may include the results of the data analysis. For example, this may be presented on a teacher’s dashboard, to enhance awareness or support assessment and evaluation. The input of the DPF mostly consists of indicators that are obtained from the pre-processed captured students’ data or aggregation of these. Key findings obtained from using artificial intelligence approaches or inferential statistics can also be shown directly to users or used by a learning system to offer recommendations or adapted functionalities.

The output of the DP depends on the context of usage. In a classroom, teachers need real-time information, if they are to use it to intervene in the learning processes in a timely manner, so as to enhance the learning–teaching experience. The data can also be used for after-class reflection. In this case, the target users may be the teachers, who want to be able to study certain aspects of the sessions in detail. Post-hoc use is also valuable for designers or researchers, aiming to improve the learning or instruction approaches.

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The instantiations of our TSCL model presented in Sections 5 and 6 focus on providing key information for use by teachers. The model also focuses on the principle of non-intrusiveness. Therefore, in the studies we report, students are not provided with any indicator or visualisation.

4. Technological Infrastructure: single and multi-tabletop environments

This section describes the technological implementation of our approach for capturing, formatting and processing student’s interactions at the tabletop. We describe two learning contexts: a single-table system for small group collaboration and a technology-enhanced classroom.

We needed to meet the sensing requirements of TSCL. But we wanted to be able to do that in a way that works with most currently available tabletop hardware. This meant that we needed to achieve tabletop touch identification, linking each touch to the person who did it. However, the very nature of face-to-face tabletop collaboration means that much of the important interaction is not between the computer and people; rather it is between the people themselves. So, we also needed to capture speech and other verbal activity, such as grunts. We wanted to achieve both these forms of user-identified sensing unobtrusively, avoiding the need for people to wear special devices, such as microphones, or use special devices, such as a stylus for interaction. We now describe the approach and hardware that was used.

The Sensing System (SS), which is part of the Data Capture Foundation (DCF), is implemented using the CollAid system (Martinez-Maldonado et al., 2011a) (Fig. 6). Our tabletop hardware is like most available systems in that it can detect multiple touches at a time, although it cannot recognise which user is providing an input. To achieve the SS needs of TSCL model, we created CollAid based on a depth sensor located above the tabletop to track the position of each user’s body and arms. CollAid matches the depth images generated by the sensor with each touch on the interactive tabletop, so capturing which user is touching the table at that precise moment.

CollAid can also capture differentiated speech and other verbal activity, through an array of microphones which can be situated above or at one of the edges of the tabletop. We use a radial 7-channel USB microphone array that distinguishes spatial location sounds, so linking this to the person speaking. As shown in Fig. 6, all this captured data is logged in a central data repository, with timestamps. Through this set of hardware, we can unobtrusively obtain a range of sources of student’s data: tabletop data logs with the authorship of each touch (without attaching any gadget to people’s hands or having additional furniture), verbal interactions between learners (without attaching microphones to people) and information about the learning artefacts built by students.

Multiple instances of CollAid can be interconnected to provide support as a classroom ecology. We created the MTClassroom (Martinez-Maldonado et al., 2013), the first classroom with multiple interactive tabletops and the associated infrastructure that supports classroom orchestration and is based on unobtrusive data capture to provide real-time visual information about student’s work (Fig. 7). Our deployed MTClassroom has had 4 or 5 multi-touch interactive tabletops, each with the CollAid sensing (Fig. 7b and c). From the teacher’s perspective, the dashboard is key as this supports their awareness of each group and orchestrating the class activities at the tabletops (Fig. 7e shown at the lower left). This

teacher's dashboard (MTDashboard) is a multi-platform teacher's tool that contains both controlling and awareness components. For example, it allows teachers to send commands to the applications running on each table. This enables the teacher to do generic actions, such as blocking the touch input to gain student attention, avoiding the distraction of the tabletop, or moving to the next stage in the learning application. In our studies, the dashboard was displayed at a handheld tablet device that the teacher carried while walking around the classroom. The dashboard also controls sending content from any of the tabletops to a connected wall projector (Fig. 7a). This enables the teacher to facilitate sharing, discussion and reflection at classroom level.

From a data capture perspective, the logging system of each tabletop also records the activity to a central synchronised repository that can be accessed in real-time by other services (Fig. 7f). One of these is the teacher's dashboard. More details about this tool will be provided in Section 6. Additionally, observation consoles (Fig. 7g) can be directly connected to the repository to record synchronised qualitative data. In our study, two observers submitted standardised annotations of the teacher's attention and interventions. These annotations will also be described in Section 6.

Finally, the host learning application. While our approach can support arbitrary applications, this paper reports results of studies with CMate (Martinez-Maldonado et al., 2010) (Fig. 7d). This is a collaborative tool that enables students to build a joint concept map to answer a focus question posed by a teacher. A concept map is a directed graph in which nodes represent the main concepts for a given topic (such as whale, fish, mammal) and the edges are labelled with a linking word (such as is-a) to form a meaningful statement called proposition (such as whale is-a fish, or whale is-a mammal) (Novak and Cañas, 2008). A sub-module of CMate performs basic pre-processing of the data captured by CollAid. This corresponds to the Data Pre-processing System (DPS), which is part of the Data Capture Foundation (DCF). This application records activity logs, traces of communication, traces of the progress on the task and information about the group artefacts. From the student view, CMate initially provides 2 tools: a list of concepts suggested by the teacher and an onscreen keyboard for typing new concept or link names. Learners can create links between 2 concepts by dragging a concept and dropping it on another target concept, so creating a link that is then labelled. They can delete elements by dropping them on one of the pair of black holes situated on the corners of the tabletop (Fig. 8, left). The application allows a teacher to structure the concept mapping activity according to a script. For example, the concept mapping activity can be semi-structured into three stages: (i) brainstorming concepts at the tabletop; (ii) the linking phase in which users build relationships between concepts and, in the case of the classroom learning environment, (iii) a sharing phase, in one group’s concept map is transmitted to the vertical display so that the group can explain their work to the rest of the class.

5. Study 1: Single-tabletop instance

Our first instantiation of the TSCL model was deployed in a single-tabletop controlled learning environment. In this study, we addressed the following research question: can we provide teachers with key information to distinguish high from low collaboration groups by identifying patterns of interaction, based on their intertwined verbal and touch actions? Addressing this question can help build a system that may automatically provide information to classroom teachers about multiple groups, enabling them to decide which group most needs attention. In this section, we frame the study according to the elements of the TSCL model and we also demonstrate the operationalisation of our model to analyse collaboration at a single tabletop.

5.1. Context of the study

A total of 60 students (30 males, 30 females, age range 21–30, mean age 25), mostly enrolled in science undergraduate courses, participated in a study. They were organised into 20 groups of 3, with varied gender and age composition (Fig. 8). Their learning goal was to enhance and share their understanding about the

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3 An earlier version of parts of the work in this section was reported in Martinez-Maldonado et al. (2012). In the current paper the study is now linked to the TSCL model and additional details regarding the evaluation of an automated approach to detect levels of group’s collaboration using a larger dataset are included (in Sections 5.1, 5.2 and 5.4).
types of food that should be included in a balanced diet, as recommended by the Dietary Guidelines 2011 published by the National Health and Medical Research Council of Australia. First, each student read the guidelines and then created a concept map to represent their individual understanding. Each student worked alone, reading the guidelines and creating a map using a desktop editor called CmapTools (Novak and Cañas, 2008). For this, they were provided with the guidelines summary and received basic training in building concept maps. Then, students were organised into groups of three and were given 30–35 min to build a joint concept map at the tabletop.

5.2. Distinguishing from groups’ high and low collaboration

There has been considerable work where a human observer has coded the collaboration level of learning groups, using aspects such as those of Meier et al. (2007). We used a similar approach to establish a ground truth assessment of collaboration. We then set out to determine whether we could automatically create similar assessments of collaboration without that expensive human coding, but exploiting the digital footprints of the SS in TSCL.

Two different raters tagged the group sessions following the method proposed by Meier et al. (2007) which quantifies nine qualitative dimensions of collaboration. These are: mutual understanding, dialogue management, information pooling, consensus, task division, time management, technical coordination, reciprocal interaction and task orientation. Each dimension is coded as a number between –2 (very bad) and 2 (very good). We summed the nine dimensions to obtain a single score. Groups with an overall negative score were considered as having low collaboration (10 groups had scores ranging from –10 to 0). Groups with positive scores were considered as having high collaboration (10 groups had scores ranging from 5 to 19). Inter-rater reliability was high – Cohen’s $k=0.80$. This qualitative rating scheme was useful to generate a quantitative measure to distinguish the groups. However, it still has the limitation of requiring human judgement.

5.3. Design

This section illustrates how we created and evaluated a set of Group Indicators (GI) that indicates whether a group appears to be collaborating well. Our goal was that these GI’s should be suitable for a glanceable display. This means that a teacher can gain benefit from a quick glance at it. Our design goal was for a visualisation which enabled a teacher to assess whether each group was either collaborating effectively or seemed in need of their attention. The requirement for a glanceable display is that it should convey information that is minimalist and specific, designed to enable users to absorb it without having their attention distracted from foreground teaching tasks (Weiser and Brown, 1996). Verbal and physical actions are captured by CollAid (Data Capture Foundation). The analysis (Data Analysis Foundation—DAF) is based on grouping and data mining techniques. Then, we used a set of visualisations to show student information to teachers (Data Presentation Foundation—DPF). We evaluated whether teachers could identify the groups that needed attention, based on looking at the visualised GI’s data only.

It is challenging to define ways to present the information about group collaboration in a manner that is easily understood and useful for educators. For this reason we decided to include teachers, experienced in classroom collaboration, in early stages of the design of the presentation tools. Part of this early stages of the iterative design was reported in Martinez-Maldonado et al. (2011b). Four teachers were involved in the design process that consisted of a series of unstructured interviews, prototypes and empirical evaluations of both the visualisations and the tool interface. Features that classroom experts believed should be useful in a truly effective educational awareness tool included those for: identifying learners (accountability, one of the key principles of social translucence introduced by Erickson and Kellogg (2000)), those who are not contributing to the group, individuals who are dominating and controlling the activity (similarly to those visualisations proposed by Kay et al. (2006) and implemented by Upton and Kay (2009)); groups that are working independently; or collaboratively (similarly to indicators of collaboration proposed by Streng et al. (2009)). As a result, we designed a visualisation tool to enable teachers to determine whether groups or individual learners need attention.

For this study, teachers suggested that presenting too many visualisations at once would make the dashboard difficult to understand. For evaluation purposes, our tool displays sets of three visualisations of group Indicators per group, with up to three groups at a time. Fig. 9 shows an example of how the user interface looked at minute 12 for three selected groups. The indicators of the group in the first row are for a group with one group member less active than the other two (a free-rider). The Indicators in the second row are for a group whose group members mostly worked independently. We now explain the design of each of the visualisations in this visualisation tool.

5.3.1. Indicator of collaboration

This indicator shows the current “level of collaboration” detected by the system. Inspired by the metaphors used by Streng et al. (2009) to represent the quality of collaboration, we designed a simple metaphor of an o-meter to indicate the level of collaboration of a small group working at the tabletop. To determine the level of collaboration, we used an external Model of

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Group Work proposed in Martinez-Maldonado (2014). This model was trained on a dataset captured from a multi-display setting and it was further extended to multi-touch tabletop systems. This model can classify each time-period of group work, based on a Best-First decision tree that considers a set of features of verbal and physical activity. It was implemented as follows:

1) the audio and touch actions of each triad are grouped into blocks of time \( t = 30 \text{ s} \);
2) a defined set of indicators of interaction is calculated per block, including: total time of all learners’ speech, total number of utterances, distribution of verbal participation among the students measured with the Gini coefficient (symmetry of speech), total number of touch actions and symmetry of these actions;
3) the generated decision tree classifies each block based on these features, as matching one of three possible values: high (H), medium (M) or low (L) collaboration; finally, 4) the group is labelled overall as having either high or low collaboration based on the proportion of blocks that appears more often.

The more blocks of information that are obtained from group’s activity, the more accurate the classification. The visual indicator shows the accumulated value of these labelled episodes. The arrow moves further to the right as there are more collaborative blocks (e.g. Fig. 9, row 2, first visualisation) or to the left with more non-collaborative blocks (e.g. Fig. 9, row 1, first visualisation).

5.3.2. Indicator of interaction with other’s objects

Studies with students working at tabletops have confirmed that interacting with objects that others have created may trigger further discussion that is beneficial for collaboration (Fleck et al., 2009). Inspired by the sociograms used to represent student’s interaction in CSCL (Jermann et al., 2009) and similar connected node-graphs used to represent interactions between group members (Kay et al., 2006; Kim et al., 2008), we designed a way to visualise the cumulative number of interactions by each learner with other student’s objects at the tabletop (see visualisations in Fig. 9, column 2). The size of the circles indicates the amount of physical activity (touches) by each learner. The width of each line that links these circles represents the number of actions that one learner performed on the concepts or links created by another learner. The colour shows the direction. For example, in Fig. 9, row 1, second visualisation, the top, yellow learner at 12 o’clock has lines to both the other two learners, indicating they acted on both these learner’s objects. But the green learner at 4 o’clock has only a very thin line to this learner. The red learner did not interact with the other two learner’s objects at all (no red lines going to any of the two learners). By contrast, in Fig. 9, row 2, the second visualisation, shows that all three students interacted with their peers’ objects (lines going from and to all the learners). Finally, in Fig. 9, row 3, the second visualisation shows high levels of activity of the students (large circles), but this is mostly on their own objects (almost no lines connecting circles).

5.3.3. Mixed indicator of participation

Groups in which learners participate asymmetrically are often associated with cases of free-riding or disengagement, while collaborative groups tend to allow contributions by all members (Dillenbourg, 1998). This is especially important in activities in which group members are supposed to have equal participation, as is the focus of this work. The mixed indicator of participation visualisation is inspired by the social proxy presented by Erickson and Kellogg (2000). It is the second prototype, building on results of a study presented in Martinez-Maldonado et al. (2011b). This indicator models the accumulated amount, and symmetry, of physical and verbal participation (see Fig. 9, column 3). The triangles (red and blue) depict the number of touches and amount of speech by each learner. Each coloured circle represents a student. The closer the corner of the triangle is to the circle, the more that student was participating. If the triangle is equilateral, learners participated equally. For example, in Fig. 9, row 1, third visualisation, we can see that the red learner had a very low level of participation in both dimensions (speech and touches). In Fig. 9, row 2, third visualisation, even though the triangles are not perfectly equilateral, the three students have similar level of participation, with the red learner more talkative than the other two (the blue triangle comes closest to the red circle). In Fig. 9, row 3, third visualisation, we see a different balance of speech and touches. The red learner focused more on the construction (touches), largely without taking. Meanwhile, the yellow and
green learners talked, both to a similar extent, but showed less tabletop activity than the red learner.

5.4. Results

First, we evaluated the classification model that is used to generate the indicator of collaboration visualisations (the leftmost ones, in Fig. 9). To evaluate this model, we assessed whether it provides useful information about group collaboration by comparing the automatic indicator with the qualitative observations for each group. The classification model was used to tag each of the half minute blocks of tabletop activity for all the 20 triads (60–70 blocks of 30 s for each group). Then we counted the number of either collaborative or non-collaborative blocks. Seventeen of the twenty group sessions (85%) were correctly identified by matching the groups that have a majority of either highly or not very collaborative blocks with their qualitative assessment described in Section 5.2.

Additionally, Table 4 shows the distribution of blocks, according to each group’s overall collaboration level. We can see that the algorithm classified more highly collaborative blocks for the high collaboration groups, compared with the low collaboration groups ($f(17) = 2.29, p = 0.034$), with 30, 17 and 12 blocks classified as high, medium and low collaboration. Groups with low collaboration levels had somewhat more medium than low collaboration blocks, but very few highly collaborative blocks ($H = 8, M = 35, L = 29$). There was a significant difference for low collaboration blocks in low collaborative groups compared with the highly collaborative ones ($f(15) = 2.4, p = 0.02$). These results indicate that it is possible to automatically achieve approximate detection of the overall level of collaboration, even with simple rules that make use of just quantitative indicators from the sensors we had available. This validation considers all of the group activity data, after the task has finished. However, we need to assess the usefulness of both this and simpler indicators, for classroom use. This must be early enough in the learning activity, for the teacher to usefully intervene with groups that may have problems.

In order to tackle this, we assessed the impact of providing teachers with the visual representations of students interwoven verbal and touch actions. Eight teachers (6 males and 2 females) participated in these evaluation sessions. All teachers were experienced in small group classroom collaboration at tertiary education-level and had taught science or engineering courses. None had been involved in the design of the visualisations. We measured the usefulness of our visualisations by asking participants if they can identify the groups that appear to have problems in collaboration and that would be candidates for intervention by the teacher. The data recorded from four selected groups was used. These groups were chosen as representative of four distinctive group behaviours. Based on the video observations, these groups’ behaviours can be described as follows: Group A performed best in terms of collaboration; we call this the Even group. Students discussed their ideas, worked together to build the group concept map. They completed the task sooner than the other groups and their final solution was simpler.

By contrast, each member of Group B worked independently most of the time, building three different concept maps rather than combining perspectives into a shared map; we call this the Independent work group. Group C was distinguished by the dominance of a single student, who lead the discussion, took most of the decisions and ended up building most of the group map without considering other’s perspectives. We call this the Dominant group. In Group D, only two learners collaborated to merge their ideas. The third learner did not contribute to the group effort and had lower levels of participation – free-riding; we call this the Free-rider group.

For the evaluation, we used the 3-group class dashboard. This simulated the real-time generation of data for the teacher, as if he or she was monitoring three groups over the 30 min sessions (for example, the snapshot of this dashboard shown in Fig. 9 at minute 12). Our 4 groups were cross-distributed among teachers so that each group was monitored by 6 teachers. The evaluation recreated the classroom orchestration loop described by Dillenbourg et al. (2011): teachers monitor the classroom, compare it to some desirable state, and intervene to mentor students. This was adopted as follows (with teachers asked to think aloud throughout the study):

1. First, teachers were asked to explore the visualisation tool, verbalising their interpretation of each visualisation.
2. Then, they were asked to state whether each group was collaborating.
3. As appropriate, they were asked to select the visualisations (by touching on them) that indicated to them that a group might have issues in terms of collaboration.
4. As appropriate, they were asked to choose one group (or none) that they would attend to at that “moment”, explaining which visualisation(s) helped them to make that decision.
5. Then teachers were asked to wait 2 min, simulating time spent working with the group, to then continue the process (from Step 1) through the 30 min of groups’ activity.

During the 2 min that teacher waited, and before re-starting the orchestration loop (step 5), they were prompted to review more detailed information about the chosen group. A detailed report of this is out of the scope for this paper as it did not affect the teachers’ decision making process. Results can be consulted in Martínez-Maldonado et al. (2012).

All teachers’ actions with the visualisation tool were logged and their think-aloud speech recorded. Results of the teacher’s actions using the tool, following the simulated orchestration loop described above, are shown in Table 5. These indicated that teachers would focus most of their attention on groups B and D (investing 44% and 40% of their time on average on them). From their think-aloud statements, they correctly identified independent work and the presence of a free-rider as their major issues. They indicated that the increased attention dedicated to those groups “would have helped to see what students were doing and encourage them to work more collaboratively” and “share their ideas with others”.

<table>
<thead>
<tr>
<th>Group</th>
<th>Attention</th>
<th>$K$</th>
<th>Observations based on the videos</th>
</tr>
</thead>
<tbody>
<tr>
<td>A</td>
<td>2 (s=1)</td>
<td>15% (s=7)</td>
<td>0.7</td>
</tr>
<tr>
<td>B</td>
<td>7 (s=2)</td>
<td>44% (s=7)</td>
<td>0.4</td>
</tr>
<tr>
<td>C</td>
<td>5 (s=1)</td>
<td>31% (s=6)</td>
<td>0.5</td>
</tr>
<tr>
<td>D</td>
<td>6 (s=3)</td>
<td>40% (s=13)</td>
<td>0.5</td>
</tr>
</tbody>
</table>

Table 5 Teachers attention per group. $Att=$Average number of times each tutor decided to monitor that group. $Att\%=$Average proportion of $Att$. $K=$Inter tutor agreement (Cohen’s kappa).
Group B gained a similar level of attention (31% of attention per tutor). In fact, the difference in the attention across these three groups was not significant (p > 0.05). By contrast, for all of the tutors Group A was “clearly performing well” and teachers would not have intervened (average of 2 visits per tutor). The difference between the attention provided to the other groups and Group A was statistically significant (p ≤ 0.002). Inter-tutor agreement was calculated to examine how different the observations were. Table 5, Column k (Cohen’s kappa) shows that the 6 tutors moderately agreed on which group most needed attention and when they needed it either at the beginning, in the middle or by the end of the task – k > 0.4 (with each of the sessions divided into three periods of 10 min each to cover the 30 min of each session).

5.5. Discussion

Through this first instantiation of our model, we demonstrated how the components of TSCL can potentially operate to automatically provide useful information to teachers. The Data Capture Foundation (DCF) was operationalised in the CollAid Sensing System, the internal Data-preprocessing was performed by the host concept mapping application (CMate) and the Central Repository synchronised and stored the sensing data coming from multiple sources: audio, touch and application log records. The Data Analysis Foundation (DAF) in this instance included the models obtained from a data mining classifier and simple agglomerative data analytics (of touch and audio). Then, we designed and implemented a visualisation tool with three different visualised group indicators, each showing a different aspect of collaboration to the teacher: overall level of collaboration as assessed by the system, interactions with other’s objects and symmetry of touch and talk. These are illustrative of the kind of support that can be offered to teachers as part of the Data Presentation Foundation (DPF). Importantly, we required that the information about students was differentiated; otherwise, it would have been impossible to model collaboration and show the kind of visualisations we created. Overall, the evaluation showed both the feasibility of creating a system that implemented the TSCL and also, that the information provided to teachers can enable them to identify groups’ collaboration levels at a glance. This study also formed the basis for our next classroom-level study in-the-wild that is described in the next section.

6. Study 2: Multi-tabletop instance

A second TSCL instantiation was deployed in the multi-tabletop classroom environment.2 The key difference from the earlier study is that we created the infrastructure to support a full class, with multiple tabletops, as well as a wall display. We designed the actual interfaces and systems in collaboration with the teacher to ensure that her pedagogic goals were served.

The study focused on understanding how the teacher can use a set of awareness tools during authentic classroom activities. We now describe how the students’ data, that was automatically captured, was processed to produce real-time group indicators, displayed in a teacher’s dashboard. In this way, we frame the classroom study in terms of the TSCL model and demonstrate a second realisation of TSCL, this time to help a teacher manage their time and provide feedback to multiple small-groups effectively in the classroom.

6.1. Context of the study

This study assessed the impact of providing information to a teacher during the classroom session by providing visualisations that contain key information about each group’s task progress and participation. The study highlights both the Data Analytics Foundation (DAF), to automatically distil student’s information; and the Data Presentation Foundation (DPF), which was implemented as a glanceable dashboard display, the MTDashboard. Teachers can configure the dashboard to display a visualisation of each group’s activity, as shown in Fig. 10. Two visualisations were explored in this study as the teacher who participated in this case requested information that would enable her to identify groups or group members who may have low levels of participation or task performance. The dashboard also provides control functions that enable the teacher to manage the macro-script of the activities (Fig. 10A1 and A2); Block, Unblock or reset all the tabletops at once (Fig. 10A3–A5); Broadcast sent one of the pre-defined messages to all the tables (Fig. 10A6); or guiding whole-class reflection by showing a specific table content to a class wall display (Send to Wall buttons) and Clear the wall (Fig. 10A7).

Two different conditions of the MTDashboard were used across the 8 tutorial sessions of a university class. For Condition 1, the dashboard had the Group Map Indicator showing the size and distance of each map from the teacher’s map (Fig. 11—condition 1 shows one example for a group that had created 16 propositions, of which 7 were from the teacher’s map). The circular shape of the visualisation was inspired by previous visualisations used to indicate the progress of students in a task using interactive tabletops (Kharrufa et al., 2010; Martinez-Maldonado et al., 2011b). The information about student’s map size and distance to the teacher’s perspective was explicitly requested by the teacher because she wanted to have a measure, showing the quality of concept mapping that is not normally available in the limited classroom time. The teacher’s reference map was drawn by the teacher before the enactment of the tutorials. This contained the propositions that the teacher considered important for students to include in their maps.

For Condition 2, the dashboard had the Indicator of Physical Participation (third iteration), which was designed based on the visualisations explored in Study 1. This visualisation shows the number of touches on the tabletop per student and the equality of touch actions among group members (Fig. 11—condition 2). For these tutorials the teacher indicated that “quantitative information about student’s actions would be useful for identifying participation”. A larger range of visualisations (some more elaborated) was offered to the teacher (including those in the previous section), but she did not want them.

The 8 tutorials were run in the middle of Semester 2, 2012, for a course titled “Management and Organisational Ethics” in the University of Sydney (this corresponds to the 6th week of the 13 weeks of the course). All these were conducted by the same teacher. A total of 143 students (73 males, 70 females, age range 19–25) attended these tutorials. Each tutorial session had 15–20 students. The teacher arbitrarily formed four groups, with 4 or 5 students at each table. Most students were enrolled in Business and Management courses. All the students knew each other. The teacher designed a problem-posing activity to cover the set topic, set in the curriculum for that week. The class time was fixed at 50 min. The learning activity was a case-resolution problem, in the context of organisational ethics. Students were requested to create concept maps for their solution to the posed-problem (using CMate as the host application in each tabletop).

6.2. Design

When teachers orchestrate multiple groups in the classroom, one of their challenges through the class is to identify the group

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2 An earlier version of parts of the work in this section was reported in Martinez-Maldonado et al. (2013). In the current paper the study is now linked to the TSCL model.
that most needs immediate attention (Dillenbourg et al., 2011). At the same time, they aim to spend a relatively balanced amount of time with each group, to be fair to all students and to maintain awareness of the work of each group. This is where MTDashboard can provide awareness support for the teacher, aiding them in making an informed decision about which group to attend to next. Following on from the previous study, we sought to address the question: \textit{How did the information provided to the teacher affect the attention given to “lower achieving” groups in the classroom?}

\subsection{Data collection}

In this case, the Data Capture Foundation (DCF) implemented functionalities for the automatic capture of synchronised logs from the host application at each tabletop (differentiated student’s actions and partial states of the concept maps), logs of teacher’s actions using the MTDashboard, and partial distances of group artefacts to the teacher map. In addition, we manually captured data based on the observed time and duration of the particular times when the teacher: (i) attended to or intervened with a group, (ii) looked at the MTDashboard, (iii) spoke to the whole class, and (iv) walked around the class or did not look at any specific group. These observations were logged and captured through a console synchronised with the application logs. A second set of observations consisted of quantitative assessments of perceived qualitative collaboration per group based on an adapted rating scheme (Meier et al., 2007) similar to the one described in Section 5.2. For this classroom context, we modified Meier et al.’s scheme to have only 4 dimensions of collaboration, quantified from –2 to 2, for each of (a) mutual understanding and dialogue management, (b) information pooling and consensus, (c) task division, time management and technical coordination, and (d) reciprocity. We simplified this schema to allow a single observer to feasibly collect this qualitative information from multiple groups in the classroom. This assessment is not exhaustive but it served to provide an independent, secondary measure of each group’s level of collaboration. In addition, the teacher also assessed groups at the end of each tutorial, using one of three possible values: low, medium or high achieving. Finally, we conducted semi-structured post-tutorial interviews with the teacher to obtain feedback on the functions and visualisations provided for classroom orchestration.

\subsubsection{Distribution of teacher’s attention and intervention}

To analyse the teacher’s attention distribution, we first define the terms \textit{attention} and \textit{intervention} in this context. We consider that a teacher pays attention to a group when their gaze is focused on that group (Fig. 12, left). Intervention is the subset of such attention that happens only when the teacher interacts with the group, therefore interrupting their work. We made this distinction based on our previous study in which the teacher stated that for some outstanding groups they would “see what they are doing” but mostly leave them work by themselves.

During the post-tutorial interviews the teacher commented that she “tried to provide equal attention to all groups”, while “focusing on groups that needed more help”. This means that the teacher dynamically chose the order in which she attended to each group. Having made this distinction, we now describe an example of the teacher’s actions at the MTClassroom.

Fig. 12 (right) shows a transition diagram where the nodes represent the elements that were at the focus of teacher’s attention in one class. The nodes correspond to each group, the MTDashboard or the whole Class. The Class node includes the times when the teacher was not attending to any particular group or was giving a message to the whole class. The directed arrows between the nodes represent the transitions recorded by the external observer (45 transitions registered in this example). In this class the teacher devoted most time to the red group (32% of attention and 29% of intervention time) compared with the others (20/8, 26/16%, and 21/10% for green, yellow and blue tables). In fact, the teacher assessed the red group as the only low achieving group in the class. This confirms that the distribution of teacher’s attention in this class was not always balanced.

We also observed that the teacher never attended to the green group after looking at the dashboard (no transition line from Dashboard to Green node). Notably, this group also received the fewest interventions. This motivated the analysis of the rest of the
cases to find evidence that could help describe how the information delivered through the dashboard affected teacher’s attention.

6.3. Results

To answer our research question for this second study, we describe the decisions made by the teacher right after looking at the dashboard. There were 38 teacher’s actions that were captured by the external observer and synchronised with the MTClassroom’s logs (17 for distance from teacher’s map and 21 for physical participation conditions). We sought to assess if the teacher was giving more attention to the ‘lower achieving’ groups according to the information provided.

**Condition (i):** For each time that the teacher looked at the dashboard, and for each group in the classroom, we calculated the quantitative indicators of size and distance of the map, as available to the teacher in the Group map visualisation at that moment. Then, the groups were ranked from the smallest and furthest map from the teacher’s map to the biggest and closest map at that point in time. There were 3 possible ranks: furthest behind group(s), the strongest group(s), and the groups in between. The strongest group at any moment was the one with more important propositions and less irrelevant propositions according to the teacher’s map. Then, we identified the group that the teacher chose to attend to next. After this, we assessed the category of the group chosen by the teacher, for example, if the teacher chose the group that was furthest behind or a strong one.

Table 6 shows the results of this analysis. Column A corresponds to the 17 cases of teacher’s attention after inspecting the dashboard of the condition under analysis (i). Column B corresponds to the other cases where the second type of information was provided (ii). Results indicate that when the information about the map size and distance to the teacher’s map was provided (column A) the teacher only decided to attend to the strongest group 18% of the times (3 out of 21). By contrast, when this information was not provided, the teacher attended to the strongest group 43% of the times (9 out of 21). This suggests that the information about each group’s artefact had some impact on the teacher who participated in the case study to decide which group to attend to next. In the post-tutorial interviews, the teacher described how she used the Group Map Indicator by stating that “looking at the number of relevant links added by each group [gave her] a better idea of the group’s performance”.

**Condition (ii):** We calculated the information provided by the visualisation radar of physical participation for the 38 cases when the teacher looked at the dashboard in this condition. We had the same 3 possible ranks. In this case, the strongest group was the most equal in terms of participation. We measured the rank using an index of dispersion, the Gini coefficient. This is a number between zero and 1, where zero means perfect equality of student’s participation. We followed the same process as the previous condition.

The results are shown in Table 7. These suggest that the participation radar, at least in the way in which we presented it, did not influence the teacher to make decisions about which group to attend to next. The teacher decided to attend to groups with low or high levels of equality at almost the same levels (33%, 38% and 28% of the times). The post-tutorials interview confirmed that the teacher did not use the information about physical participation, justifying this with the argument that “not everyone was touching the tabletop but they were speaking a lot and this is good from a learning perspective”. The teacher also commented that this information “would be very helpful in a bigger class”. The teacher described this as follows: “I cannot observe 80 people but I can...
observe 20 people, I could tell who was talking. It would be fantastic to check the participation information for a bigger group”. Further research is needed to gain deeper understanding of the impact of different visualisations on the teacher’s decision making process and how differently teachers react to the information provided.

6.4. Discussion

In this second study we demonstrated the feasibility of using our TSCL model for the design of awareness support for the teacher in authentic classrooms. We additionally described how a teacher used indicators of small group collaboration that were provided by our implementation of the components of TSCL. We showed the implementation of the Data Capture Foundation (DCF) in the form of the MTClassroom itself, and the Data Analytics Foundation (DAF) by the provision of the mechanisms to generate real-time, minimalist, small-group visualisations for the teacher’s dashboard. Regarding the Data Presentation Foundation (DPF), we found in our case-study that different data presented to the teacher in the classroom directed her attention for the particular case when information about the quality of students work was delivered. The teacher described this as follows: “I think the dashboard was really good, especially because it showed things about the quality of their work. If I hadn’t had this information about the relevant links then I had to look at the whole diagram so it would take longer to look at each map”. Indeed, like many complex learning artefacts, the concept map that a group produces requires some time for a teacher to identify important features. In this case, it called for finding those propositions the teacher identified as crucial. The teacher also suggested that she would value indicators of group work and individual participation for post-hoc analysis. She described this as follows: “…more information can be provided after the tutorials for assessment, like who did what, when, and the quality of the work”.

7. Conclusions

Interactive tabletops can be used in a wide range of learning contexts. For example, they can be used in connected small group activities in the classroom for a number of sessions. In this case, the teacher would be the main user, harnessing the data made available by tabletops to help students achieve the learning goals. The visualisations can be used in training settings, for example, where a single group of people engages in a collaborative activity. Another scenario would be the long-term series of group tasks performed by a team working on a project. In this case, learners would be interested in the affordances of tabletops to keep track of their milestones and products. In all such cases, the teachers, designers or researchers (the users) can perform, orchestrate, design or analyse, respectively, the learning activities according to the affordances and/or limitations offered by the multi-touch tabletop technologies. Further work should be done to explore how to extend this to deliver valuable information to students.

This paper presented the Tabletop-Supported Collaborative Learning Conceptual Model (TSCL) which establishes the forms of student data that can usefully be captured, filtered, processed, analysed and shown back to the users of the learning environment to enhance the collaborative processes. The model is strongly influenced by theories and principles from the CSCL field, as well as Educational Analytics and HCl. The model has three operational components, dealing with the data capture, analysis and presentation of key indicators to teachers, students, designers, researchers.

The TSCL model, can be used as a basis to build supportive tabletop-based learning systems. The aim of the formulation of this model is that interactive tabletops can offer enhanced affordances that the multi-touch hardware itself cannot provide. In general, the TSCL defines the elements that are needed to enhance the visibility of the learning processes occurring at the tabletop. For example, so that the users can be more aware about learner’s contributions, these include equality of the participation, possible problems faced by students or trends in the collaborative interaction. In all cases, the goal of the system is to provide support to the group of learners via student’s self-reflection, teacher’s actions, improved system design or even automated systems actions.

We demonstrated the feasibility of the application of the TSCL to provide teachers with valuable student information in two specific learning contexts: a single-tabletop setting and a multi-tabletop classroom. We reported evaluations of these in terms of the elements of the TSCL model. Our first study, under experimental conditions, captured rich data about learners’ collaborative interactions, based on traces of differentiated speech and physical actions on the interactive tabletop. Using a machine learning algorithm and basic visualisation techniques, we created visualisations of data that characterised valuable aspects of collaboration in a class with three groups working at tabletops. We assessed their meaningfulness and usefulness in identifying problems in group collaboration, with 8 teachers. For this study, the tool simulated the concurrent generation of student’s logs to give teachers a real sense of the use of the visualisations in a classroom environment. Authentic data was used in all cases. We found that these visual representations of student’s collaboration enabled the teachers to accurately identify likely collaboration problems in groups. Teachers agreed and were able to identify the low achieving groups that needed closer attention and help based on inspecting only the visual group indicators provided.

Our second study demonstrated the feasibility and usefulness of deploying a solution based on the TSCL model in-the-wild. Applying the lessons learned from the first study, we implemented this solution to enhance teacher’s awareness in the classroom. In this case, the sources of information included differentiated application logs, comparison measures of the group’s artefact with the teacher’s, activity logged through the teacher’s dashboard and logs of the teacher’s activity recorded by an external observer. We found that presenting different group information through the dashboard had a significant impact on the teacher’s classroom awareness and the ways she distributed the attention among groups. This teacher wanted information about the quality of student’s artefacts, particularly as such information is not readily available to a teacher in a timely fashion that fits tightly limited classroom time.

7.1. Implications for the implementation of the TSCL

The first challenge to implement the TSCL is posed by the current limitations of surface devices, which generally offer only basic functionalities for capturing users’ actions. The importance of this limitation has motivated considerable exploration of ways to overcome it (Annett et al., 2011; Ballendat et al., 2010; Dietz and Leigh, 2001). However, the core requirement for user differentiation is not currently provided by the widely available of hardware tabletop products (Blazica et al., 2013; Clayphan et al., 2013). Beyond the data capturing hardware limitations, a second challenge is that there is little research on guidelines to provide effective solutions that foster collaborative learning in authentic learning contexts. Scott et al. (2003) presented a series of design guidelines for tabletop-based systems that support general collaborative work in a mono-tabletop situation. Although useful, these guidelines are not sufficient for multi-tabletop environments, where multiple small-groups are collaborating in parallel, and which are most likely to be used in real learning scenarios. Some
recent work presented a series of guidelines, based upon success-
fully deployed tabletops in the classroom (Kharrufa et al., 2013b).
However, design guidelines for mining or analysing collocated
lerning data do not exist yet. Nor are there guidelines for designing
enhanced support and awareness tools for the actors in the
learning processes. The TSCL makes a step forward, providing
scaffolding to design such tabletop-based systems.

7.2. Limitations and future work

The visualisations presented in this paper are not intended to
be the final word in ways to present collaborative learning activity.
Nor can we claim that they are generalisable to other contexts. We
presented the two studies to show the kinds of information that
are now available for teachers and the teacher in all the class
sessions. Further work should test the system against a control condion
where the technology is not used.

Finally, future work on this strand of research should include
the exploration of the implementation of the TSCL model to target
other actors of the collaborative learning process, particularly the
students themselves. In another important direction, with all the
students’ information that can be captured from the enriched
tabletop environment, it should be possible for the system itself
to automatically generate alarms in case some unwanted group
behaviour or student’s clear misconceptions are detected.

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